

INDUSTRY 4.0 AND SUSTAINABILITY

Integrating Digital Technologies and Circular Models for a Sustainable Future



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Integrating Digital Technologies and
Circular Models for a Sustainable Future

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Preface

The Fourth Industrial Revolution has transformed the way the world conceives, designs, manufactures, distributes, and consumes products. Artificial intelligence, the Industrial Internet of Things, digital twins, additive manufacturing, blockchain, and advanced analytics have moved from intriguing possibilities to operational realities on factory floors and in supply chains across the globe. At the same time, societies are grappling with climate change, resource depletion, social inequity, and an imperative to decouple growth from environmental harm. This volume *Industry 4.0 and Sustainability: Integrating Digital Technologies and Circular Models for a Sustainable Future* emerged from the conviction that these two megatrends must be understood and steered together rather than in parallel. This book asks how digital transformation can become an engine of sustainable development rather than a catalyst of rebound effects, new inequities, or unanticipated risks. It also examines how sustainability goals can inspire new directions for digital innovation, business models, policy, and human-centered design.

The journey to this book began with a simple observation: although technical treatises on Industry 4.0 abound and sustainability research has matured into a rigorous, interdisciplinary field, few scholarly resources weave the two strands into an integrated narrative. The editorial team working across energy systems, advanced manufacturing, environmental engineering, and digital innovation witnessed this gap in our classrooms, research collaborations, and

industry engagements. We therefore sought contributions that would illuminate not only technical capabilities but also organizational, policy, ethical, and socio-economic dimensions. The response was remarkable: twenty-five chapters from five continents trace the arc from foundational principles through cutting-edge applications to forward-looking frameworks for a just and circular economy.

This book is organized deliberately to serve multiple readerships. The opening chapters ground readers in the fundamentals of Industry 4.0 and the sustainability imperatives facing contemporary manufacturing. Subsequent sections analyze enabling technologies—AI, big data, digital twins, additive manufacturing, blockchain, and predictive maintenance—linking each to concrete environmental and social outcomes. Later chapters explore organizational change, leadership, workforce development, and policy instruments that translate technological potential into real-world impact. The final portion of this book offers integrative perspectives, critical social analyses, life-cycle assessment insights, and empirically grounded guidelines that practitioners, policymakers, and researchers can adapt to their own contexts. Collectively, the chapters illuminate synergies between circular economy logic and advanced digital tools, while candidly confronting unresolved challenges, data gaps, and governance dilemmas.

We are particularly proud of the diversity represented in these pages. Authors hail from research institutions, start-ups, multinational manufacturers, governmental

bodies, and civil-society organizations. Many offer perspectives from emerging and middle-income economies where the stakes of sustainable industrialization are especially acute. Their voices underscore that inclusive innovation and equitable access must accompany efficiency gains if Industry 4.0 is to advance the UN SDGs and wider societal well-being.

This book benefited from the steadfast support of Elsevier's editorial team, whose guidance helped to refine the proposal and steer a large, distributed author group toward a coherent final manuscript. We are indebted to our contributing authors for their intellectual generosity, resilience in meeting tight deadlines, and commitment to interdisciplinarity. Without their expertise, this project would exist only as an aspiration.

We hope that readers whether academics seeking research frontiers, practitioners designing next-generation factories, or policymakers crafting innovation roadmaps will find in this volume both inspiration and actionable knowledge. The challenge before us is formidable: to harness unprecedented digital power in service of regenerative, circular, and socially just industrial systems. The editors offer this book as one step toward that goal and invite others to extend, challenge, and enrich the dialogue.

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Acknowledgment

The editors express their sincere gratitude to Elsevier for the opportunity to develop this volume, Industry 4.0 and Sustainability, and for the professional guidance provided by the editorial, production, and project-management teams throughout commissioning, review, and preparation. We also extend our heartfelt thanks to all chapter

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Fundamentals of Industry 4.0 and sustainability[☆]

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1.1 Introduction

The global manufacturing industry faces escalating pressure to balance economic growth with environmental sustainability, demanding a critical reevaluation of production and consumption patterns. This challenge is exacerbated by the escalating consequences of climate change, resource depletion, and ecosystem degradation, demanding a fundamental shift in how the goods are designed, produced, and consumed. Within this context, Industry 4.0, the ongoing Fourth Industrial Revolution characterized by the fusion of digital, physical, and biological systems, emerges not merely as a technological advancement, but as a potential catalyst for achieving sustainable manufacturing.

[☆] This chapter is adapted from the authors' previously published review (Khan et al., 2025).

The Fourth Industrial Revolution, commonly referred to as Industry 4.0, represents a transformational shift in industrial production driven by the integration of advanced digital technologies and intelligent connected systems across manufacturing value chains (Koh et al., 2019; Xu et al., 2018). While the economic and productivity benefits of Industry 4.0 have been widely discussed, its broader implications for sustainability have attracted growing interest in recent years (Berg et al., 2021; Ghobakhloo, 2020; Moeuf et al., 2020; Stock & Seliger, 2016; Varriale et al., 2024). Sustainability, in this context, refers to the balanced and efficient utilization of resources to meet present industrial and societal needs, while conserving the environment and ensuring economic viability, without compromising the ability of future generations to meet their own needs. As the world confronts escalating and interconnected sustainability challenges, from climate change to biodiversity loss, proponents argue that Industry 4.0 technologies, strategically implemented, can pave the way for a more environmentally responsible, socially equitable, and economically viable industrial paradigm (Bai et al., 2020; Javaid et al., 2022a; Tiwari et al., 2024). The potential for transformation lies in the specific capabilities of Industry 4.0 technologies, such as real-time data acquisition, resource optimization, and supply chain transparency, which require careful implementation to achieve sustainable manufacturing outcomes. For instance, real-time data acquisition and analysis, enabled by interconnected sensors and intelligent algorithms, can optimize resource consumption, minimize waste generation, and mitigate environmental impacts across the product lifecycle (Jena et al., 2020; Ren et al., 2019). The adaptability of smart factories, enabled by flexible production systems, may contribute to reducing overproduction by aligning manufacturing output more closely with real-time demand (Oluyisola et al., 2022; Zhong et al., 2017). Furthermore, the enhanced connectivity and transparency inherent in Industry 4.0 can facilitate the development of closed-loop manufacturing systems, promoting circularity and resource recovery, thereby minimizing waste and environmental impact (Bag et al., 2023; Schögl et al., 2023). Industry 4.0 technologies have been increasingly adopted by companies across various sectors to enhance customization, efficiency, and sustainability. For instance, Adidas' Speed factory in Germany exemplifies how Industry 4.0 enables mass customization through advanced robotics and 3D printing, allowing rapid production of personalized footwear (Galluccio & Agrell, 2022). This shift not only meets consumer demand for customized products but also significantly reduces production time and material waste. Similarly, Rolls-Royce has integrated predictive maintenance and real-time monitoring into their after-sales services for aircraft engines, which has significantly enhanced service capabilities and reduced downtime. Furthermore, General Electric (GE) has utilized digital twins (at its Nevada facility) and data analytics to innovate in industrial equipment design, reducing development timelines and improving product performance (Attaran et al., 2023). Similarly, Walmart's implementation of blockchain technology in its food supply chain has greatly improved traceability, ensuring product safety while minimizing waste.

Despite this promise, the relationship between Industry 4.0 and sustainability is complex and multifaceted (Aslam et al., 2024; Beltrami et al., 2021). Deploying Industry 4.0 technologies without adequate foresight risks exacerbating existing social and environmental challenges related to job losses due to increased automation, widening inequality, and rebound effects leading to increased consumption (Guenat et al., 2022; Kunkel et al., 2023). For instance, the increased computational power required for AI and data analytics can lead to significant energy consumption, potentially offsetting efficiency gains. Similarly, the automation of labor-intensive tasks, while increasing productivity, raises concerns about job displacement and social inequality.

Early studies primarily focused on conceptualizing the potential of Industry 4.0 technologies to enhance sustainability performance, often highlighting specific applications in areas such as energy efficiency (Chen, Sinha, et al., 2021; Matsunaga et al., 2022), waste reduction (Javaid et al., 2022a; Zhang et al., 2023), supply chain management (Fatorachian & Kazemi, 2021; Qader et al., 2022), and resource optimization (Kumar & Verma, 2023; Ocakci et al., 2023). For instance, researchers have explored the use of Internet of Things (IoT) for real-time energy monitoring and optimization (Hossein Motlagh et al., 2020; Wang et al., 2018), the application of AI-powered predictive maintenance to reduce downtime and material waste (Scaife, 2024; Shahin et al., 2023), and the role of additive manufacturing in enabling distributed production and minimizing transportation-related emissions (Huang et al., 2016; Peng et al., 2018). While these studies provide valuable insights into the sustainability potential of individual technologies, they often fail to account for the broader, more complex interdependencies among different technologies and sustainability dimensions. The existing literature indicates that Industry 4.0 technologies can potentially either enable or inhibit sustainability outcomes (Lange et al., 2020; Müller et al., 2018; Vinuesa et al., 2020). This dual potential underscores the necessity of adopting a holistic approach that goes beyond assessing individual technologies in isolation. A holistic perspective is essential to fully understand and harness the synergies between Industry 4.0 technologies while also identifying and mitigating potential trade-offs between environmental, economic, and social sustainability goals. Without such an integrative approach, there is a risk of unintended consequences where improvements in one area (e.g., energy efficiency) may lead to negative impacts in another (e.g., increased resource consumption).

To maximize the sustainability benefits of Industry 4.0, a multifaceted approach is required, one that aligns technological innovations with specific sustainability objectives, supported by appropriate governance frameworks and social considerations (Stock et al., 2018). However, much of the current literature continues to examine Industry 4.0 and sustainability in isolated silos, often neglecting the complex interplay between various technologies, sustainability dimensions, and organizational contexts. This fragmented approach limits our ability to fully grasp the broader implications of Industry 4.0 for sustainable development.

Developing comprehensive, integrative perspectives is therefore critical to direct ongoing Industry 4.0 transformations towards eco-friendly, socially equitable, and economically viable production systems. While the technological capabilities of Industry 4.0 have been extensively examined, their implications for sustainability remain less systematically investigated. Existing reviews often lack comprehensive analyses needed to capture the intricate relationships between Industry 4.0 technologies and sustainability outcomes across diverse organizational contexts. As the proliferation of Industry 4.0 technologies continues, it is increasingly important to adopt holistic frameworks that consider these complex dynamics. By elucidating the interrelationships between individual technologies, organizational factors, and the multifaceted dimensions of sustainability, future research can better inform strategies to leverage Industry 4.0 innovations for sustainable development.

This review aims to synthesize insights across the emerging body of scholarship situated at the intersection of Industry 4.0 and sustainability, providing guidance for strategies, policies, and future research. Specifically, this review addresses the following key questions:

- What are the specific Industry 4.0 technologies with the greatest potential to enhance the environmental, economic, and social dimensions of sustainability in manufacturing?

- How can these technologies be strategically implemented to maximize their positive impact while mitigating potential risks and unintended consequences?
- What are the critical organizational, institutional, and policy factors that influence the successful integration of Industry 4.0 for sustainable manufacturing?
- What are the key research gaps and future directions that warrant further investigation to unlock the full potential of Industry 4.0 for a sustainable future?

1.2 The genesis and evolution of Industry 4.0

The term “Industry 4.0” originated in 2011 from a project in the high-tech strategy of the German government promoting the computerization and connectivity of manufacturing (Kagermann et al., 2013). This national initiative, bringing together companies, academia, and policymakers, highlighted the potential of emerging digital technologies like industrial Internet of Things (IIoT), artificial intelligence (AI), big data analytics, advanced robotics, additive manufacturing, augmented reality (AR), and cyber-physical systems to transform industrial production. There after the term and strategic vision of Industry 4.0 quickly proliferated worldwide (Ghobakhloo, 2018; Nascimento et al., 2019) as companies and governments pursued the tremendous productivity and competitiveness gains promised by the digitalization and automation of industrial operations (Da Costa et al., 2019; Roblek et al., 2016). The terminology was adopted as an umbrella construct representing the Fourth Industrial Revolution in manufacturing, building on three prior breakthrough phases—mechanization, mass production, and computerization (Lasi et al., 2014). Global technology giants like IBM and Cisco propagated the digital manufacturing revolution through international initiatives like the Industrial Internet Consortium, founded in 2014. Innovative manufacturers like Bosch, Siemens, and GE helped realize the Industry 4.0 vision through groundbreaking production pilot projects and testbeds (Hofmann & Rüsch, 2017). Fig. 1.1 illustrates the core components of an Industry 4.0 architecture spanning smart machines, products, controls, sensors, networks, and data analytics platforms. The main pillars of Industry 4.0 technologies can be broadly categorized into digital and physical technologies. Digital technologies primarily encompass modern information and communication systems that enable data-driven decision-making, real-time monitoring, and connectivity across industrial operations. They facilitate the seamless integration of digital and physical systems, leading to increased efficiency, transparency, and automation. Physical technologies, on the other hand, mainly refer to the hardware and engineering aspects of Industry 4.0, transforming traditional manufacturing processes into smart, automated, and adaptive systems. Physical technologies enable the real-time interaction between machines, products, and human operators, leading to enhanced flexibility and efficiency in production systems. The synergy between digital and physical technologies is what truly defines Industry 4.0, creating smart, interconnected systems that can autonomously optimize production processes. Table 1.1 provides an overview of key Industry 4.0 technologies, grouped under the digital and physical categories, along with their definitions.

The current Industry 4.0 transformation builds on three previous revolutionary shifts in industrial production driven by technological innovations. Fig. 1.2 illustrates the stages of

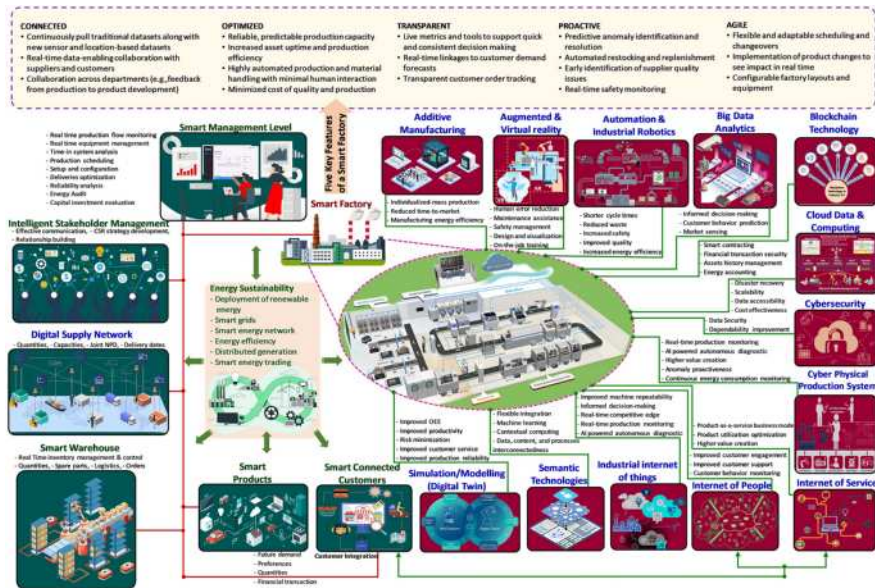


FIGURE 1.1 The schematic presentation of Industry 4.0 architecture. Source: Adapted from Burke et al. (2017); Conti et al. (2017); Ghobakhloo & Fathi (2021); FAS (2023); Ghobakhloo et al. (2021); Nagasawa et al. (2017); Qi & Tao (2019).

TABLE 1.1 Main pillars of Industry 4.0 technologies.

Technology	Category	Description
AI	Digital	AI involves the development of computational systems that can perform tasks normally requiring human intelligence, such as learning, reasoning, and problem-solving. AI technologies such as machine learning, natural language processing, and computer vision enable machines to learn from data and make decisions autonomously or with minimal human intervention.
IIoT	Digital	A network of interconnected devices, sensors, and machines within industrial settings that autonomously collect and exchange data in real-time, enabling enhanced monitoring, control, and optimization of industrial processes without the need for human intervention
DT and advanced simulation	Digital	DTs are virtual representations of physical assets, processes, or systems that mirror their real-world counterparts. Advanced simulation techniques leverage these digital models to predict behavior, optimize performance, and test different scenarios in a virtual environment before implementation in the real world.
Big data analytics	Digital	Big data analytics involves the processing and analysis of large and complex datasets to identify patterns, correlations, market

(Continued)

TABLE 1.1 (Continued)

Technology	Category	Description
		trends, customer preferences, and insights that can inform decision-making. This is achieved through the use of advanced statistical and machine learning techniques, such as predictive modeling, clustering, and decision trees, to uncover hidden relationships and correlations within the data.
Blockchain	Digital	A decentralized, distributed ledger technology that records and verifies transactions across multiple parties (a network of computers) in a secure, transparent, and tamper-proof manner. It enables the creation of a permanent, unalterable record of transactions, enhancing transparency, traceability, and trust in data management, eliminating the need for a central authority.
Cloud and edge computing	Digital	A technology that allows for the on-demand availability of a shared pool of configurable computing resources, such as servers, storage, networks, and applications, that can be rapidly provisioned and released with minimal management effort. This allows for scalable, flexible, and cost-effective access to computing resources over the Internet.
CPS	Digital-physical	Systems that integrate computational elements with physical processes, enabling real-time data exchange, analysis, and optimization of industrial processes, improving safety, efficiency, and productivity
AR/VR	Physical	AR involves the overlapping of digital information onto the physical environment, enhancing the user experience and improving decision-making, while AR technologies (e.g., smart glasses) enable the visualization of complex data, instructions, and guidance, improving productivity, quality, and safety
Advanced industrial robotics and automation	Physical	Involves the use of advanced robots and automated systems to perform tasks traditionally done by humans, enhancing efficiency, precision, and safety in industrial environments
Additive manufacturing (3D printing)	Physical	A process of building three-dimensional objects layer-by-layer from a digital design, enabling the rapid production of complex geometries and customized products with minimal material waste
Advanced sensors	Physical	Devices that detect and respond to physical inputs from the environment, such as temperature, pressure, or motion, and convert them into digital signals for monitoring and control of industrial processes, allowing for predictive maintenance, quality control, and optimized production
Drones	Physical	Remotely controlled or autonomous UAVs equipped with sensors and cameras, used for monitoring, inspection, transportation, and data collection in industrial environments, enhancing operational efficiency

AI, Artificial intelligence; *AR*, augmented reality; *CPS*, cyber-physical systems; *DT*, digital twins; *IIoT*, Industrial Internet of Things; *UAVs*, unmanned aerial vehicles; *VR*, virtual reality.

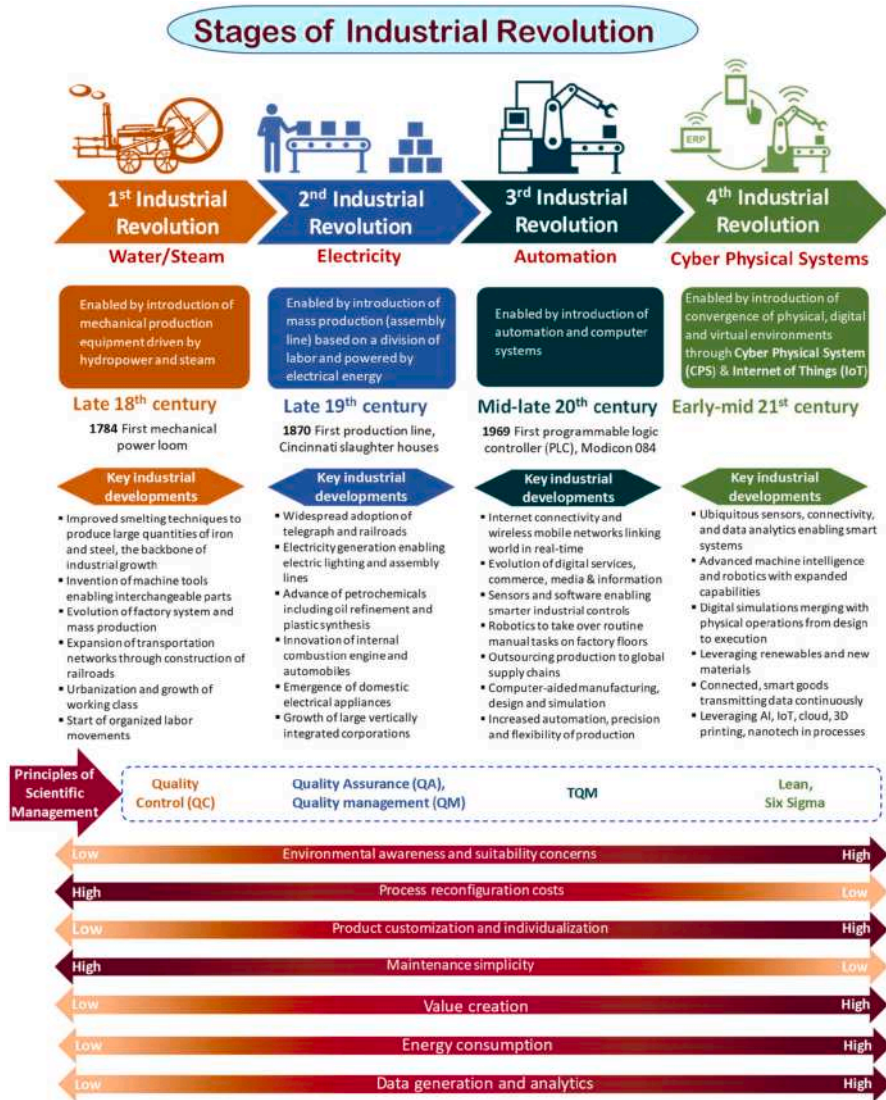


FIGURE 1.2 Stages of Industrial revolution from Industrial revolution 1–4.

industrial revolution and characteristics of each stage. While the exact boundaries between these phases are porous, each transition has ushered revolutionary shifts in industrial technology, processes, and value creation paradigms. The first industrial revolution displaced hand production through mechanization. The second enabled economies of scale via electricity and assembly lines. The third automated workflow uses electronics and IT. The fourth is creating smart, decentralized, and hyperconnected production systems powered by advanced algorithms, robotics, and real-time data integration.

The transition from traditional manufacturing to Industry 4.0-enhanced processes represents a paradigm shift in industrial production. Table 1.2 provides a comparison between traditional manufacturing processes and their Industry 4.0-enhanced counterparts across various operational dimensions. This comparison reveals significant improvements in areas

TABLE 1.2 Comparison of traditional manufacturing processes versus Industry 4.0-enhanced processes.

Sustainability metric	Traditional manufacturing	Industry 4.0-enhanced manufacturing
Energy consumption	- Typically higher energy consumption due to inefficiencies in processes, equipment, and facility management - Limited visibility and control over energy usage	Optimized energy consumption through real-time monitoring, predictive maintenance, and smart energy management systems
Waste generation and management	- Higher waste due to inefficient processes, defects, and lack of real-time monitoring - Limited traceability of waste and byproducts, hindering recycling and circularity efforts	- Minimized waste through demand-driven production, process optimization, and real-time quality control (e.g., reduced waste through additive manufacturing and AI-optimized processes) - Real-time data on waste generation and composition, enabling optimization of waste management processes - Enables circular economy principles through closed-loop manufacturing, product lifecycle management, and waste tracking systems
Resource utilization	- Suboptimal resource utilization due to inefficient planning, scheduling, and inventory management - Limited visibility into material flows and usage patterns across the supply chain	- Optimizes resource utilization through data-driven planning, real-time tracking, and automated inventory management - Implementation of closed-loop systems for resource recovery and reuse - Real-time data on resource consumption across the supply chain, enabling informed decision-making
Greenhouse gas (GHG) emissions	- Higher emissions due to inefficient processes and lack of real-time monitoring - Limited capabilities for emissions monitoring and reporting	Reduces emissions through optimized energy consumption and real-time monitoring, enabling proactive mitigation strategies
Operational efficiency	- Lower due to manual and semiautomated processes - Limited data analytics capabilities for process improvement	Enhances operational efficiency through automated workflows, real-time process monitoring, and optimization

(Continued)

TABLE 1.2 (Continued)

Sustainability metric	Traditional manufacturing	Industry 4.0-enhanced manufacturing
Production flexibility	- Limited flexibility to adjust production volumes and product variations due to rigid production lines and long lead times - Challenges in responding quickly to changing market demands	High flexibility with reconfigurable and adaptive production lines, and customization capabilities
Supply chain integration, efficiency, and resilience	- Fragmented supply chains with limited real-time visibility and collaboration among stakeholders, leading to inefficiencies and higher environmental impact - Lack of transparency and traceability makes it difficult to ensure ethical and sustainable sourcing practices - Slow response times to unexpected events, leading to production delays and increased costs	- Fully integrated, transparent, and traceable supply chains from raw materials to end products enabled by real-time visibility and collaboration among suppliers, manufacturers, and distributors - Increases agility and responsiveness to changing market demands and supply chain dynamics
Product lifecycle management	- Limited capabilities for tracking products throughout their lifecycle, from design to disposal - Challenges in implementing circular economy principles, such as product reuse and recycling - Lack of data on product performance and environmental impact over time	- Comprehensive product lifecycle management with digital product passports and closed-loop systems - Collects and analyzes data on product performance and environmental impact throughout its lifecycle - Facilitates product design for disassembly, remanufacturing, and recycling
Workplace safety and well-being	Higher risk of workplace accidents and injuries due to manual handling of materials, repetitive tasks, and exposure to hazardous environments	- Improves worker safety through automation of dangerous tasks, collaborative robots (Cobots), and real-time safety monitoring systems - Use of AR/VR for immersive safety training and hazard identification
Economic viability	- Potentially lower initial costs but higher long-term operational costs due to inefficiencies, waste, and downtime - Limited agility and responsiveness to market changes, potentially impacting profitability	- Increases economic viability through cost savings from optimized processes, reduced waste, and improved operational efficiency - Increases competitiveness with innovative business models and improved market responsiveness

Adapted from Arana-Landín et al. (2023); Centobelli et al. (2022); Duda et al. (2022); Ghobakhloo (2020); Ibarra et al. (2018); Javaid et al. (2022b); Jena et al. (2020); Kumar & Verma (2023); Matsunaga et al. (2022); Mohamed et al. (2019a); Rajab et al. (2022); Zeltst et al. (2020); Zonta et al. (2020).

such as production flexibility, resource efficiency, quality control, and supply chain integration. For instance, while traditional processes often rely on rigid production lines and manual quality checks, Industry 4.0-enhanced processes leverage adaptive manufacturing systems and real-time data analytics for optimized production (Javaid et al., 2022a) and predictive quality control (Lee, Lee, et al., 2019). These advancements not only boost operational efficiency but also contribute to improved sustainability outcomes by reducing waste, energy consumption, and resource use.

Industry 4.0 refers to the integration of advanced digital technologies such as cyber-physical systems, the Internet of Things (IoT), and big data analytics into manufacturing, with the aim of improving process efficiency, flexibility, and data-driven decision-making in production systems. It enables the creation of “smart factories” where physical machinery and digital processes are deeply integrated, allowing for intelligent optimization, flexibility, and transparency across industrial value chains (Castelo-Branco et al., 2019; Hofmann & Rüsch, 2017). While there is no universally accepted definition (Culot et al., 2020; Hofmann & Rüsch, 2017), Industry 4.0 broadly can be considered as set of technologies, devices and processes that enable integrated, self-sufficient production systems with decentralized decision-making and minimal human intervention across supply chain phases. Industry 4.0 is characterized by fuses four types of disruptive technologies across the physical, digital and biological realms (Agrawal et al., 2020; Hermann et al., 2016; Weyer et al., 2015; Zhong et al., 2017) (as shown in Fig. 1.3): (1) connectivity, data and computing power through innovations like cloud technology, the Internet, blockchain and sensors; (2) analytics and intelligence via advanced analytics, machine learning and AI; (3) human-machine interaction through virtual reality, robotics, and automation; and (4) advanced engineering with additive manufacturing, renewable energy and nanoparticles. This enables “smart factories” where physical machinery and digital processes are deeply integrated, allowing intelligent optimization, flexibility, and transparency across industrial value chains.

Fundamentally distinct from previous industrial revolutions, which centered on technological substitution, Industry 4.0 represents a managerial revolution focused on integrating disruptive technologies into existing assets and processes to transform operations, business models, and organizational capabilities. A key distinction of Industry 4.0 compared to prior industrial paradigms is the integration of digital technologies that enable and inform physical manufacturing processes within a continuous cycle known as physical-digital-physical (PDP) loop (Fig. 1.4). This closed-loop facilitates bidirectional flows of real-time data and intelligence between the physical and digital spheres, whereby the virtual digital environment monitors and optimizes physical operations, which in turn generate data to enhance virtual models. The PDP cycle marks a shift from linear manufacturing chains towards cyber-physical production ecosystems where interconnected digital and physical components interact dynamically. The convergence of physical and digital systems in Industry 4.0 thus enables more efficient, data-driven production processes, though the complexity of integration poses challenges related to infrastructure, security, and workforce adaptation.

This paradigm shift poses managerial challenges across three dimensions (McKinsey & Company, 2015): enhancing operational effectiveness through data-driven optimization, capitalizing on shifting value pools enabled by technology convergence, and laying digital foundations to transform legacy factories. Industry 4.0 technologies have the potential to significantly alter the relationships between manufacturing systems and their surrounding

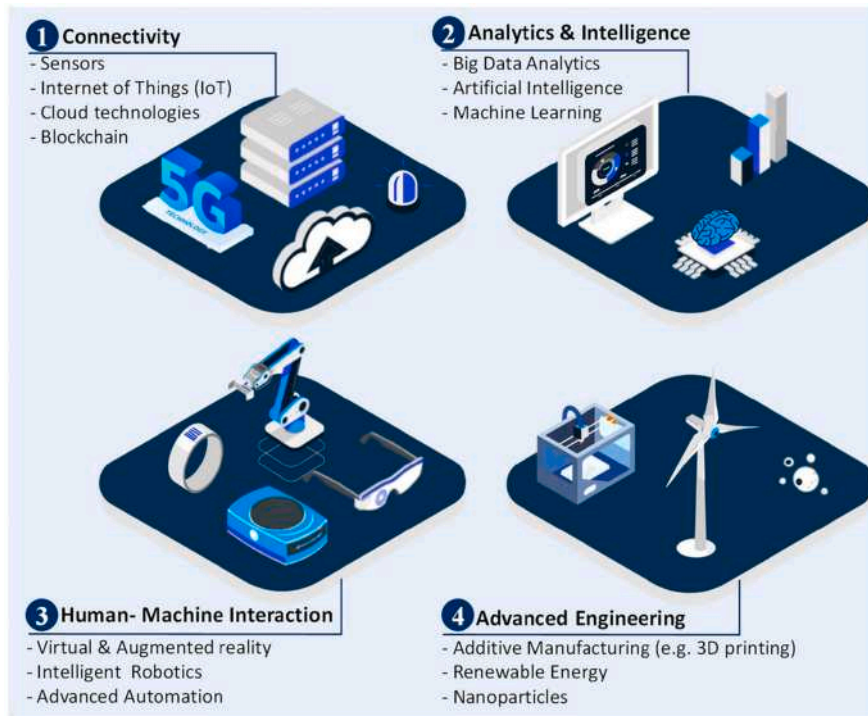


FIGURE 1.3 Industry 4.0 has four main disruptive technologies along the value chain. Source: Adapted from Agrawal, M., Eloat, K., Mancini, M., & Patel, A. (2020). *Industry 4.0: Reimagining manufacturing operations after COVID-19*. McKinsey & Company.

environments by enhancing resource efficiency, fostering closer integration with local communities, optimizing value chain operations, and improving human-machine collaboration (Stankovic et al., 2017); the factory and value chains by facilitating distributed, flexible, and collaborative processes for mass customization; and the factory and humans through advanced human-machine interfaces and improved working conditions (Stock & Seliger, 2016). Industry 4.0 encompasses developments across previously disconnected fields like AI, robotics, nanotechnology, 3D printing, genomics, and biotechnology (Stankovic et al., 2017). Illustrative examples include genome editing, new forms of machine intelligence, breakthrough materials, and cryptographic approaches to governance such as blockchain. The disruptive potential of these emerging technologies raises complex economic, legal, regulatory, and ethical challenges for existing governance models. In particular, Industry 4.0 is expected to substantially impact labor markets, global value chains, education, health, the environment, and broader economic and social aspects (Xu et al., 2018).

Unlike the widespread global diffusion of the third industrial revolution, the emergent Fourth Industrial Revolution centered on Industry 4.0 thus far remains concentrated in a handful of leading countries, underpinned by economies of scale (Freire et al., 2022). While building upon the digital infrastructure established during the third revolution, Industry 4.0 represents profoundly disruptive capabilities for integrating advanced technologies within

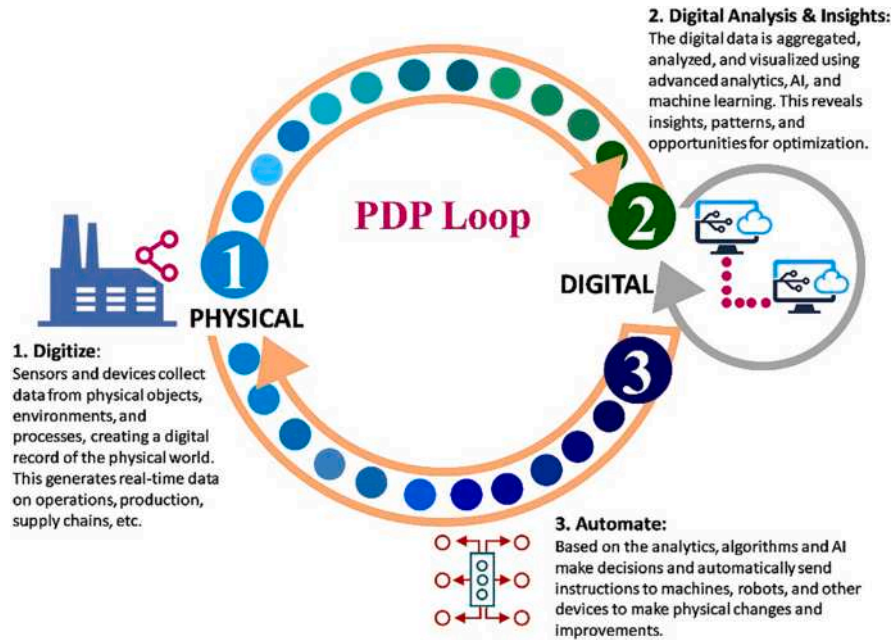


FIGURE 1.4 The core of Industry 4.0: the PDP loop (physical-to-digital-to-physical).

production systems, business models, societies, and even the human body (Stankovic et al., 2017; *The Fourth Industrial Revolution: what it means and how to respond*, 2016). Industry 4.0 encompasses innovations across previously disconnected domains, including AI, robotics, nanotechnology, 3D printing, genomics, and biotechnology. Salient examples include CRISPR genome editing, machine learning algorithms surpassing human capabilities, novel engineered materials like graphene, and distributed ledger approaches to governance such as blockchain. The ongoing maturation and convergence of these technologies is anticipated to broadly disrupt existing models of economic, legal, regulatory, and ethical governance (Stankovic et al., 2017). In particular, Industry 4.0 may significantly transform labor markets, education systems, global value chains, healthcare, environmental sustainability, and broader socioeconomic dimensions (McKinsey & Company, 2015; Stankovic et al., 2017). While digital technologies hold significant promise for enhancing sustainability, it is crucial to avoid viewing digitalization as a panacea. A fundamental paradigm shift, a “Digital Reset,” is necessary to redirect digital technologies towards supporting a deep sustainability transformation (Lange et al., 2022). This involves addressing the root causes of unsustainability rather than merely optimizing the existing, unsustainable status quo.

As Industry 4.0 reshapes the industrial landscape, understanding its core attributes becomes essential to examine its transformative potential. The convergence of advanced digital and physical technologies introduces a set of defining characteristics that set it apart from previous industrial revolutions. These key features gives insights into how Industry 4.0 is set to revolutionize manufacturing, supply chains, and business models, while laying the foundation for more sustainable industrial practices.

1.2.1 Key characteristics and envisioned benefits of Industry 4.0

Industry 4.0 represents a paradigm shift from centralized to decentralized smart manufacturing and production, whereby physical objects are seamlessly integrated into information networks (Gabriel & Pessl, 2016; Kawaguchi, 2019). This facilitates decentralized intelligent decision-making, integrated operations, and self-optimization of production systems in response to real-time data. The advent of Industry 4.0 is blurring conventional boundaries between manufacturing and service sectors, as digital technologies converge with physical products to create hybrid offerings (Stankovic et al., 2017). Within modular, structured smart factories, interconnected cyber-physical systems continuously monitor physical processes to construct virtual simulations of the production environment. By collecting and analyzing smart data across the product lifecycle, Industry 4.0 aims to optimize flexible, demand-driven supply chains, distribution models, and efficient asset utilization to enable rapid and intelligent decision-making that meets shifting customer needs while minimizing costs (Oztemel & Gursev, 2020).

The emergence of connected supply chains and digitized production processes promises to enable seamless data exchange between workers, machine components, materials, manufactured objects, and logistics operations (Nagasawa et al., 2017). Through digital product identities, embedded sensors, and networked communication infrastructure, both machines and physical objects will gain enhanced capabilities to cooperate, self-optimize, and auto-configure. For example, a product moving through a smart factory could algorithmically determine its optimal manufacturing pathway based on real-time system conditions and autonomously reroute itself in case of disruptions to avoid halting production (Hofmann & Rüsch, 2017; Zhong et al., 2017). Such distributed intelligence and autonomy of cyber-physical systems can facilitate largely self-organizing and self-optimizing factories with minimal centralized control. Production systems are transformed from rigidly structured environments into agile, adaptive ecosystems (Hermann et al., 2016). Key features and capabilities Industry 4.0 technologies and architectures frequently cited in the academic literature include:

- Increase production flexibility and customizability to meet diverse customer demands, through innovations like smart connected products and flexible reconfigurable production systems (Fragapane et al., 2022; Niaki et al., 2019);
- Enhance the sustainability and functionality of industrial processes by leveraging renewable energy, custom biologics, and advanced materials like composites, graphene, and nanomaterials (Ghobakhloo & Fathi, 2021; Mohamed et al., 2019b);
- Enhance supply chain agility and accelerate time-to-market through reduced inventory levels and lead times, facilitated by real-time data connectivity across the value chain (Bechtsis et al., 2018; Stock & Seliger, 2016);
- Blurring of boundaries between physical and digital spheres with emerging human-machine interfaces like augmented/virtual reality, collaborative robotics, and brain-computer interaction (Jiao et al., 2021; Schwab, 2017);
- End-to-end tracking and traceability of materials and products throughout the entire lifecycle using sensors, IoT, and blockchain (Esmailian et al., 2020; Kulkarni et al., 2022);
- New digitally-enabled business models such as cloud-based manufacturing, data-driven services, and process-oriented delivery models creating novel forms of value (Czvetkó et al., 2022; Ibarra et al., 2018);

- Increase manufacturing productivity, efficiency, and quality enabled by technologies like intelligent robotics, predictive maintenance, and production optimization algorithms (Horvat et al., 2019; Hughes et al., 2022; Kagermann et al., 2013);
- Modular and reconfigurable production systems that can adapt to changing requirements by adding, removing, or modifying specific modules (Stock et al., 2018; Torn & Vaneker, 2019);
- Enhance integration and data exchange across intra- and interorganizational operations, from R&D to suppliers, manufacturing, and distribution (Kagermann et al., 2013; Lasi et al., 2014);
- Machine learning capabilities that allow assets to continuously improve performance by analyzing data from past production runs (Pagoropoulos et al., 2017);
- Simulation and modeling capabilities to digitally design, test, and validate new products, processes, and production systems prior to physical implementation (Stock et al., 2018; Tao et al., 2018);
- Enhance vertical integration from product design down to manufacturing, logistics, and sales (Kagermann et al., 2013; Tabim et al., 2021);
- Greater horizontal integration across the value chain from suppliers to customers (Abiodun et al., 2023; Kagermann et al., 2013; Pérez-Lara et al., 2020);
- End-to-end digital integration of business processes using cyber-physical systems, from factory floor to services (Garrido-Hidalgo et al., 2019; Pivoto et al., 2021).

Overall, the Industry 4.0 technologies, if strategically integrated, can foster improved productivity, mass customization, and supply chain responsiveness, but these benefits depend on overcoming significant technical, organizational, and regulatory challenges within specific industrial contexts (Hofmann & Rüsch, 2017). As shown in Fig. 1.5, it impacts diverse aspects of industrial operations from inventory to quality, demand/supply matching, time-to-market, services, labor utilization, and more.

1.3 Sustainability: a modern imperative

Sustainability has emerged as an existential imperative for industries and societies amid escalating climate change, biodiversity decline, and environmental degradation that now threaten the Earth's habitability (Griggs et al., 2013; Whiteman et al., 2013). The landmark 1987 Brundtland Report by the United Nations first conceptualized sustainable development as "meeting the needs of the present without compromising the ability of future generations to meet their own needs" (UN, 1987). This definition was further used in different initiatives, for example, the 2015 Sustainable Development Goals (SDGs) UN initiative. The 17 SDGs adopted by all member states provide shared targets across poverty, health, education, reduced inequalities, responsible production, and environmental protection to be achieved by 2030 (UN, 2016). The SDGs make it clear that sustainability is now a business imperative, not just an ethical obligation. Companies can create value and gain a competitive advantage by embedding sustainability into strategy and operations (Lacy et al., 2010; Porter & Kramer, 2006). This requires going beyond incremental improvement and compliance toward fundamentally reimagining entire value chains, technologies, and business models using

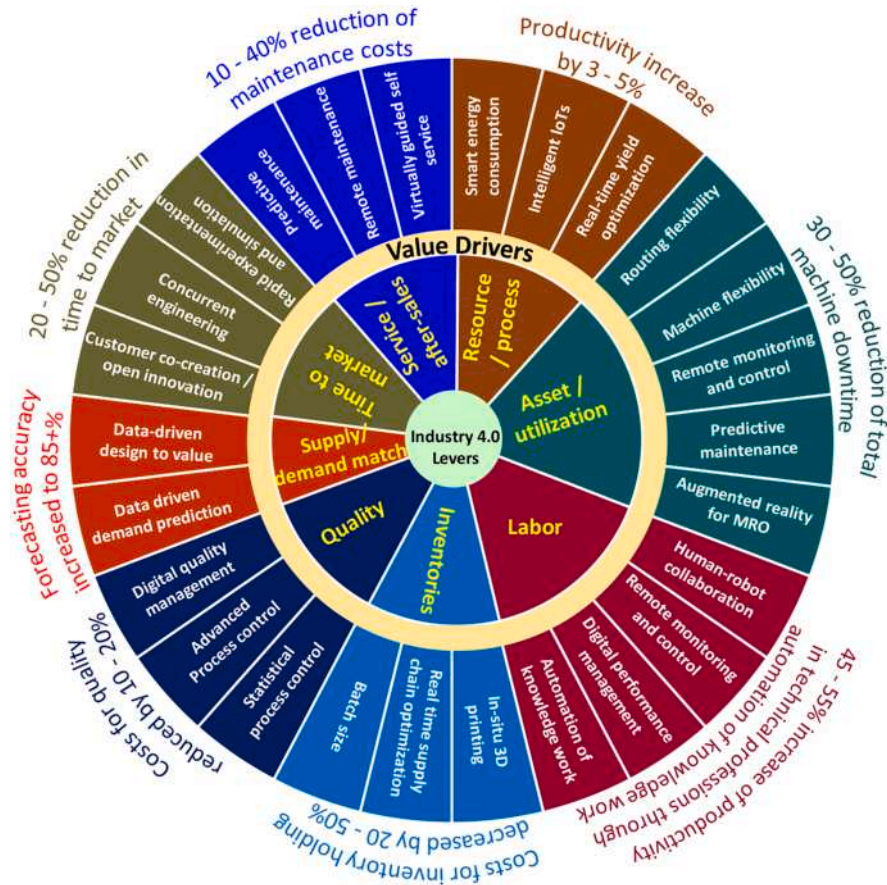


FIGURE 1.5 Digital compass showing aspects of Industry 4.0. Source: Adapted from Baur & Wee, 2015; Caylar et al., 2016; McKinsey & Company, 2015.

sustainability as an organizing framework and touchstone for decision-making (Dunphy et al., 2007; Laszlo & Zhexembayeva, 2011). The urgency of sustainability is evidenced by breached planetary boundaries, from climate change and ocean acidification to biodiversity erosion, that disrupt the Earth's self-regulating capacity (Steffen et al., 2015). Climate change is already driving increasingly frequent extreme weather events, altering habitats, damaging infrastructure, and contributing to crop failures, with projections indicating that global temperatures could rise by more than 2°C within this century (Change, 2022). Concurrently, unsustainable resource extraction and waste mismanagement have led to widespread deforestation and plastic pollution, pushing ecosystems toward a sixth mass extinction (Cowie et al., 2022). Industrial systems and financial markets, driven by growth and short-term profitability, have contributed to unsustainable consumption patterns, necessitating a shift toward models that better align with ecological limits and long-term environmental sustainability. Operationally, sustainability means decoupling economic activity from environmental destruction through circular models and innovations that

serve human and ecological well-being rather than profits alone (Geissdoerfer et al., 2017; Pieroni et al., 2019).

The pioneer definition of sustainability by the UN is not entirely suitable for industrial processes, as it lacks operational clarity for the manufacturing sector (Sartal et al., 2020). For manufacturing, sustainability involves holistic strategies to boost value creation while minimizing environmental footprints across energy, water, materials, chemicals, and waste (Haapala et al., 2013; Jayal et al., 2010). Several efforts have been made to propose a definition for sustainable manufacturing in previously published studies (Haapala et al., 2013; Jayal et al., 2010). Jayal et al. (2010) defined sustainable manufacturing as the design of an industrial system that can ensure the natural resources for quality of life and have minimum negative impact on environmental and human health. According to Haapala et al. (2013), sustainable industrial processes cover the three basic elements involved in manufacturing, that is, processes, products, and systems, which enables economic growth and sustainable value creation in industries. The US Department of Commerce defined sustainable manufacturing as “the creation of products through the processes that minimize both negative environmental impacts and consumption of energy and natural resources, being also safe for employees, communities, consumers and economically viable” (McElnea et al., 2011).

At the core of sustainable industrial processes is the 3Ps concept of sustainability—Planet, Profit, and People, often referred to as the Triple Bottom Line (TBL). This framework underscores the need to balance three critical dimensions: environmental stewardship (Planet), economic viability (Profit), and social responsibility (People). The Triple Bottom Line concept emphasizes that for a manufacturing system to be truly sustainable, it must deliver integrated and balanced benefits across these three pillars. This entails not only conserving resources and minimizing waste but also maintaining profitability while promoting health, safety, and overall quality of life for all stakeholders involved.

Fundamentally, sustainability in the industrial context is about advancing these interconnected dimensions in harmony, as depicted in Fig. 1.6. The environmental aspect (Planet) focuses on reducing the ecological footprint through resource conservation, waste minimization, and the adoption of cleaner technologies. The economic aspect (Profit) emphasizes maintaining profitability by improving efficiency, reducing costs, and ensuring long-term economic viability. The social aspect (People) involves safeguarding the well-being of employees, communities, and consumers by fostering safe working conditions, fair labor practices, and contributing to the overall social fabric.

For industrial systems and processes to be sustainable, they must embody the principles of the 3Ps, ensuring that economic growth does not come at the expense of environmental degradation or social inequity (Eslami et al., 2019; Lucato et al., 2017). By integrating these principles into the core of industrial operations, sustainability offers a transformative lens through which industrial production systems, technologies, and business models can be reimaged. This approach fosters an ecologically regenerative, socially just, and economically viable manufacturing sector, capable of meeting present needs without compromising the ability of future generations to meet theirs.

The rapid evolution of industrial paradigms, driven by the emergence of advanced technologies, demands a reevaluation and refinement of the traditional concept of sustainability to reflect the transformative potential of Industry 4.0. Building on the principles of the 3Ps, sustainability in the context of Industry 4.0 can be defined as “the synergistic integration of

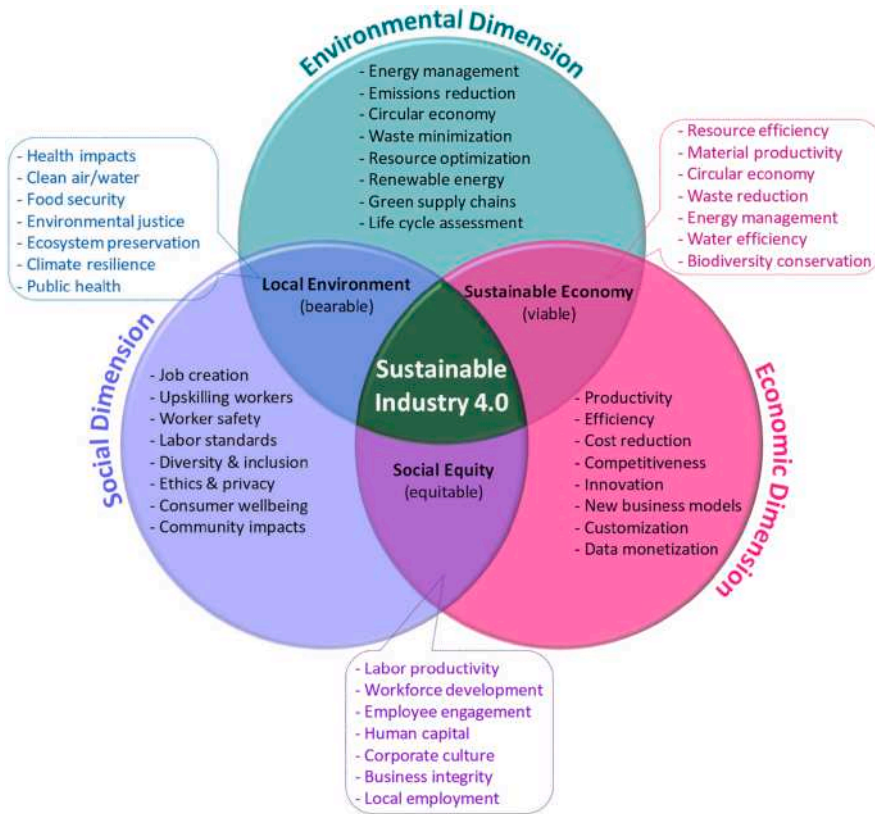


FIGURE 1.6 Triple bottom line (TBL) or the three interconnected pillars of sustainability—environmental, economic, and social in the context of Industry 4.0, often referred to as the 3Ps: Planet, Profit, and People.

advanced digital, physical, and biological systems into the design, operation, and management of industrial systems and processes to simultaneously optimize environmental resilience, economic prosperity, and social equity, thereby ensuring long-term resilience and regenerative growth.”

While sustainability has emerged as a global imperative across all sectors, the urgency is particularly pronounced within the industrial sector. As a major driver of resource consumption and environmental impact, industries face the complex challenge of meeting growing global demands while simultaneously minimizing their ecological footprint. Achieving this balance requires a fundamental shift in how industries operate, innovate, and create value. By exploring the specific sustainability imperatives within this context, the scale of the challenges and the transformative potential of emerging technologies can be better understood, such as those associated with Industry 4.0.

1.3.1 Sustainability imperatives in the industrial sector

Industry has contributed substantially to human progress and welfare through the mass production of goods and employment generation. However, current patterns of industrial

activity focused on unlimited growth and profits are ecologically unsustainable and socially inequitable (McWilliams et al., 2016). Production systems reliant on intensive resource extraction, carbon emissions, and waste generation have breached multiple planetary boundaries threatening climate stability, biodiversity, and ecosystem integrity (Steffen et al., 2015). This transition is imperative as persisting with business-as-usual practices will deplete natural resources, accelerate climate change, destroy biodiversity, and exacerbate ecological crises (Bonilla et al., 2013). The supposed right to human well-being while ignoring ecological limits has resulted in unsustainable consumption and production patterns (Bonilla et al., 2013). Environmental sustainability requires restricting production within ecological constraints—resource exploitation rates should not exceed regeneration rates, waste generation should not surpass ecosystem assimilative capacity, and nonrenewable resource depletion must have commensurate substitution. Producing within environmental sustainability requires rational resource allocation, waste minimization or proper treatment, and industrial ecology approaches. Fundamentally, sustainability in manufacturing requires the development of new industrial paradigms that prioritize long-term value creation, considering trade-offs among economic performance, social equity, and environmental stewardship. It calls for innovating regenerative production technologies, adopting circular economy principles, implementing ethical supply chains, and upholding human rights across global industry value networks (Geissdoerfer et al., 2017).

Manufacturing activities currently impose massive burdens on the planet and society. Industrial emissions contribute to around 25%–28% of anthropogenic greenhouse gases, 20% of water pollution, and 85% of ocean plastic wastes (IEA, 2022; IRENA and Industry Leaders Launch the Alliance for Industry Decarbonisation, 2022, 2023). It is also inextricably linked to biodiversity loss, deforestation, toxic emissions, and public health threats from hazardous chemicals and activities. At the same time, manufacturing sector caters to the needs of over 7 billion people, employs over 470 million people, contributes 25% of global GDP, driving livelihoods and development (IRENA and Industry Leaders Launch the Alliance for Industry Decarbonisation & 2022,22, 2023; UNIDO, 2019). Expanding populations and rising living standards will increase demand for essential manufactured goods (Stock et al., 2018), requiring radical resource efficiency, renewables adoption, waste reduction, recycling, and positive social impacts across industry value chains to meet these needs sustainably (Jayal et al., 2010).

Key sustainability challenges for the industrial and manufacturing sector comprise (Furstenau et al., 2020; Garetti & Taisch, 2012; Herrmann et al., 2014; Jayal et al., 2010; Tonelli et al., 2013; Tseng et al., 2021):

- **Decarbonizing energy:** Adopting renewable energy, electrification of processes, energy efficiency, demand management and low-carbon supply chains to reduce greenhouse gas emissions in line with 1.5/2°C trajectories. A major challenge in decarbonizing the industry is the transition from fossil fuels to renewable energy sources. For instance, steel and cement industries, which account for approximately 7%–9% (Iron and Steel Technology Roadmap: Towards more sustainable steelmaking, 2020; Pandit et al., 2020) and 7% (Alain, 2023; COP27: UN report shows pathways to carbon-neutrality in “energy intensive” steel, chemicals and cement industries & UNECE, 2024; Global Cement And Concrete Industry Announces Roadmap To Achieve Groundbreaking ‘Net Zero’ CO₂

[Emissions By 2050, 2024](#)) of global CO₂ emissions, respectively, face significant hurdles in this transition due to the highly energy-intensive nature of their production processes. Companies like ArcelorMittal (the world's largest steel producer) and LafargeHolcim (cement producer) are tackling this challenge by exploring alternative fuels, such as biomass and waste-derived fuels, and investing in carbon capture and storage (CCS) technologies.

- **Legacy infrastructure:** Existing assets and infrastructure pose challenges, as many physical facilities and production systems predate current technologies and sustainability best practices. Many industrial facilities still operate using outdated equipment and processes that are highly energy-intensive and generate significant waste. Upgrading these facilities to meet modern sustainability requirements is a significant challenge. For example, a large portion of the global steel industry faces the challenge of retrofitting old blast furnaces (responsible for more than 70% of global steel production) with modern electric arc furnaces (EAFs) that are more energy-efficient and produce fewer emissions.
- **Organizational culture:** Resistance to change and lack of cross-functional coordination, whereas sustainability requires company-wide strategy alignment and stakeholder engagement. Shifting organizational culture toward sustainability is a major challenge, especially in industries with deeply entrenched practices. For instance, oil and gas production companies have faced criticism for resisting organizational changes that prioritize sustainability ([IPIECA U, 2017](#)). Despite external pressure, internal resistance to abandoning profitable yet unsustainable practices remains a barrier to transformation ([Okeke, 2021](#)). According to a Deloitte survey ([Core beliefs and culture: Chairman's survey findings, 2012](#)), only 19% of executives believe their company culture is widely upheld within their organizations, indicating a significant challenge in aligning organizational culture with sustainability goals. This disconnect underscores the need for companies to move beyond simply acknowledging the importance of sustainability and actively integrate it into their core values and practices.
- **Supply chain oversight:** Lack of control and oversight over sustainability standards across their supply chain. Complex global supply chains often lack transparency, making it difficult to monitor and address social and environmental issues. For example, the fashion industry, particularly fast fashion brands like Zara and H&M, has been criticized for poor supply chain oversight, leading to issues such as labor exploitation and environmental degradation in sourcing countries. Many companies still struggle to ensure safe working conditions and fair labor practices throughout their supply chains. The 2013 Rana Plaza collapse in Bangladesh, which killed over 1100 garment workers, exposed the severe lack of oversight in global supply chains, particularly in the fashion industry ([Backer, 2016](#)). These companies are now attempting to address these challenges by improving transparency and adopting more sustainable sourcing practices.
- **Resource efficiency:** Minimizing material inputs, water usage, and waste generation through circular design, recycling, process optimization, digitization, and industrial symbiosis. Achieving resource efficiency is critical but challenging, especially in resource-intensive industries. For instance, the electronics industry faces challenges with the extraction of rare earth minerals and the growing problem of electronic waste, which is increasing five times faster than recycling efforts. In 2022, 62 million tons of e-waste were generated, with only 22.3% properly recycled ([Baldé et al., 2024](#)). This highlights the urgent need to improve e-waste management and increase recycling rates to prevent

resource loss and environmental harm. Companies like Apple have made strides by introducing the “Daisy” robot to disassemble iPhones and recover valuable materials, but achieving full circularity remains a distant goal due to the complex design and short lifecycle of electronic products ([Apple expands the use of recycled materials across its products, 2024](#); [Lefebvre, 2023](#)).

- **Sustainability planning:** Absence of knowledge and capabilities to develop a concrete sustainability strategy and roadmap. Developing and implementing a comprehensive sustainability strategy can be complex and resource-intensive, particularly for small and medium-sized enterprises (SMEs) with limited resources and expertise ([Das et al., 2020](#); [Jayasundara et al., 2019](#)). A 2020 study by the World Economic Forum found that while nearly 7,000 companies disclosed climate-related data, only 25% of companies have a clear vision or target for sustainability, highlighting the widespread lack of concrete sustainability strategies and roadmaps ([Herhold & Farnworth, 2020](#)).
- **Pollution and toxicity:** Eliminating hazardous chemicals, volatile air emissions, and effluent discharges through cleaner production, treatment solutions, and full lifecycle stewardship. Reducing pollution and toxicity in industrial processes is a persistent challenge. For example, the chemical industry, which contributes heavily to air and water pollution, continues to face challenges in eliminating hazardous substances and reducing volatile organic compound (VOC) emissions. Many companies still rely on toxic substances for various processes, such as bisphenol A (BPA), which has been widely used as a coating inside food and beverage cans to prevent corrosion, complicating the transition to greener alternatives ([Almeida et al., 2018](#); [Palsania et al., 2024](#)).
- **Biodiversity loss:** Preventing habitat destruction, soil degradation, and protecting ecosystems through responsible sourcing, site rehabilitation, product alternatives assessment, and net positive impacts. Industrial activities often lead to habitat destruction and biodiversity loss. For example, the expansion of palm oil plantations is a leading cause of deforestation in Southeast Asia, threatening the habitat of endangered species like orangutans ([Endangered species threatened by unsustainable palm oil production, 2024](#); [Palm oil and biodiversity: Issues Brief, 2018](#)). Companies like Wilmar International have been criticized for their role in deforestation, despite commitments to sustainable sourcing ([Rijk et al., 2022](#)). Similarly, Cargill, a US based food corporation, has faced challenges in preventing habitat destruction and protecting ecosystems in their supply chain, highlighting the need for greater collaboration with stakeholders and more effective conservation measures (e.g., Cargill’s efforts to protect biodiversity in its soybean supply chain) ([Milliken et al., 2020](#); [Stanwick & Stanwick, 2022](#)).
- **Workforce well-being:** Ensuring decent work environments, wages, health and safety protections, skills development, and social dialogue through ethical sourcing, capability building, and freedom of association. Ensuring decent working conditions and fair wages in global supply chains is a critical challenge, particularly in industries like garment manufacturing. Despite subsequent improvements, ensuring workforce well-being across all tiers of the supply chain remains a major challenge in some industries. For example, garment workers in some developing countries often face exploitative working conditions and low wages ([Anner, 2020](#); [Rafay, 2024](#)).
- **Product sustainability:** Designing products for circularity, low-carbon footprints, positive social impacts, and accessibility across user groups. Designing sustainable products

that minimize environmental impact throughout their lifecycle is a major challenge. However, many products are still designed for obsolescence, leading to shorter lifespans and increased waste (*The New Plastics Economy: Rethinking the future of plastics, 2016*).

Addressing these multifaceted sustainability challenges requires technological upgrades, greener engineering, adapted business models, upgraded standards and metrics, policy incentives, multistakeholder partnerships, and crucially, system-level transformations rather than incremental improvements (*Schwab, 2017*). Industries must also balance competitiveness with sustainability during economic transitions. But embedding environmental and social value in business purpose and strategy is imperative for industry leadership and resilience in a resource-constrained world.

1.4 The nexus between Industry 4.0 and sustainability

The ongoing digital transformation of manufacturing through Industry 4.0 technologies intersects with escalating global sustainability imperatives in the 21st century. An emergent body of integrative scholarship at the nexus of engineering, management, and sustainability sciences reveals both synergies and tensions between Industry 4.0 adoption and economic, social, and ecological sustainability (*Harikannan et al., 2021; Tavera Romero et al., 2021*). As depicted in *Fig. 1.7*, Industry 4.0 and sustainability are converging toward a common vision

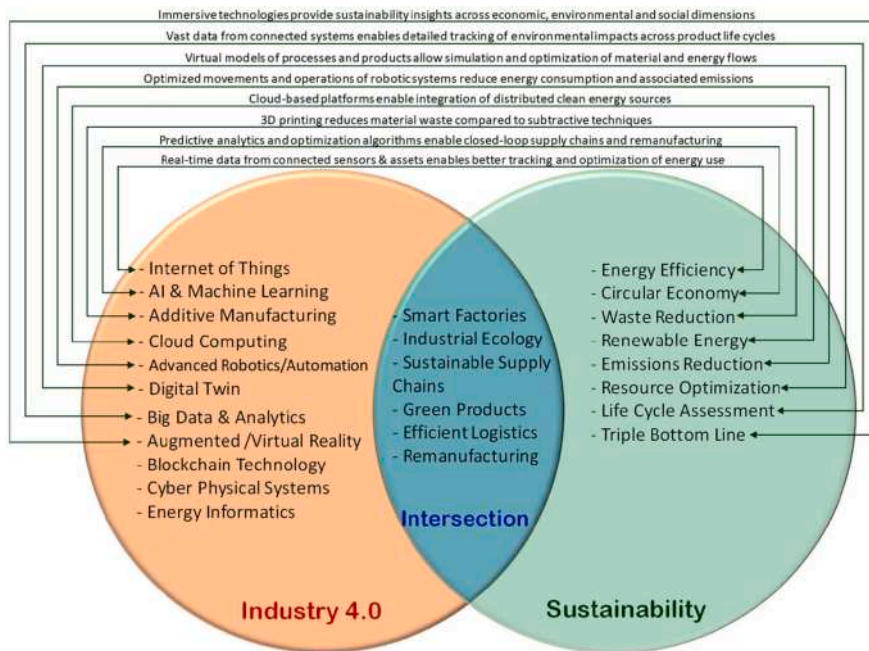


FIGURE 1.7 The convergence of Industry 4.0 and sustainability paradigms and practices through disruptive technologies.

of responsible production and consumption enabled by disruptive technologies, data, and connectivity. Fig. 1.8 further exemplifies this synergy by demonstrating how Industry 4.0 technologies can drive both operational performance and sustainability gains through eco-efficiency. This principle, central to Industry 4.0 transformative potential, leverages technological advancements to optimize resource utilization, minimize waste, and reduce environmental impact, ultimately enhancing both profitability and environmental stewardship (Betti et al., 2021; WEF, 2021a).

Industry 4.0 presents significant opportunities for enhancing sustainability across all its dimensions. As Stock and Seliger (2016) argue, this potential can be unlocked through several avenues: developing data-driven business models that offer novel product-service systems; fostering closed-loop product lifecycles and industrial symbiosis; leveraging cyber-physical systems (CPS) to retrofit SMEs for digitalization; utilizing ICT technologies for training and competency development; promoting worker motivation and creativity through CPS-supported programs; enabling decentralized, sustainability-oriented organizations focused on resource efficiency; and implementing sustainable process design using technologies like AM to enable closed-loop lifecycles and cradle-to-cradle approaches.

While the adoption of Industry 4.0 technologies across industrial sectors has accelerated, given the promise of advanced connectivity, automation, intelligence, and customization for productivity and competitiveness (Luthra & Mangla, 2018). However, implications for ecological sustainability and human well-being require more critical evaluation, as these technologies could either ameliorate or exacerbate sustainability challenges. For instance,

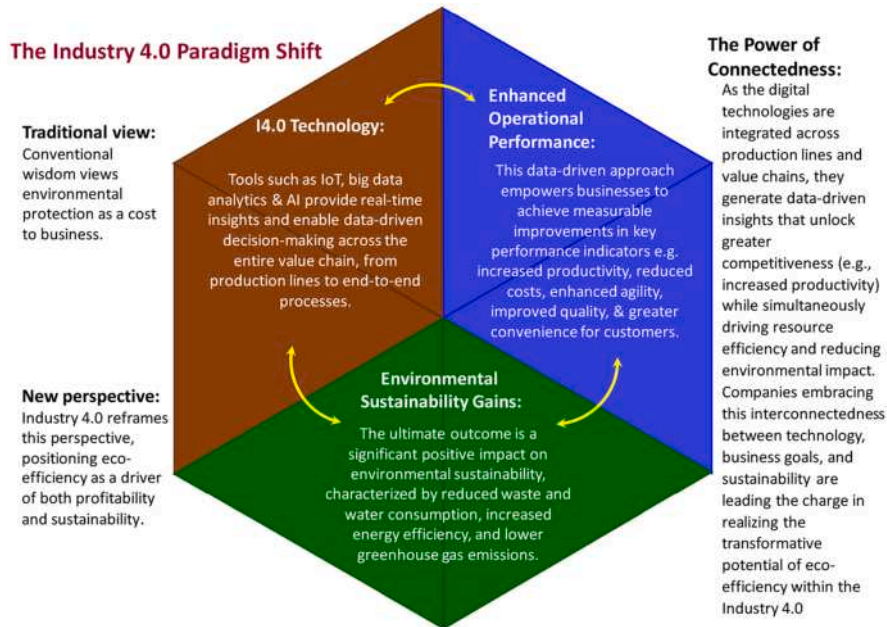


FIGURE 1.8 Industry 4.0 technologies enable synergies between eco-efficiency and enhanced business performance.

while Industry 4.0 promises enhanced productivity and efficiency, traditional production systems are associated with massive ecological footprints across energy, resources, emissions, waste, and pollution that threaten climate stability, biodiversity, and environmental health (Tseng et al., 2018). Manufacturing activities also risk perpetuating social problems like economic inequality, poor labor conditions, and lack of inclusive prosperity (Organisation for Economic Co-operation and Development OECD, 2014). For example, increased automation risks labor displacement, while improved supply chain transparency could enable ethical practices (de Sousa Jabbour et al., 2018; Marengo, 2022).

Furthermore, it is crucial to recognize the interconnected nature of sustainability dimensions. Each dimension represents a distinct system evolving around digital value creation solutions (Stark et al., 2014). Consequently, a single Industry 4.0 solution can directly impact one dimension while indirectly influencing others. The interactions between these systems can manifest in various forms: causal relationships, where a solution's implementation triggers direct and indirect impacts; magnitude and scale drivers that determine the extent of these impacts based on the breadth of solution dissemination; and latency and time dependencies, which govern the timeframe between a solution's implementation and its observable impacts (Machado et al., 2020).

Industry 4.0 technologies can potentially address these interconnected challenges that span economic, social, and ecological dimensions—but only if strategically oriented toward sustainability from the outset (Stock et al., 2018). Recent studies reveal that Industry 4.0 can support environmental sustainability through optimization, efficiency, waste reduction, and circularity, if strategically oriented (Herrmann et al., 2014; Stock et al., 2018). However, rebound effects could also increase energy demand, e-waste, and overproduction if not holistically assessed (Belaïd et al., 2020; Kopp & Lange, 2019; Lange et al., 2020). For instance, Birkel and Müller (2021) noted that while additive manufacturing can reduce waste and streamline logistics, it also tends to consume more energy per unit produced than traditional manufacturing processes. Regarding social sustainability, both positive and negative relationships are reported—while automation may displace jobs, it could also create safer working conditions (Beier et al., 2017; Isaías et al., 2015).

Specific technologies like blockchain, industrial Internet of Things, and AI have demonstrated potential for advancing circular economy models, energy efficiency, supply chain transparency, and humanitarian objectives if purposefully implemented (Charles et al., 2023; Hasan & Trianni, 2023; Nascimento et al., 2019). As shown in Table 1.3, Industry 4.0 innovations hold promise for advancing all 17 of the UN SDGs spanning economic prosperity, social inclusion, and environmental sustainability. In general, key sustainability issues related to industrial production and consumption that Industry 4.0 could potentially address include

- Climate change mitigation—Reducing greenhouse gas emissions from manufacturing through energy efficiency, renewables, electrification, circularity, and low-carbon supply chains (IEA, 2019).
- Resource efficiency—Optimizing material, water, and energy usage through real-time monitoring, closed loops, and waste reduction (Stock et al., 2018).
- Circular economy—Enabling closed-loop material flows, product life extension, refurbishment, and high-value recycling through improved traceability, monitoring, and disassembly (de Sousa Jabbour et al., 2018).

TABLE 1.3 Potential synergies between United Nations Sustainable Development Goals (UN SDGs) and Industry 4.0 technologies and applications. [The content of this table has not been approved by the UN and does not reflect the views of the UN or its officials or Member States.]

SDG	Target areas	Relationship with Industry 4.0 technologies
SDG 1: No poverty	Eradicating poverty in all its manifestations	- AI-powered social welfare programs, blockchain for financial inclusion, big data for targeted interventions, increased access to resources and services, efficient allocation of funds, improved monitoring (Verbeek & Lundqvist, 2021). - AI and data analytics can develop predictive models to identify regions most in need of poverty alleviation efforts, ensuring efficient allocation of resources and targeted interventions (G20 policy recommendations for advancing financial inclusion and productivity gains through digital public infrastructure, 2023).
SDG 2: Zero hunger	Attaining food security, improving nutrition, and promoting sustainable agriculture	- Big data, IoT, and AI can help to implement precision agriculture techniques for optimized crop yields and resource use, alongside efficient supply chain management reducing food wastage (Belaud et al., 2019). - Blockchain can enable transparent supply chains and food traceability to combat food fraud (Venkatesh et al., 2020).
SDG 3: Good health and well-being	Promoting health and well-being for all ages	- Telemedicine, AI-powered diagnostics and treatments, robotics for assisted living, can improve healthcare outcomes, reduce costs, and increase accessibility (Gualtieri et al., 2020). - IoT can help to utilize health monitoring devices to track patient health in real-time, offering improved diagnostic capabilities and personalized healthcare (Aghdam et al., 2021; Li et al., 2024).

(Continued)

TABLE 1.3 (Continued)

SDG	Target areas	Relationship with Industry 4.0 technologies
SDG 4: Quality education	Ensuring inclusive and equitable quality education and lifelong learning opportunities	- AI & VR/AR can offer personalized learning experiences and virtual classrooms to overcome geographical and physical barriers, enhancing educational accessibility (Gandedkar et al., 2021; Lampropoulos, 2023). - Cloud computing enables access to a vast array of educational resources and collaborative tools, fostering global learning and knowledge sharing (Al-Samarraie & Saeed, 2018; Khan et al., 2021).
SDG 5: Gender equality	Achieving gender equality and empowering all women and girls	- Big data analytics can help to identify and address gender gaps in various sectors, informing policy and practice (Gender Equality and Big Data: Making Gender Data Visible, 2018; Rana, 2020). - Advanced automation systems can minimize gender bias in labor by automating tasks, thereby creating a more level playing field in employment opportunities (Filippi et al., 2023).
SDG 6: Clean water and sanitation	Ensuring water and sanitation availability and sustainable management for all	- Smart water grids with IoT sensors, AI-powered leak detection and optimization, and remote monitoring of sanitation systems can improve water quality and efficiency, reduced water waste, and better access to sanitation (Islam et al., 2022; Saiteja & Ponnappalli, 2023). - AI, CPS, and satellite data can help to track water quality and optimize water usage in agriculture (Schulze et al., 2019).

(Continued)

TABLE 1.3 (Continued)

SDG	Target areas	Relationship with Industry 4.0 technologies
SDG 7: Affordable and clean energy	Ensuring affordable, reliable, sustainable, and modern energy access for all	- IoT, AI, and advanced simulation can help to develop smart grid and microgrid technologies for more efficient energy distribution and use, and forecast the intermittent nature of solar and wind energy (Meliani et al., 2021). - Blockchain can facilitate decentralized energy trading platforms, enabling peer-to-peer energy transactions and supporting renewable energy integration (Dong et al., 2022).
SDG 8: Decent work and economic growth	Fostering inclusive and sustainable economic growth, employment, and decent work	- AI-powered job matching platforms, online training and upskilling programs, automation for dangerous or repetitive tasks can increase productivity, creation of new jobs, improved worker safety (Braccini & Margherita, 2018; Yuan et al., 2017). - Blockchain smart contracts can ensure labor rights in supply chains by automating the enforcement of fair labor practices, ensuring compliance with labor laws, and providing transparent, immutable records of employment terms and conditions (Fiorentino & Bartolucci, 2021; Wang et al., 2019).
SDG 9: Industry, innovation and infrastructure	Building resilient infrastructure, promoting sustainable industrialization, and innovation	3D printing and digital twins, through rapid prototyping, accelerated innovation, and process optimization, can drive advancements across manufacturing by enabling innovative solutions and enhanced efficiency (Shen & Li, 2024; Singh & Sehgal, Applications). - IoT and cyber-physical systems can drive smart infrastructure practices and develop resilient infrastructure, supporting sustainable industrialization (Rani et al., 2022).

(Continued)

TABLE 1.3 (Continued)

SDG	Target areas	Relationship with Industry 4.0 technologies
SDG 10: Reduced inequalities	Reducing inequalities within and between countries	- AI and digital platforms for social services delivery can develop accessible technologies for marginalized communities, bridging the digital divide and enhancing inclusivity (Raja, 2016; Samuel-Okon & Abejide, 2024). - Blockchain for transparent governance can provide financial services to the unbanked, promoting economic inclusion and reducing inequalities (Mhlanga, 2023; Schuetz & Venkatesh, 2020).
SDG 11: Sustainable cities and communities	Creating inclusive, safe, resilient, and sustainable cities and settlements	- Smart transportation systems with AI and IoT, waste management with robotics and sensors, green buildings with energy-efficient technologies, improved air quality, reduced congestion, efficient resource utilization, increased quality of life (Wen et al., 2020; Whig et al., 2024). - VR/AR can enable advanced urban design and simulation, aiding in the development of sustainable and resilient communities (De Fino et al., 2023; Imottesjo & Kain, 2018).
SDG 12: Responsible consumption and production	Ensuring sustainable production and consumption patterns	- AI-powered supply chain optimization, blockchain for product traceability, digital platforms for product-sharing and repair can reduce waste generation in production processes, increase resource efficiency, and extend product lifecycles (Han et al., 2023). - Digital technologies-based circular economy practices can encourage recycling and reuse of materials, reducing waste and supporting sustainable production (Hariyani et al., 2024).

(Continued)

TABLE 1.3 (Continued)

SDG	Target areas	Relationship with Industry 4.0 technologies
SDG 13: Climate action	Undertaking urgent action to combat climate change and its impacts	- IoT and AI can monitor climate parameters and control emissions, contributing to effective climate action strategies (Kumari & Pandey, 2023). - Big Data analytics can support climate change research and policy formulation through comprehensive data analysis and modeling (Ikegwu et al., 2024).
SDG 14: Life below water	Sustainably using oceans, seas, and marine resources	- AI-driven fishing fleet monitoring, underwater drones for ocean mapping and pollution detection, data-driven platforms for managing marine protected area can help to reduce overfishing, improve fisheries management, better understand marine ecosystems, and effectively pollution control (Bakker, 2022). - Satellite remote sensing can help to track marine ecosystems (Fingas, 2019).
SDG 15: Life on land	Sustainably managing forests, combating desertification, and halting biodiversity loss	- AI-powered wildlife monitoring, precision agriculture with drones and satellites, and remote sensing for deforestation detection can reduce biodiversity loss, enable sustainable land use, and improve food security (Haq et al., 2024). - Drones, IoT sensors, and antipoaching technologies can assist in land restoration, reforestation, conservation efforts, and wildlife tracking to promote biodiversity and prevent deforestation (Pimm et al., 2015; Singh et al., 2022).

(Continued)

TABLE 1.3 (Continued)

SDG	Target areas	Relationship with Industry 4.0 technologies
SDG 16: Peace, justice, and strong institutions	Promoting just, peaceful, and inclusive societies.	- Blockchain, AI, and encryption can enhance governance transparency, legal efficiency, institutional accountability, and access to justice by enabling solution like AI-powered legal document analysis, digital platforms for citizen engagement and dispute resolution (Laptev & Feyzrakhmanova, 2024; Patil & Desai, 2023). - Cybersecurity teach can protect individual rights and privacy, ensuring a secure digital environment for all.
SDG 17: Partnerships for the goals	Revitalizing global partnerships for sustainable development	- Cloud Computing and IoT can foster collaborative platforms and data sharing, enhancing global partnerships for sustainable development (Schniederjans & Hales, 2016). - AI and Big Data can enable cross-sectoral partnerships through advanced analytics, supporting coordinated action toward the SDGs (Vinuesa et al., 2020).

AI, Artificial intelligence; IoT, Internet of Things.

- Biodiversity and toxicity—Eliminating hazardous substances through green chemistry, reducing pollution, and assessing ecosystem impacts using sensor data ([Director UE, 2019](#)).
- Workforce well-being—Protecting labor rights, wages, health, and safety in global supply chains through auditing, tracking, and corrective systems ([Bavaresco et al., 2021](#); [Leso et al., 2018](#)).
- Product sustainability—Assessing and optimizing environmental and social attributes like embedded carbon, end-of-life, and accessibility over the product lifecycle ([Enyoghasi & Badurdeen, 2021](#); [Jamwal et al., 2021](#)).

However, realizing this potential requires integrative frameworks and responsible governance such that Industry 4.0 deployments are directed toward enhancing human

and ecological well-being. Policymakers, companies, and civil society organizations have crucial roles to play in guiding the strategic orientation of Industry 4.0 innovations toward sustainable and just futures.

To leverage Industry 4.0's disruptive power for sustainability requires responsible governance across multiple axes:

- Workforce transitions: Extensive reskilling, social protections, and change management are imperative to mitigate risks of job losses, inequality, and poor quality of work arising from increased automation (ADB, 2021).
- Legacy infrastructure: Upgrading production assets, data systems integration, interoperability, cybersecurity, and technical standardization involves heavy investment, especially challenging for SMEs (Moeuf et al., 2020).
- Environmental externalities: Industry 4.0 growth must be decoupled from resource consumption and emissions through renewable energy, circularity, and ecological efficiency (Lange et al., 2020).
- Societal alignment: Companies must orient Industry 4.0 deployment toward shared value creation and UN Sustainable Development Goals through multistakeholder collaboration (Lopes de Sousa Jabbour et al., 2018).
- Integrative innovation: Advancing from conceptual possibilities to evidence-based pathways for maximizing sustainability requires synthesizing technology, culture, policy, and governance dimensions (Jamwal et al., 2023).

The adoption of Industry 4.0 technologies has far-reaching implications across different sustainability metrics. Fig. 1.9 depicts the impact range of Industry 4.0 adoption on

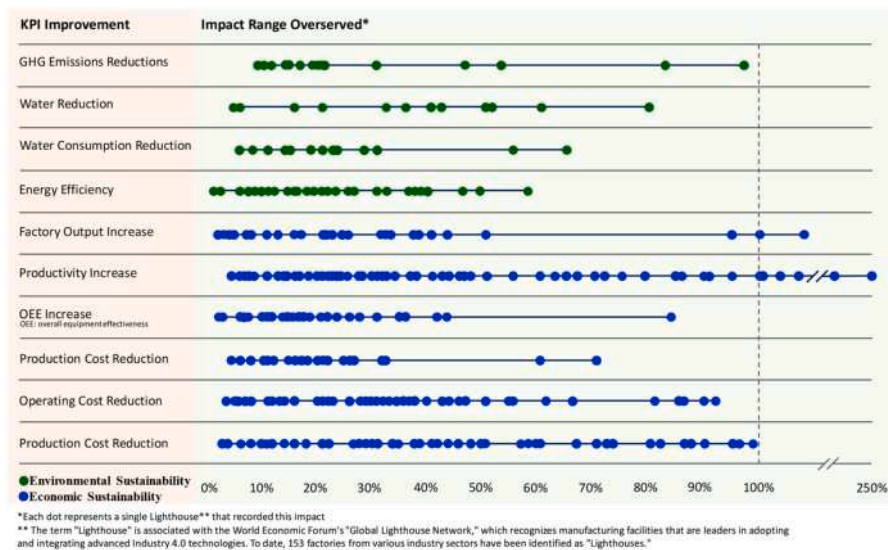


FIGURE 1.9 Impact range of Industry 4.0 adoption on environmental and economic sustainability. Source: Generated by authors based on the data of WEF (2021). *Global lighthouse network: Unlocking sustainability through fourth industrial revolution technologies*. Cologny, Switzerland: World Economic Forum.

environmental and economic sustainability, overserved by various manufacturers across different who adopted and integrated advanced Industry 4.0 technologies, showcasing the potential improvements in key performance indicators such as energy consumption, emissions, resource efficiency, waste reduction, and economic viability. The figure demonstrates that while the implementation of Industry 4.0 technologies generally yields positive outcomes, the magnitude of impact varies across different sustainability indicators. For instance, significant improvements are observed in energy efficiency and waste reduction, with potential reductions ranging from 20% to 30%. Economic indicators such as productivity and cost savings also show substantial positive impacts. However, the figure also highlights areas where the impact is more variable or less pronounced, such as water usage or biodiversity protection.

In summary, the convergence of Industry 4.0 and sustainability paradigms represents a historic opportunity to reshape production systems toward ecological integrity, human dignity, and collective well-being through disruptive technological capabilities strategically harnessed. Realizing this tremendous potential requires multidimensional perspectives and responsible governance.

1.5 Navigating the sustainability dimensions of key Industry 4.0 technologies

While Industry 4.0 technologies offer significant potential for enhancing industrial sustainability, their impacts vary considerably depending on the specific technology and its implementation. The sustainability implications of Industry 4.0 technologies are multifaceted, encompassing both opportunities and challenges across environmental, social, and economic dimensions. [Table 1.4](#) provides a detailed analysis of key Industry 4.0 technologies, outlining their potential positive and negative impacts on environmental, economic, and social sustainability dimensions. This analysis reveals that while technologies like IoT, AI, and advanced robotics can significantly enhance operational efficiency and resource management, they also pose risks such as increased energy consumption, e-waste generation, and potential job displacement. By understanding these multifaceted impacts, industries can develop strategies to maximize the positive sustainability outcomes of Industry 4.0 while mitigating potential negative consequences.

1.5.1 Environmental sustainability: impacts, challenges, and mitigation strategies

[Table 1.4](#) illustrates that Industry 4.0 technologies hold substantial promise for enhancing environmental sustainability, particularly in the areas of resource efficiency and waste management. The integration of IoT, AI, and big data analytics into industrial processes, for instance, has been shown to optimize resource consumption, reduce waste, and improve energy efficiency ([Stock et al., 2018](#); [Li et al., 2020](#)). IoT, through its ability to monitor entire networks of devices and seamlessly integrate real-time data from suppliers and customers, enhances material efficiency by enabling better coordination in the supply chain and reducing overproduction ([Javaid et al., 2021](#); [Manavalan & Jayakrishna, 2019](#)). The potential for IoT to effectively track and manage resources across the supply chain is a critical factor in reducing material waste, optimizing materials use, and improving overall operational efficiency.

TABLE 1.4 Sustainability dimensions of key Industry 4.0 technologies: impacts, challenges, and mitigation strategies (Javaid et al., 2022a; Beltrami et al., 2021; Stock et al., 2018; Ibarra et al., 2018; Esmailian et al., 2020; Machado et al., 2020; Birkel & Müller, 2021; Venkatesh et al., 2020; Gualtieri et al., 2020; Braccini & Margherita, 2018; Schniederjans & Hales, 2016; Ashok et al., 2022; Nagy et al., 2018; Pasi et al., 2021; Alladi et al., 2019; Büchi et al., 2020; Thiede, 2018; Liang et al., 2018; Esmat et al., 2021; Ardanza et al., 2019; Watanabe et al., 2016; Allaoui et al., 2019; Zhang et al., 2020; Yadav, Kumar, et al., 2020; Yadav, Luthra, et al., 2020; Beier et al., 2018; Bonilla et al., 2018; Ford & Despeisse, 2016; Kiel et al., 2017; Birkel et al., 2019; Nam, 2019; Teng et al., 2021).

Technology	Sustainability dimension	Potential positive impacts	Potential negative impacts	Mitigation strategies and research needs
Artificial intelligence (AI) and machine learning	Environmental	- Optimizes energy consumption and reduces emissions through intelligent control systems - Enhances environmental monitoring and pollution control with AI-powered sensors and data analysis - Optimizes resource allocation and waste reduction through predictive analytics - Development of new sustainable materials and manufacturing processes.	- Increases energy consumption due to high computational needs - Potential for rebound effects if efficiency gains lead to increased consumption - Potential e-waste from hardware upgrades - Ethical concerns regarding AI-driven decisions and environmental justice	- Develop energy-efficient AI algorithms and hardware - Research on lifecycle assessment of AI systems to minimize environmental footprint - Recycling programs for AI hardware - Establish ethical guidelines for environmental applications of AI
	Economic	- Drives innovation and new business models based on AI-driven insights - Enhances decision-making and operational efficiency - Improves supply chain management and reduces costs	- Potential job displacement leading to economic instability - Potential for widening economic inequalities if benefits are not distributed equitably	- Develop policies and regulations to address potential economic disruptions caused by AI - Promote inclusive business models that share benefits with workers and communities
	Social	- Potential for enhanced citizen engagement in environmental monitoring and decision-making - Improved working conditions and reduced	Algorithmic bias and discrimination if not developed and deployed responsibly (e.g., Amazon AI-based recruitment system taught itself that	Implement ethical frameworks and regulations for AI development and deployment

Industrial Internet of Things (IIoT)			workplace risks through automation of hazardous tasks	male candidates were preferable over women)	• Design human-centered workplaces and promote collaboration between technologists, policymakers, and the public to address societal impacts of AI
			• Enhanced decision-making for social good, such as in healthcare and disaster response	• Potential for increased social isolation due to automation and reduced human interaction	
				• Reduces human autonomy and critical thinking due to overreliance on AI	
				• Ethical concerns regarding AI bias, privacy, and potential misuse	
				• Job displacement and skills gap, leading to social unrest and inequality	
	Environmental		• Real-time monitoring and data collection for improved resource consumption (e.g., energy and water)	• Increases e-waste from discarded numerous IoT devices	• Design for circularity: prioritize durable, repairable, and recyclable IoT devices
			• Optimization of logistics and transportation, reducing emissions.	• Increases energy consumption of a vast network of connected devices	• Development of low-power renewable energy-driven IoT infrastructure
			• Enhances waste management and recycling processes	• Potential for data breaches and misuse of environmental data due to the high risk of cyber threats	• Implement robust cybersecurity measures to protect environmental data and prevent misuse
	Economic		• Enhanced operational efficiency	• High initial setup costs	• Develop cost-effective IoT solutions
			• Increased asset utilization and reduced downtime through predictive maintenance	• Vulnerability to cyberattacks impacting economic stability	• Build redundancy and resilience into IoT systems to mitigate risks
			• Enhances supply chain management and optimizes logistics	• Increases complexity of managing and securing large-scale IoT deployments	• Phased implementation of IoT infrastructure
					• Prioritize cybersecurity measures and invest in robust data protection strategies

(Continued)

TABLE 1.4 (Continued)

Technology	Sustainability dimension	Potential positive impacts	Potential negative impacts	Mitigation strategies and research needs
Digital twins and advanced simulation	Social	- Improves workplace safety through real-time remote monitoring - Enhances transparency and traceability in supply chains. - More efficient and responsive public services (e.g., smart grids and transportation) - Enhances quality of life through smart homes and cities (e.g., traffic management)	- Potential for job displacement in traditional monitoring and control roles - Privacy concerns due to pervasive data collection - Digital divide and unequal access to IoT benefits	- Retraining programs for workers in impacted sectors - Implement strong data privacy regulations and ensure transparent data governance practices - Promote digital inclusion and equitable access to IoT technologies and their benefits through digital literacy initiatives
	Environmental	- Reduces the need for physical prototypes and testing, minimizing material waste and energy consumption - Optimizes product design and manufacturing processes for reduced environmental impact - Reduces environmental impact through virtual testing - Optimizes product lifecycles for circularity and reduced environmental impact	- High computational energy requirements for running complex simulations - Potential overreliance on virtual models vs. real-world testing - Risk of creating digital waste	- Develop energy-efficient simulation tools and utilize renewable energy sources for data centers - Balanced approach combining virtual and physical testing - Develop data lifecycle management and disposal protocols to minimize digital waste
	Economic	Accelerates product development cycles and reduced time-to-market for new products	- High initial investment for technology adoption - Potential job displacement in traditional design roles	- Develop cost-effective and user-friendly digital twin platforms - Phased implementation of digital twin technologies

Big Data Analytics		• Improves product quality and reduced defects through virtual testing and optimization • Enhance decision-making and risk mitigation through data-driven insights • Reduces operation cost savings through virtual prototyping	• Potential obsolescence of physical testing facilities	
	Social	• Improved worker safety through virtual training and simulation of hazardous environments • Enhances worker training and skill development through realistic simulations	• Risk of overreliance on simulations, potentially leading to unforeseen consequences in the real world • Potential overreliance on simulations leading to reduced hands-on skills	• Develop ethical guidelines for human-centric simulations • Develop standards for simulation accuracy
	Environmental	• Identifies environmental trends and patterns for improved resource management • Optimizes waste management and recycling processes through data insights • Enhances resource efficiency through data-driven insights	• High energy consumption for storing and processing large datasets • Potential e-waste from data storage hardware • Potential for data bias to perpetuate unsustainable practices or lead to inaccurate environmental assessments.	• Develop energy-efficient data storage and processing technologies • Implement data governance frameworks to ensure data quality, transparency, and ethical considerations in data analysis
	Economic	• Provides data-driven Insights for enhancing operational efficiency, productivity, and cost savings • Enhances decision-making and strategic planning • Develops new business models and revenue streams from data-driven insights	• High costs associated with data infrastructure and analytics capabilities • Potential market concentration among data-rich companies • Job displacement in data analysis and decision-making roles • Potential for misuse of data for unfair competition or market manipulation	• Develop cost-effective and scalable big data solutions for businesses of all sizes • Implement robust cybersecurity measures to protect environmental data and prevent unauthorized access • Open data initiatives to democratize access • Establish ethical guidelines and regulations for data usage and privacy

(Continued)

TABLE 1.4 (Continued)

Technology	Sustainability dimension	Potential positive impacts	Potential negative impacts	Mitigation strategies and research needs
Blockchain	Social	- Improves public services and healthcare through data insights - Enhances disaster preparedness and response through real-time data analysis - Enhances transparency and accountability	- Data privacy concerns and potential for misuse of personal information - Risk of exacerbating existing social inequalities if data is not collected and analyzed equitably	- Implement strong data privacy regulations and ensure ethical data governance practices - Address potential biases in data collection and analysis to ensure equitable outcomes
	Environmental	- Enhances transparency and traceability for sustainable supply chains, enabling the tracking of sustainable products and reducing fraud - Potential for facilitating renewable energy trading and peer-to-peer energy sharing - Enhances monitoring and verification of environmental data, reducing fraud in carbon credits and other environmental initiatives - Enhances waste management through transparent tracking - Improves traceability reducing illegal resource extraction	- High energy consumption of some blockchain networks, particularly those using proof-of-work consensus mechanisms - Potential for e-waste generation from discarded hardware used for blockchain mining	- Transition to more energy-efficient blockchain consensus mechanisms (e.g., Proof-of-Stake) - Explore the use of renewable energy sources for blockchain operations - Develop regulations and incentives to promote responsible blockchain mining practices
	Economic	- Increases transparency and trust in transactions, reducing transaction costs and increasing efficiency - Creation of new business models and revenue streams	- High costs for implementation and maintenance - Regulatory uncertainty and lack of standardized frameworks for blockchain applications.	- Research on cost-effective blockchain solutions - Develop clear and consistent regulations for blockchain technology - Integration with existing financial systems

Cloud and edge computing		based on blockchain technology	• Volatility and security risks associated with cryptocurrencies and blockchain platforms	• Promote financial literacy and responsible investment in blockchain-based assets
		• Improves access to finance for small and medium-sized enterprises (SMEs) through blockchain-based platforms		• Foster international cooperation and standardization efforts for blockchain governance.
	Social	• Enhances fair trade practices and improves trust among stakeholders • Increases transparency and accountability in supply chains, promoting fair labor practices and ethical sourcing (Esmailian et al., 2020) • Empowerment of individuals through decentralized systems • Facilitate secure and transparent charitable giving and aid distribution	• Potential for misuse of blockchain for illicit activities, such as money laundering and fraud • Complexity and lack of accessibility for individuals and businesses to adopt blockchain technology • Potential for exacerbating existing inequalities if access to blockchain technology and its benefits is not equitable	• Promote blockchain literacy and develop user-friendly interfaces for wider adoption • Implement robust antimoney laundering and know-your-customer (KYC) regulations for blockchain-based platforms • Foster dialogue and collaboration between technologists, policymakers, and civil society organizations to ensure the responsible development and use of blockchain technology
	Environmental	• Reduces energy consumption through optimized data processing compared to traditional on-premises data centers • Enhances resource management and utilization	• High energy consumption of large-scale cloud data centers • Potential for generating e-waste due to frequent turnover of hardware and cooling equipment in data centers	• Research on energy-efficient cloud and edge computing technologies
	Economic	• Reduces IT infrastructure costs for businesses through scalable solutions • Enhances scalability and flexibility of operation, enabling businesses to adapt to changing demands	• Dependency on service providers, potentially leading to vendor lock-in and data sovereignty • Job displacement in traditional IT roles	• Support for local cloud and edge computing providers • Promote competition in the cloud computing market • Implement robust cybersecurity measures and data privacy regulations

(Continued)

TABLE 1.4 (Continued)

Technology	Sustainability dimension	Potential positive impacts	Potential negative impacts	Mitigation strategies and research needs
Cyber-physical systems (CPS)	Social	- Facilitate innovation and entrepreneurship by lowering barriers to entry for startups and small businesses - Enhance collaboration and knowledge sharing across geographical boundaries - Improves access to computing resources for education and research - Increases access to information and resources through cloud-based platforms - Enables global collaboration and access to information - Enable remote work opportunities, promoting work-life balance and reducing commutes	- Data security and privacy concerns with sensitive information stored in the cloud. - Dependence on Internet connectivity and potential for disruptions - Data privacy concerns and potential for misuse of personal information - Digital divide and unequal access to cloud computing resources - Potential job displacement in IT maintenance roles	- Programs to improve cloud access in underserved areas - Implement strong data privacy regulations and ensure ethical data governance practices
	Environmental	- Enhances energy management through integrated systems, reducing emissions - Optimize industrial processes for resource efficiency and waste reduction - Real-time monitoring and control of environmental parameters	- High energy consumption of some CPS components, such as sensors and data centers - Potential for cyberattacks on critical infrastructure with environmental consequences	- Develop energy-efficient CPS components and explore the use of renewable energy sources - Redundancy and resilience in CPS design to protect critical infrastructure from cyberattacks
	Economic	Improves operational efficiency and productivity, leading to cost savings and economic growth.	High initial setup and integration costs	Develop cost-effective and scalable CPS solutions for businesses of all sizes

Advanced industrial robotics and automation		• Enhances safety and reliability of critical infrastructure, reducing economic losses from accidents and disruptions • Enables new business models and service offerings based on CPS capabilities	• Cybersecurity risks potentially affecting business operations • Need for specialized skills and expertise to design, operate, and maintain CPS • Potential job displacement in sectors where tasks are automated by CPS	• Invest in education and training programs to develop a skilled workforce in CPS technologies
	Social	• Enhances safety and reliability of critical infrastructure • Potential for CPS to enable smart cities (e.g., traffic management) and improve quality of life • Improves worker interaction with machines, enhancing productivity and job satisfaction	• Potential for job displacement in monitoring and control roles • Cybersecurity risks and potential privacy violations from increased data collection and analysis	• Policies for fair transition to CPS-enabled systems • Develop ethical guidelines and regulations for data usage, privacy, and algorithmic transparency in CPS
	Environmental	• Increased efficiency and reduced waste through precision manufacturing • Enable hazardous waste handling and environmental remediation in challenging environments	• Potential for increased resource extraction and environmental damage if automation leads to unsustainable consumption patterns • High energy consumption of robotic systems • Potential for increased e-waste from discarded robotic components	• Promote sustainable consumption patterns and decouple economic growth from resource depletion • Develop energy-efficient robots and explore the use of renewable energy sources to power automation systems
	Economic	• Increases productivity, efficiency, quality, and cost savings in manufacturing through automated processes • Enhances the competitiveness of industries adopting advanced automation technologies	• Job displacement in sectors heavily reliant on manual labor • High initial investment costs for implementing robotic/automation systems	• Explore flexible automation models and human-robot collaboration

(Continued)

TABLE 1.4 (Continued)

Technology	Sustainability dimension	Potential positive impacts	Potential negative impacts	Mitigation strategies and research needs
Additive manufacturing (3D printing)	Social	- Improves worker safety by automating hazardous tasks - Enhances job satisfaction with reduction of repetitive tasks - May lead to job displacement but also creates new roles	- Potential job losses and social inequality - Human-robot interaction challenges - Potential for increased social isolation if human interaction is minimized	- Policies for fair transition to automation - Promote human-centered design principles for robots and workplaces - Establish ethical guidelines and regulations for robot development and deployment
	Environmental	- Reduces material waste through precise production (Ford & Despeisse, 2016) - Potential for using recycled materials in 3D printing - Reduces transportation emissions due to localized production	- Tends to consume more energy per unit produced than traditional manufacturing processes - Limited availability of recyclable and sustainable materials for some 3D printing technologies - Potential for release of harmful nanoparticles during printing	- Develop energy-efficient 3D printing processes and explore the use of renewable energy sources - Development of sustainable printing materials - Research and mitigate potential health and environmental risks of printing materials
	Economic	- Lower production costs for small batch sizes - Enhances customization at scale and innovation - Enhances mass customization, on-demand production, and innovation - Enables rapid prototyping and product development, reducing lead times - Reduces need for large inventories and warehousing, lowering costs - Potential for localized production, creating new	- High initial investment for equipment - High maintenance and material costs - Potential job displacement in traditional manufacturing sectors - Intellectual property challenges - Limited scalability for mass production compared to traditional manufacturing methods	- Develop more affordable and accessible 3D printing technologies - Explore hybrid manufacturing models combining 3D printing with traditional methods - Development of new IP frameworks - R&D to overcome scalability and material limitations

Augmented reality (AR)/virtual reality (VR)		jobs and supporting local economies		
		• Reduces reliance on global supply chains		
	Social	• Increases accessibility to customized products, e.g., customized medical devices and prosthetics • Democratizes manufacturing capabilities, enabling individuals and small businesses to create products • Enhances design freedom and creativity, fostering innovation and entrepreneurship	• Job losses in traditional manufacturing • Potential for unregulated/illegal production of harmful items such as counterfeiting or weapon production • Health risks from exposure to printing materials	• Implement regulations and monitoring mechanisms to prevent the misuse of 3D printing technologies • Support for local manufacturing hubs for transition to additive manufacturing
	Environmental	• Enhances remote monitoring and maintenance of infrastructure, reducing the need for on-site visits and associated emissions • Enhances training for sustainable practices • Enhances visualization for environmental planning and management	• High energy consumption of AR/VR devices and supporting infrastructure • Potential for increased e-waste generation from short lifecycle hardware	• Develop energy-efficient AR/VR devices and explore the use of renewable energy sources for supporting infrastructure • Design AR/VR hardware for durability, repairability, and recyclability
	Economic	• Increases productivity and efficiency in various sectors through improved training, design, and collaboration • Enables development of new AR/VR-based products and services, creating new markets and economic opportunities	• High initial investment costs for AR/VR hardware and software • Need for specialized skills and expertise to develop and implement AR/VR solutions	• Develop more affordable and accessible AR/VR technologies
	Social	• Enhances learning and training experiences, improving knowledge	• Potential for social isolation and addiction if AR/VR technologies are not used responsibly	• Promote responsible use of AR/VR technologies and develop guidelines for

(Continued)

TABLE 1.4 (Continued)

Technology	Sustainability dimension	Potential positive impacts	Potential negative impacts	Mitigation strategies and research needs
		retention and skill development • Improves accessibility for people with disabilities, enabling them to participate more fully in various activities • Potential for AR/VR to foster empathy and understanding by creating immersive experiences that simulate different perspectives and environments • Cultural preservation and virtual tourism • Enhances remote work capabilities	• Ethical concerns regarding privacy, data security, and the potential misuse of AR/VR technologies	ethical design and content creation • Programs promoting balanced use of virtual and physical interactions

As elucidated by [Beier et al. \(2017\)](#) and [Müller and Voigt \(2018\)](#), IoT's ability to integrate and analyze data across entire supply chains enables more precise resource management, thereby potentially reducing overproduction and minimizing waste. This interconnectedness supports more accurate forecasting of material needs, lowering the risk of overstocking and minimizing waste due to obsolescence. These findings align with the findings of [Manavalan and Jayakrishna \(2019\)](#), who highlight IoT's role in facilitating real-time coordination with suppliers and customers, thereby optimizing purchasing processes and production schedules. The real-time monitoring capability significantly curtails material waste, fostering a more sustainable production environment.

Energy consumption, a critical factor in environmental sustainability, stands to be significantly impacted by Industry 4.0 technologies. The integration of cyber-physical systems (CPS), big data analytics, and AI provides advanced tools for energy-efficient optimization in manufacturing processes ([Matsunaga et al., 2022](#); [Mohamed et al., 2019b](#); [Qiao et al., 2021](#)). By analyzing data from sensors and production systems, AI algorithms can predict equipment failures before they occur, allowing for timely maintenance and preventing energy-intensive disruptions. This proactive approach not only contributes to economic savings but also aligns with environmental sustainability goals by reducing energy waste. [Liang et al. \(2018\)](#) demonstrate how these technologies can be applied to optimize machining operations and system parameters, leading to substantial energy savings. Similarly, [Schulze et al. \(2019\)](#) demonstrated the potential of CPS in reducing the water consumption in Automotive industry. Moreover, while the adoption of digital twins and data-driven methods under Industry 4.0 is poised to significantly enhance energy savings, the true challenge lies in managing data communication and infrastructure rather than merely advancing modeling techniques ([Teng et al., 2021](#)). The potential of AI in this domain is particularly promising, with several studies ([Vinuesa et al., 2020](#); [Bonilla et al., 2018](#); [Ahmad et al., 2021](#); [Cavalcanti et al., 2024](#)) highlighting its capacity to drive significant energy efficiencies through process optimization.

Similarly, additive manufacturing, another key technology of Industry 4.0, offers significant sustainability benefits by reducing material usage through the extension of product lifecycles and the upcycling of waste into new products ([Ford & Despeisse, 2016](#)). This technology also enhances the recycling and remanufacturing of products, contributing to the circular economy and promoting more sustainable production practices. The ability of additive manufacturing to produce customized products on demand reduces the need for large-scale production runs, thereby minimizing waste and excess inventory. The synergy between additive manufacturing and other digital technologies, such as IoT and Big Data, creates a powerful ecosystem for sustainable production. For instance, [Bressanelli et al. \(2018\)](#) describe how these technologies enable comprehensive product lifecycle monitoring, facilitating easier updates and repairs, which in turn reduces material consumption and enhances recyclability.

However, despite these positive impacts, Industry 4.0 technologies also pose significant challenges. One of the primary concerns is the increased energy consumption and consequent environmental implications associated with the deployment and operation of these technologies ([Huertas-García et al., 2023](#)). For example, the computational power required for AI and data analytics can lead to substantial energy use, potentially offsetting the efficiency gains achieved through other means, a phenomenon referred to as the "rebound effect"

(Bonilla et al., 2018; Chen, Song, et al., 2021; Henderson et al., 2020). This has given rise to the field of 'Green AI', which emphasizes developing AI solutions that are not only effective but also environmentally friendly (Alzoubi & Mishra, 2024; Bolón-Canedo et al., 2024). Moreover, the infrastructure supporting Industry 4.0, including data centers and network equipment, has a considerable carbon footprint. The energy required to power these facilities, particularly if sourced from fossil fuels, poses a significant challenge to the overall sustainability of these technologies. The large data centers needed to manage and analyze big data consume significant amounts of energy, raising concerns about the environmental footprint of these technologies (Stock et al., 2018). Furthermore, the production of electronic devices required for CPS, smart products, and robotics increases the demand for scarce raw materials, leading to further environmental degradation (Vinuesa et al., 2020). Therefore the environmental benefits of Industry 4.0 technologies must be weighed against the challenges they introduce, particularly in terms of energy consumption. The energy required to operate advanced manufacturing processes and the computational demands associated with Big Data and AI can be substantial, potentially offsetting the material efficiency gains (Vinuesa et al., 2020; Bonilla et al., 2018). The deployment of these technologies also necessitates the production of new electronic devices, which contributes to increased e-waste and the consumption of scarce raw materials (Stock et al., 2018). The environmental impact of these processes cannot be overlooked, as the production and disposal of electronic devices introduce additional environmental burdens, particularly in terms of resource extraction and waste generation.

To mitigate these challenges, it is imperative to integrate energy-efficient design principles into the development and operation of Industry 4.0 technologies. For instance, the incorporation of renewable energy sources into the energy grids that power these technologies can significantly reduce their environmental footprint. This can be facilitated through smart grids and energy storage systems that balance supply and demand (Bonilla et al., 2018). Furthermore, optimizing algorithms for energy efficiency (Liang et al., 2018) can help lower the energy demands of AI and data processing tasks. This includes employing advanced cooling technologies, implementing energy-efficient hardware, and utilizing machine learning algorithms to optimize server loads and reduce power consumption. Another critical strategy is the implementation of circular economy principles at the design stage of these technologies. This approach involves designing devices for disassembly, reuse, and recycling, as well as developing take-back programs for electronic devices, thereby minimizing e-waste and promoting resource sustainability. By adopting these strategies, the environmental impact of Industry 4.0 technologies can be significantly reduced, enhancing their contribution to sustainability.

While the direct impact of Industry 4.0 technologies on water consumption and quality is less explored, there are emerging opportunities and challenges in this area. Cyber-physical systems (CPS) and big data analytics could be employed to monitor and manage water usage in manufacturing processes (Schulze et al., 2019). These technologies can adjust operational parameters in real-time, thereby reducing water consumption and improving water quality through more efficient wastewater management. AI technologies also offer promising applications in water quality monitoring, where they can analyze vast amounts of data from sensors to detect and predict contamination events. This proactive approach not only safeguards water resources but also reduces the environmental impact of industrial effluents. However, certain Industry 4.0 technologies, particularly those related to

electronics manufacturing, can be water-intensive. The production of semiconductors, for example, requires substantial amounts of ultrapure water, posing a challenge to water sustainability (Stock et al., 2018). This highlights the need for further research to fully understand and harness the potential of these technologies in water resource management.

To mitigate these challenges, implementing closed-loop water systems within manufacturing facilities can significantly reduce freshwater consumption. Technologies that enable the recycling and reuse of wastewater, as well as the recovery of valuable materials from effluents, should be integrated into Industry 4.0 frameworks to enhance water sustainability. Moreover, the integration of IoT and AI into water management systems can optimize water use across industrial operations. For instance, smart irrigation systems in agribusiness contexts or precision water management in manufacturing can reduce water waste and improve overall water use efficiency.

1.5.2 Economic sustainability: impacts, challenges, and mitigation strategies

Beyond environmental sustainability, Industry 4.0 technologies also have significant implications for economic sustainability, particularly in terms of cost efficiency and productivity. Numerous studies have consistently highlighted the potential for increased efficiency, reduced costs, and enhanced productivity through the implementation of Industry 4.0 technologies (Nagy et al., 2018; Watanabe et al., 2016; Li et al., 2020). Technologies such as IoT, CPS, and big data analytics enable the continuous real-time monitoring and control of physical processes (Nouiri et al., 2019; Shrouf & Miragliotta, 2015), leading to improved productivity, improved material selection efficiency (Horváthová et al., 2019), enhanced material reuse and recycling (Stock et al., 2018; Pasi et al., 2021), reduced downtime, lowered operational costs, and enhanced decision-making capabilities. The studies by Nagy et al. (2018) and Watanabe et al. (2016) highlight how these technologies facilitate predictive maintenance, which not only extends equipment life but also reduces maintenance costs and prevents costly breakdowns. Similarly, CPS implementation can boost productivity through enhanced human-robot collaboration (Gualtieri et al., 2020). The integration of these technologies into manufacturing processes can also lead to significant cost savings by optimizing resource use, reducing waste, and improving energy efficiency (Nouiri et al., 2019; Shrouf & Miragliotta, 2015). For instance, cloud computing can reduce energy consumption and operating costs by enabling more efficient use of resources and facilitating collaboration across the supply chain (Schniederjans & Hales, 2016). Furthermore, AI and machine learning technologies can optimize supply chain management by predicting demand, optimizing inventory levels, and reducing lead times, thereby lowering operational costs and improving customer satisfaction (Ahmad et al., 2020).

Industry 4.0 technologies are also reshaping traditional business models, enabling new revenue streams, enhancing customer engagement, and fostering innovation. IoT, for instance, enables the development of smart products that can be customized and updated remotely, offering new revenue streams through subscription services or product-as-a-service models. This shift from product ownership to service models can create more stable revenue streams and closer customer relationships (Kiel et al., 2017). Additionally, the use of digital twins and virtual prototyping allows companies to simulate and optimize product performance before physical production, reducing time-to-market and development costs.

This not only enhances product quality but also fosters innovation by enabling rapid iteration and testing (Bressanelli et al., 2018).

The circular economy, a key concept in sustainable manufacturing, is also closely linked to the adoption of Industry 4.0 technologies. The integration of IoT, big data analytics, and CPS into closed-loop supply chains can enhance the efficiency of resource use and waste management, contributing to the development of more sustainable production systems (Belaud et al., 2019; Strandhagen et al., 2017). These technologies enable the tracking and monitoring of products throughout their lifecycle, facilitating the recycling, reuse, and remanufacturing of materials (Meng et al., 2020). By promoting circularity and reducing the environmental impact of production, Industry 4.0 technologies can play a crucial role in advancing the goals of the circular economy (Kristoffersen et al., 2020).

However, it is essential to recognize that the economic benefits of Industry 4.0 are not guaranteed and require careful consideration of implementation costs, potential risks, and the need for ongoing investment in infrastructure and workforce development (Kiel et al., 2017; Müller et al., 2018). The high initial investment required for the deployment of these technologies and training poses significant challenges for companies, particularly small and medium-sized enterprises (SMEs) (Kiel et al., 2017; Müller & Voigt, 2018). Additionally, while the long-term benefits of these technologies are well-documented, the return on investment (ROI) can be uncertain due to rapidly changing technology landscapes and market conditions. Furthermore, the rapid pace of technological change and the increasing complexity of digital systems can lead to higher maintenance costs and the need for continuous updates and upgrades (Watanabe et al., 2016). Companies may face challenges in justifying these investments, particularly in industries with tight profit margins (Müller et al., 2018). Resultantly, companies must carefully evaluate the cost-benefit ratio of adopting Industry 4.0 technologies and develop strategies to manage the associated economic risks (Beier et al., 2017). Regarding the shift toward digital business models can disrupt traditional industries, leading to job losses and the obsolescence of existing skills and business practices. Companies that fail to adapt to these changes may struggle to remain competitive (Bremer, 2015). Furthermore, the increased reliance on data-driven business models introduces significant risks related to data privacy and security. Companies must navigate complex regulatory environments and protect sensitive customer data, which can be challenging and costly (Gill, 2016).

To mitigate these economic risks, companies can adopt a phased approach to implementing Industry 4.0 technologies, allowing them to gradually integrate new technologies, assess their impact, and scale up as needed. This approach not only improves cost management but also enhances the likelihood of a positive ROI. Additionally, developing collaborative platforms where companies can share resources, knowledge, and infrastructure can reduce the individual financial burden of adopting these technologies. This is particularly relevant for SMEs, which can benefit from economies of scale and shared expertise. To manage the transition to new business models, companies can adopt hybrid approaches that combine traditional and digital elements, allowing them to leverage the benefits of Industry 4.0 technologies while maintaining stability in their core business operations. Additionally, investing in robust cybersecurity measures and ensuring compliance with relevant regulations are crucial for mitigating the risks associated with data privacy and security. This includes implementing encryption, access controls, and regular

audits to protect sensitive data. Moreover, the pursuit of economic gains should not come at the expense of social or environmental sustainability. A holistic approach that integrates economic considerations with social and environmental responsibility is crucial for achieving truly sustainable development in the context of Industry 4.0. This requires businesses to adopt a triple bottom line approach, measuring their success not just in terms of financial performance but also in terms of their social and environmental impact.

1.5.3 Social sustainability: impacts, challenges, and mitigation strategies

Turning to the social dimensions of sustainability, Industry 4.0 presents a complex landscape of opportunities and challenges, particularly in terms of employment, labor practices, and working conditions. The impact on working conditions is multifaceted. On one hand, the automation of routine tasks and the reduction of manual labor can improve working conditions by reducing physical strain and enhancing worker safety (Gualtieri et al., 2020; Pinzone et al., 2020). For example, human-robot collaboration in manufacturing environments can improve ergonomics and prevent posture-related injuries, contributing to better occupational health and safety (Pasi et al., 2021). AR technologies can further enhance workplace safety by providing workers with real-time information about potential hazards, thereby reducing the risk of accidents (Gualtieri et al., 2020; Damiani et al., 2020). Blockchain technology can be used to create tamper-proof records of working conditions in factories, making it more difficult for companies to hide exploitative practices. Similarly, IoT sensors can monitor worker safety in real-time, alerting supervisors to potential hazards and enabling rapid response. Cagliano et al. (2019) suggest that Industry 4.0 implementation may provide workers with greater autonomy and increase social interactions. Technologies like blockchain, big data, and IoT also offer the potential to enhance transparency in labor practices, potentially preventing abuses related to working conditions, wages, and equity (Venkatesh et al., 2020).

A new concept, social manufacturing, has recently emerged within this landscape, where manufacturers and individuals collaborate in the production of physical goods (Jiang et al., 2016; Hamalainen & Karjalainen, 2017). This model leverages the collective intelligence and creativity of diverse stakeholders, enabling more inclusive and socially responsive manufacturing processes. Cloud manufacturing complements this concept by facilitating the crowdsourcing of information and the simulation of innovative designs, thereby democratizing access to manufacturing resources and fostering greater social engagement in the production process (Fisher et al., 2018; Ren et al., 2017). Through these collaborative and cloud-based approaches, social manufacturing not only enhances the inclusivity of production systems but also promotes shared ownership and participation, which can lead to more socially sustainable outcomes.

On the other hand, the widespread adoption of these technologies can lead to significant social challenges, particularly in terms of employment and job security. The automation of low-skilled jobs and the increasing reliance on technology in the workplace can result in job displacement, particularly in industries heavily reliant on manual labor, exacerbating social inequality and leading to economic dislocation for affected workers (Stock et al., 2018; Bremer, 2015). This challenge intersects with gender dynamics, as numerous studies suggest that women may face a disproportionately higher risk of job displacement due

to automation. Analyses by the Institute for Women's Policy Research [add citation], International Monetary Fund (Brussevich et al., 2019), Inter-American Development Bank (Egana-delSol et al., 2022), Office for National Statistics, UK (White et al., 2019), International Labor Organization (Chang & Huynh, 2016), and Statistics Canada (Frenette & Frank, 2020) all indicate a higher likelihood of women being employed in occupations susceptible to automation. This disparity underscores the need for targeted interventions to ensure that the benefits of Industry 4.0 are distributed equitably and that women are not left behind in the transition to a more automated workforce. However, it is important to acknowledge that some studies, such as those by the McKinsey Global Institute (Madgavka et al., 2019) and the Metropolitan Policy Program at Brookings (Muro et al., 2019), present a contrasting view, suggesting that men in the United States might face a higher risk of job displacement by 2030. These conflicting perspectives highlight the complexity of this issue and the need for further research to fully understand the gendered impacts of automation across different contexts.

The psychological stress associated with job insecurity and the fear of job loss can negatively impact workers' well-being, further complicating the social sustainability of these technologies (Pasi et al., 2021; Coldwell, 2019). Moreover, the rapid pace of technological change can create a skills gap, where the existing workforce lacks the necessary skills to operate and maintain Industry 4.0 technologies. This skills gap can hinder the adoption of these technologies and lead to a mismatch between job availability and the skills of the workforce (Nam, 2019). To address these challenges, companies and governments must invest in reskilling and upskilling programs. These initiatives can help workers transition to new roles within Industry 4.0 environments and ensure a steady supply of skilled labor (Coldwell, 2019). Additionally, implementing inclusive workforce policies that promote diversity and provide opportunities for all workers to participate in the Industry 4.0 economy can help mitigate the social impacts of job displacement. This includes initiatives to support underrepresented groups and ensure equitable access to new job opportunities.

The increased use of AI and big data analytics raises significant ethical and privacy concerns, particularly related to data collection, surveillance, and algorithmic bias (Vinuesa et al., 2020; Ashok et al., 2022; Gill, 2016; Stahl & Wright, 2018; Sugiyama et al., 2017). While technologies like blockchain and IoT can enhance transparency and traceability in supply chains, helping to prevent unethical practices such as labor exploitation and environmental degradation, they also pose challenges related to the loss of privacy and personal autonomy. Individuals may be subjected to constant surveillance, and their data could be used in ways that infringe on their rights (Gill, 2016; Sugiyama et al., 2017). Moreover, AI and machine learning algorithms can perpetuate or exacerbate existing biases if not properly designed and monitored, leading to discriminatory outcomes in areas such as hiring, lending, and law enforcement (Vinuesa et al., 2020). These issues underscore the need for robust governance frameworks and policies that protect workers' rights, ensure fair wages, and promote ethical AI practices (Venkatesh et al., 2020). To mitigate these risks, companies must prioritize ethical AI development, implementing fairness checks, bias audits, and transparency measures in AI systems to ensure that they operate in a nondiscriminatory manner (Milano et al., 2014). Adhering to data privacy regulations, such as the General Data Protection Regulation (GDPR) in Europe, is also crucial for protecting individual privacy rights. Companies should implement clear data governance policies and ensure that they collect, store, and use data in a manner that respects user privacy (Isaias et al., 2015).

The key to harnessing the social benefits of Industry 4.0 lies in proactively addressing the potential negative impacts while simultaneously leveraging its transformative potential to create a more equitable and just society. This requires a multistakeholder approach, involving governments, businesses, and civil society organizations, to develop ethical guidelines, regulations, and workforce development programs that ensure a just and inclusive transition to an Industry 4.0-driven economy.

1.6 Rebound effects of Industry 4.0 technologies on sustainability

While Industry 4.0 technologies hold transformative potential for enhancing sustainability across various industrial sectors, it is critical to recognize and address the possibility of rebound effects—unintended consequences that may partially or fully offset the anticipated environmental, social, and economic benefit (Kunkel et al., 2023). Rebound effects occur when the efficiency gains and resource savings achieved through technological advancements lead to increased consumption, production, or other activities that ultimately undermine sustainability objectives. Rebound effects, first observed in energy efficiency improvements by William Stanley Jevons in 1865, describe the phenomenon where technological advancements aimed at improving resource efficiency paradoxically lead to increased overall resource consumption. Rebound effects are a well-documented phenomenon in the field of energy efficiency, but their implications in the domain of Industry 4.0 remain underexplored. The core principle of the rebound effect is rooted in the economic theory of demand: as technological advancements improve the efficiency with which a resource (e.g., energy, materials, and time) is utilized, the cost associated with using that resource decreases. This reduction in cost, in turn, can lead to an increase in demand, ultimately resulting in higher overall consumption of the resource at a macrolevel. In the context of Industry 4.0, the rebound effect can manifest in several ways:

- **Direct rebound effect:** This effect occurs when efficiency improvements lead to increased consumption as a result of reduced operational costs. For instance, energy-efficient manufacturing processes may result in lower energy costs, which could encourage increased production and, consequently, higher total energy consumption, offsetting initial energy savings (Lange et al., 2020; Amjadi et al., 2022; Kunkel & Tyfield, 2021; Wang et al., 2023). In the context of Industry 4.0, the widespread adoption of additive manufacturing (AM) technologies exemplifies this issue (Ford & Despeisse, 2016). While AM allows for precision manufacturing with minimal waste, the reduced costs and enhanced flexibility can stimulate demand for customized products, thereby increasing resource use and waste generation over time. Similarly, the enhanced manufacturing efficiency and reduced production costs enabled by Industry 4.0 can boost demand and consumption, potentially accelerating resource depletion. For example, the accessibility of cheaper, customized products through AM could encourage higher consumption rates and shorter product lifecycles. Similarly, the adoption of industrial robots in China has shown that while these technologies can reduce carbon emissions, they also lead to an energy rebound effect, partially offsetting the intended carbon reduction benefits (Wang et al., 2023).

Furthermore, while AI-driven predictive maintenance systems can reduce energy use, they may also enable longer machinery operation and increased production hours, ultimately raising overall energy demand (Ahmad et al., 2021; Kunkel & Tyfield, 2021; Gossart, 2015). Another example of the direct rebound effect can be observed in data centers. Significant progress has been made in improving the energy efficiency of data centers, with the Power Usage Effectiveness (PUE) of recent facilities halving over the past 20 years (Masanet et al., 2020; Davis, 2024). Additionally, modern data centers now deliver four times more computational power for the same energy consumption compared to just eight years ago. However, despite these efficiency gains, data centers have experienced a slight increase in overall power consumption, with a 6% rise between 2010 and 2018. Thus while efficiency improvements have been substantial, the surge in demand has more than offset these gains, leading to an overall rise in energy use (Bordage et al., 2021). The rebound effects of automation are seen in the automotive industry, where despite a tripling of robot density since the 1990s, overall employment has remained stable (Butollo, 2024). This is because the complexity of production processes has increased, with more jobs shifting toward indirect areas like development, planning, and logistics, thus offsetting the labor-saving potential of automation. The introduction of 5G technology provides another compelling illustration of the direct rebound effect. The increased efficiency and speed of 5G networks are expected to boost data consumption due to the enhanced user experience and the proliferation of high-bandwidth applications like 4K/8K video streaming, AR, and virtual reality (VR). While these technologies may improve certain aspects of productivity and user engagement, they also drive up energy demand across the network infrastructure and end-user devices. The case study notes that a 5G connection could generate nearly three times more traffic than a 4G connection, which, despite the higher efficiency of 5G, may result in an overall increase in energy consumption, thus offsetting the environmental benefits initially expected from the deployment of 5G. Another pertinent example of the direct rebound effect in the context of Industry 4.0 can be observed in the adoption of autonomous vehicles (AVs). Although AVs are anticipated to improve road safety and driving efficiency, studies suggest (Bordage et al., 2021) that their widespread adoption could increase the total vehicle miles traveled (VMT) due to the convenience they offer. As nondrivers gain access to autonomous transportation and existing drivers can engage in other activities while commuting, the demand for car travel could rise, leading to higher overall energy consumption. Additionally, the potential reduction in public transport use and the increase in road congestion associated with AVs could exacerbate environmental impacts, offsetting the expected benefits of autonomous driving.

- **Indirect rebound effect:** Indirect rebound effects occur when the savings or efficiencies from I4.0 technologies are reallocated toward consuming other goods and services, potentially with their own environmental footprints or social impacts. For instance, a company that saves costs through automation may reinvest those savings into expanding production capacity or diversifying product lines, both of which could lead to increased resource consumption (Kunkel & Tyfield, 2021). These effects are more challenging to quantify and often manifest over longer time scales, complicating sustainability assessments. Widespread adoption of Industry 4.0 technologies could accelerate economic growth, potentially increasing overall energy demand and resource extraction.

Focusing solely on optimizing existing production paradigms through Industry 4.0 might divert resources and attention away from developing radically sustainable technologies and business models. This technological lock-in could hinder the transition toward a truly circular economy. Efficiency gains in one sector can stimulate economic activity in others, leading to broader resource consumption patterns. For instance, widespread adoption of Industry 4.0 technologies could accelerate economic growth, potentially increasing overall energy demand and resource extraction.

- **Economy-wide rebound effects:** These effects occur when greater efficiency drives overall economic growth, leading to structural changes in production and consumption at a macroeconomic level. These effects result from the combined impact of direct and indirect rebound effects and are often overlooked due to their complexity and long-term nature. A pertinent example is the Internet's arrival, which has catalyzed significant economic growth and innovation but also led to increased energy consumption and resource use across multiple sectors. In the context of Industry 4.0, economy-wide rebound effects may manifest as a result of increased automation, connectivity, and data processing capabilities. While these advancements can lead to significant efficiencies within individual processes or sectors, their cumulative impact across the economy may result in higher overall energy consumption and resource use, thereby undermining sustainability goals. [Sorrell \(2009\)](#) argues that economy-wide rebound effects are particularly pronounced with energy efficiency improvements linked to general-purpose technologies, such as those under Industry 4.0, because these technologies are widely applicable across multiple sectors. This contrasts with dedicated energy-efficiency technologies, where such widespread rebound effects are less likely to occur, making the Jevons' Paradox ([Jevons, 1866](#)) less applicable ([Berkhout & Hertin, 2001](#)). Therefore despite the potential environmental benefits of Industry 4.0 technologies, their status as general-purpose technologies suggests that these benefits are likely to be absorbed by economy-wide rebound effects ([Gossart, 2015](#)). [Kunkel et al. \(2023\)](#) further support this by noting that the proliferation of Industry 4.0 technologies in Chinese manufacturing sectors has not led to significant reductions in energy consumption, indicating the presence of direct, indirect, and economy-wide rebound effects that may counteract the anticipated environmental benefits. Consequently, policies that focus solely on lowering emissions in the context of Industry 4.0 may be insufficient without addressing the broader economic impacts ([Bildirici & Ersin, 2023](#)).
- **Technological rebound effect:** Technological rebound effects occur when an improvement changes the availability or affordability of certain resources or technologies, leading to changes in consumption. In the context of Industry 4.0, these effects occur when advancements in one technology create demand for other resource-intensive technologies. For example, the development of sophisticated sensors for Industry 4.0 applications might require energy-intensive manufacturing processes and materials, offsetting some sustainability gains. Similarly, the integration of AI/ML in industrial processes can lead to increased demand for high-performance computing infrastructure, which is often energy-intensive to operate and maintain. Another aspect of technological rebound effect is the rapid obsolescence of Industry 4.0 technologies, driven by continuous innovation cycles. Newer, faster models quickly replace older ones, even if the latter remain functionally adequate for many users ([Gossart, 2015](#)). This continuous cycle of upgrades

contributes to the growing problem of electronic waste (e-waste) and resource depletion, as exemplified by the rapid turnover of computers and smartphones (Baldé et al., 2024; Bachér et al., 2020). The complex material composition of these technologies complicates recycling and safe disposal, potentially leading to environmental pollution and health hazards (Ilankoon et al., 2018; Bordage, 2019).

1.6.1 Challenges and mitigation strategies for rebound effects

Assessing and quantifying rebound effects, particularly in the context of Industry 4.0 technologies, presents significant methodological and conceptual challenges. These challenges stem from the complex interplay of technological, economic, and social factors that collectively influence the manifestation and magnitude of these effects. Rebound effects are rarely attributable to a single factor; rather, they are inherently systemic and dynamic, influenced by a web of interactions that resist simplistic quantification (Amjadi et al., 2022; Freeman, 2018; Guzzo et al., 2023). The challenge is further compounded by the nonlinear relationships and feedback loops inherent in complex sociotechnical systems, which can lead to emergent behaviors that are difficult to predict or model accurately (Guzzo et al., 2024). A key difficulty in understanding and estimating rebound effects associated with Industry 4.0 technologies lies in their pervasive and cross-sectoral influence. Industry 4.0, characterized by the convergence of digital technologies such as the IoT, AI, and big data, permeates nearly every aspect of industrial production and consumption. This pervasive nature leads to a cascade of secondary and tertiary effects that transcend traditional sectoral boundaries, making it challenging to trace and quantify specific rebound effects. This pervasiveness creates intricate webs of indirect and induced effects that transcend traditional sectoral boundaries, making it challenging to isolate and quantify specific rebound effects. The interconnectedness of these technologies means that efficiency gains in one domain can trigger unforeseen consequences in others, amplifying or mitigating rebound effects in unpredictable ways. The innovative potential of these technologies further complicates the analysis, as they continuously reshape production processes, consumption patterns, and market structures, necessitating dynamic modeling approaches that can adapt to rapid technological evolution. However, existing research predominantly focuses on the micro-level impacts of Industry 4.0 technologies, often emphasizing their potential for energy efficiency improvements in specific processes or applications (Santarius et al., 2020). Furthermore, a reliance on projected rather than actual energy savings creates a disconnect between theoretical models and empirical realities (Santarius et al., 2020). The challenges in assessing rebound effects associated with Industry 4.0 technologies underscore the need for continued scientific inquiry and methodological innovation. To accurately capture the full scope of these effects, future research must adopt more holistic approaches that integrate both micro- and macrolevel analyses, accounting for the complex, dynamic nature of modern sociotechnical systems (Kunkel & Tyfield, 2021).

Mitigating rebound effects requires a holistic approach that considers both technological and societal dimensions (Kunkel et al., 2023; Bonilla et al., 2018; Kunkel & Tyfield, 2021). Integrating lifecycle thinking into product and process design is crucial to minimize environmental impacts throughout the value chain, including energy consumption, material use, and end-of-life management during the design phase (Bildirici & Ersin, 2023).

Implementing policies that promote sustainable consumption patterns, such as extended producer responsibility schemes, product lifespan labeling, and eco-taxes, can help mitigate rebound effects by internalizing environmental costs. Transitioning from linear to circular economy models, enabled by Industry 4.0 technologies like blockchain for material traceability and AI for resource optimization, can decouple economic growth from resource depletion and minimize waste generation. Additionally, raising social awareness among consumers and manufacturers about the potential rebound effects of Industry 4.0 is crucial to encourage responsible consumption and production practices. To address the rebound effects in an economy-wide perspective, an approach comparing efficiency gains and rebound effects within the planetary boundaries is more relevant, taking also econometric and social parameters into account. By proactively addressing rebound effects through integrated technological and policy interventions, the transformative potential of Industry 4.0 can be harnessed to achieve genuine sustainability transitions in manufacturing. Further research is needed to develop robust methodologies for quantifying and mitigating rebound effects across different Industry 4.0 technologies and application contexts.

1.7 Industry 4.0 adoption and sectoral sustainability impacts

The adoption of Industry 4.0 technologies varies significantly across different industrial sectors, reflecting diverse operational needs, technological readiness, and strategic priorities. As shown in Fig. 1.10, sectors such as automotive, electronics, and aerospace have been at the forefront of adopting these advanced technologies, driven by the need for precision manufacturing, complex supply chains, and high-value products. In contrast, industries like textiles and food processing show lower adoption rates, possibly due to factors such as lower profit margins or less complex production processes. This disparity in adoption rates

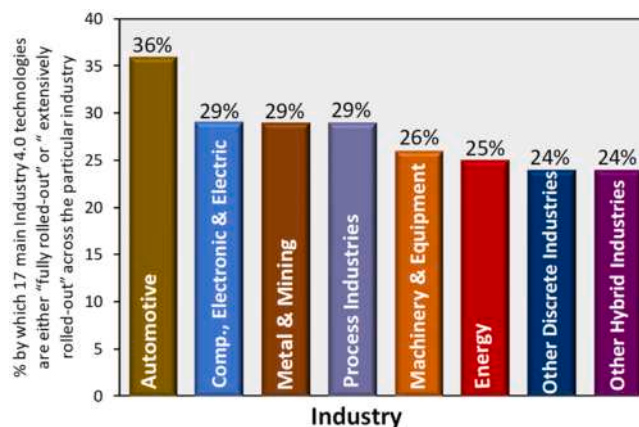


FIGURE 1.10 Industry 4.0 technology penetration by industry. Data represent the percentage of respondents ($n=150$) from a 2020 IoT Analytics Research survey ([Industry 4.0 Adoption 2020](#)) indicating that each of the 17 distinct Industry 4.0 technologies is either "fully rolled-out" or "extensively rolled-out" within their organizations. The 17 distinct Industry 4.0 technologies include AI, 3D Printing, 5G, AR, VR, AGVs, Blockchain, Cloud, Cobots, Cybersecurity, DT, Drones, IoT, IoT Platforms, Machine Vision, Edge Computing, and Quantum Computing.

highlights the need for tailored strategies to promote Industry 4.0 implementation across all sectors, ensuring a balanced and sustainable industrial transformation.

Building on the insights from Fig. 1.9, Table 1.5 presents a detailed comparative analysis of Industry 4.0 adoption across various sectors and its impact on key sustainability metrics. This analysis reveals that sectors with higher Industry 4.0 adoption rates generally show more significant improvements in sustainability indicators such as energy efficiency, waste reduction, and resource optimization. For instance, the automotive sector, with its high adoption of smart manufacturing and IoT, demonstrates substantial reductions in energy consumption and material waste. However, the table also highlights that some sectors with lower adoption rates, such as agriculture, show potential for significant sustainability gains through targeted Industry 4.0 implementation.

1.8 Discussion

The integration of Industry 4.0 technologies with sustainability initiatives presents a complex landscape of opportunities and challenges across economic, environmental, social, and governance dimensions.

1.8.1 Economic implications

Industry 4.0 technologies, such as IoT, AI, and advanced robotics, have demonstrated significant potential to drive economic growth through enhanced productivity, operational efficiency, and the creation of new business models (Koh et al., 2019; Xu et al., 2018; Pereira & Romero, 2017). For instance, the adoption of predictive maintenance and real-time data analytics can reduce downtime and maintenance costs, leading to substantial cost savings and increased profitability (Schleichert et al., 2017; Achouch et al., 2022; Hawkins, 2021). Moreover, the integration of digital twins and advanced simulations enables manufacturers to optimize production processes, thereby reducing waste and improving resource utilization (Soori et al., 2023; Leng et al., 2021; Wang et al., 2022). However, the economic benefits of Industry 4.0 are not without challenges. The high initial investment costs for implementing these technologies can be a significant barrier, particularly for small and medium-sized enterprises (SMEs) (Müller et al., 2018). Additionally, the rapid pace of technological change necessitates continuous investment in workforce training and development to ensure that employees possess the necessary skills to operate and maintain advanced systems (Sima et al., 2020; Mittal et al., 2018). Future research should focus on developing cost-effective solutions and frameworks that support SMEs in adopting Industry 4.0 technologies, as well as strategies for upskilling the workforce.

1.8.2 Environmental impacts

Industry 4.0 technologies hold immense promise for enhancing environmental sustainability by optimizing energy consumption, reducing emissions, and enabling circular economy models. By enabling resource-efficient production processes, optimizing energy consumption, and facilitating the adoption of circular economy principles, Industry 4.0 can contribute to

TABLE 1.5 Comparative analysis of Industry 4.0 adoption in various sectors and its impact on sustainability metrics.

Sector	Industry 4.0 technologies adopted	Key applications	Sustainability metrics	Impact on sustainability
Automotive	• IoT • AI • Robotics and automation • Digital twins • Additive manufacturing	• Smart factories • Predictive maintenance • Optimized production lines • Autonomous vehicles • Automated assembly and quality control	• Reduced material waste and energy consumption • Increased fuel efficiency and reduced emissions from vehicles • Improved resource efficiency in vehicle lifecycle management	• More sustainable manufacturing processes and supply chains • Enhanced recycling and waste management through smart sorting and processing • Improved resource utilization via predictive maintenance and smart manufacturing • Reduced environmental impact of transportation, e.g., by implementing IR.0 solutions, Bosch Automotive, China, achieved 18% decrease in energy consumption, 36% reduction in production lead time, 50% reduction in change over time, 25% reduction in maintenance cost, and 20% increase in labor productivity

(Continued)

TABLE 1.5 (Continued)

Sector	Industry 4.0 technologies adopted	Key applications	Sustainability metrics	Impact on sustainability
Electronics	• IoT • AI • AR/VR • CPS • Cloud computing	• Smart factories and automated production lines • Predictive maintenance and quality control	• Reduced energy consumption in manufacturing and product use • Electronic waste reduction • Product durability	• Increased e-waste recycling through smart product lifecycle management • Lower carbon footprint of electronics manufacturing and energy-efficient technologies • For example, Siemens Electronics Works Chengdu (SEWC), China, has reduced energy consumption per unit product by 24% and production waste by 48%, while increasing production by 92% through the establishment of a comprehensive Industry 4.0 technologies
Chemical/ Process Industry	• IoT • AI • Robots • Blockchain • Big Data Analytics • Digital Twins	• Predictive maintenance • Real-time monitoring of chemical processes • Automation of hazardous tasks • Predictive equipment maintenance • Waste reduction and resource efficiency • Energy consumption optimization	• Energy consumption • Emissions reduction • Waste reduction • Resource efficiency • Water usage	• Increases production cycle time through advanced analytics-based cycle time optimization • Decrease steam consumption through IoT-enabled dynamic heating process control • Optimizes energy consumption by predictive

TABLE 1.5 (Continued)

Sector	Industry 4.0 technologies adopted	Key applications	Sustainability metrics	Impact on sustainability
		Advanced process control and optimization		analytics and process optimization - Improves yield and throughput improvement using IIOT and advanced analytics - Reduces chemical waste and byproducts due to precise control and real-time adjustments - Enhances resource efficiency by optimizing raw material usage - Decreases water usage through real-time monitoring and smart water management systems - Enhances safety with reduced risks and improves incident response, e.g., to respond to external challenges, such as 30% overcapacity and higher costs due to market volatility, China based Huayi New Material company has deployed various II.0 technologies,

(Continued)

TABLE 1.5 (Continued)

Sector	Industry 4.0 technologies adopted	Key applications	Sustainability metrics	Impact on sustainability
Energy and power	• IoT • AI • Big data analytics • CPS • Blockchain	• Smart grids and microgrids • Predictive maintenance • Energy trading • Renewable integration • Demand-side management	• Energy production efficiency improvement • Emissions reduction • Resource optimization	resulting 33% increase in labor productivity, 31% reduction in energy consumption, 22% reduction in 22% material waste, and recordable safety incidents reached zero • Improved energy efficiency and reduced emissions through smart grids • Better resource optimization with predictive maintenance • Enhanced grid reliability and resilience, e.g., by implementing I4.0 solutions, CATL, a China-based energy storage battery manufacturer, has achieved 17% increase in production speed, 100% increase in assembly efficiency, 14% reduction in waste, 63% reduction in product inspection time, and 100% reduction in work safety incidents

TABLE 1.5 (Continued)

Sector	Industry 4.0 technologies adopted	Key applications	Sustainability metrics	Impact on sustainability
Pharmaceuticals	• IoT • AI • Blockchain • Robotics	• Precision (personalized) medicine • Smart manufacturing • Supply chain integrity and optimization • Drug discovery and development • Real-time process monitoring and control	• Waste reduction • Emissions reduction • Resource and energy efficiency • Waste reduction • Product traceability • Product safety	• Reduced pharmaceutical waste through precise manufacturing and quality control • Enhanced supply chain transparency and traceability • Reduced drug development time • Improved drug safety and efficacy, e.g., Johnson & Johnson, India deployed Industry 4.0 solutions such as demand sensing, smart logistics, robotics, and 3D printing. As a result, they reduced OTIF losses by 66%, accelerated new product introduction by 33% and improved cost per piece by 34%.
Food and beverage	• IoT • AI • Blockchain	• Supply chain optimization	• Water usage • Waste reduction	• Reduced food waste and spoilage throughout the supply chain

(Continued)

TABLE 1.5 (Continued)

Sector	Industry 4.0 technologies adopted	Key applications	Sustainability metrics	Impact on sustainability
Textiles	Robotics and automation	- Smart packaging and logistics - Automated food processing - Real-time monitoring of food safety and quality	- Energy reduction in food processing and logistics - Resource efficiency	- More sustainable and efficient food production systems - Lower water usage - Enhanced food safety and traceability - Reduced environmental impact of the food industry, e.g., implementing Industry 4.0 solutions Coca-Cola plant, Ballina, Ireland, reduced production cost by 16%, manufacturing cycle time by 17%, and delivery shortages by 15%
	- IoT - AI - Blockchain - Robotics and automation - AV/VR	- Smart textiles production system - Water and energy efficient dyeing and finishing technologies - Virtual design and digital textile printing - Supply chain optimization - On-demand and customized clothing production	- Minimized water and energy consumption - Chemical usage reduction - Waste reduction and management - Energy efficiency - Improvement in worker health and safety - Enhancing product durability	- Reduces water, chemical, and energy consumption in dyeing processes - Enhances recycling of textile products through smart sorting and processing - Improves safe working conditions in textile factories - Reduces textile waste and pollution from dyeing and finishing processes

TABLE 1.5 (Continued)

Sector	Industry 4.0 technologies adopted	Key applications	Sustainability metrics	Impact on sustainability
Construction	- IoT - AI 3D printing - Drones - Building information modeling (BIM) - AR/VR	Traceability of raw materials and ethical sourcing practices		Enhances resource utilization and customization capabilities
		- Smart construction - Smart building management - Resource management - Worker safety	- Waste Reduction - Energy use in building construction - Energy consumption in building operation - Worker health and safety in construction operations - Lifespan of buildings and infrastructure	- Optimizes use of construction material - Reduces material waste and construction debris through smart waste management systems - Decreases energy consumption in building operations - Optimizes material and resource usage through precise planning - Lower energy consumption in building operations through smart building technologies and energy-efficient designs - Enhances health and safety metrics of workers - For example, by implementing I4.0 solutions, MantaMESH, Germany has achieved 73% growth in production volumes, 32% reduction in energy

(Continued)

TABLE 1.5 (Continued)

Sector	Industry 4.0 technologies adopted	Key applications	Sustainability metrics	Impact on sustainability
Agricultural	• IoT • AI • Robotics • Drones and sensors • Big data analytics	• Precision agriculture and smart farming • Crop monitoring • Soil health monitoring • Yield optimization • Automated irrigation • Early detection and prevention of crop diseases and pests • Optimizing irrigation and fertilizer application	• Water usage • Fertilizer consumption • Pesticide and herbicide application • Soil health	consumption, and 99% decrease in change over time • Enable smart farming, e.g., John Deere (a US-based leading manufacturer of agricultural machinery) uses IoT, GPS, cloud computing, AI, and automation to optimize the performance of its agricultural machinery • Increase crop yield through data-driven decision-making and real-time monitoring • Improves land use efficiency • Minimizes water usage through precision farming techniques • Enhances traceability of raw materials and ethical sourcing practices, e.g., companies like Nestlé implements sustainable sourcing practices to ensure raw materials such as cocoa and coffee are produced in environmentally and socially responsible ways

TABLE 1.5 (Continued)

Sector	Industry 4.0 technologies adopted	Key applications	Sustainability metrics	Impact on sustainability
Healthcare	• IoT • AI • Robotics • Big data analytics • AR/VR • 3D printing	• Remote patient monitoring • Precision (personalized) medicine • Smart diagnostics • 3D printing for personalized medical devices and prosthetics • Big data analytics for population health management • Remote patient monitoring	• Energy efficiency • Waste reduction • Resource utilization and efficiency • Patient outcomes and healthcare costs • Hospital readmissions and patient satisfaction • Accessibility of care • Personalized treatment plans and optimized medication dosage	• Enhances soil health indicators • Improves livelihoods for farmers • Minimizes pesticide and herbicide application • For example, through I4.0, AGCO (Agricultural equipment), Germany, has increased productivity by 24% while reducing cycle time by 60% • More sustainable and patient-centered healthcare systems • Improves energy efficiency and waste reduction in healthcare facilities • Enhances resource utilization through precision medicine and diagnostics • Reduces environmental impact of healthcare operations • Improves access to quality healthcare

(Continued)

TABLE 1.5 (Continued)

Sector	Industry 4.0 technologies adopted	Key applications	Sustainability metrics	Impact on sustainability
		• Diagnostics and treatment planning • Surgical robots • Dosage optimization • Real-time monitoring of patient health and early intervention • Proactive identification of potential health risks and outbreaks • AR-assisted surgeries		• Enhances personalized medicine and treatment, e.g., 3D-printed implants • Reduces hospital readmissions and improves patient satisfaction • Enables remote patient monitoring through Internet of Medical Things (IoMT) • Improves accuracy and speed of disease diagnosis • For example, by implementing I4.0 solutions, GE Healthcare, Japan achieved a 30% increase in production efficiency, 30% reduction in costs, and 46% decrease in cycle times
Logistics	• IoT • AI • Autonomous vehicles (drones, trucks, ships) • Robotics • Blockchain	• Automated warehouses • Predictive logistics • Real-time tracking • Optimized delivery routes and reduced transportation costs • Real-time tracking of goods and improved supply chain	• Emissions reduction • Energy efficiency • Resource utilization • Route Optimization and Predictive • Optimized logistics operations and reduced waste	• Enhances energy efficiency and reduces emissions from logistics operations by reducing fuel consumption and greenhouse gas emissions from transportation • Enhances resource utilization and real-time tracking capabilities

TABLE 1.5 (Continued)

Sector	Industry 4.0 technologies adopted	Key applications	Sustainability metrics	Impact on sustainability
		• Supply chain transparency and security visibility • Smart warehousing	• Improved delivery times and reduced spoilage of perishable goods • Enhanced transparency and accountability in the supply chain	• AI for Route Optimization and Predictive results improvement in delivery accuracy • Improves supply chain resilience and responsiveness • Enhances security and reduces risk of theft or damage to goods by using IoT for Real-Time Cargo Tracking and Monitoring

AI, ARTIFICIAL INTELLIGENCE; IOT, INTERNET OF THINGS.
Adapted from [The Fourth Industrial Revolution: what it means and how to respond](#) (2016); WEF (2021a); [Global Lighthouse Network: Four Durable Shifts for a Great Reset in Manufacturing](#) et al. (2020); WEF (2023a, 2023b, 2019, 2021b, 2022); Machado et al. (2020); Javaid et al. (2022a).

reducing greenhouse gas emissions, minimizing waste generation, and promoting sustainable resource management (Rajput & Singh, 2020; Fatimah et al., 2020). Empirical evidence from industry leaders suggests that Fourth Industrial Revolution technologies can yield substantial sustainability benefits when strategically deployed. For instance, some manufacturing plants have reported up to 50% reductions in energy consumption and CO₂ emissions through the implementation of industry 4.0 solutions, for example, Haier, a Chinese home appliances manufacturer, achieved a 35% reduction in energy consumption and a 36% decrease in GHG emissions through the implementation of these technologies (WEF, 2023a).

Technologies like digital twins, blockchain, and IoT can enable the tracking and tracing of materials and products throughout their lifecycle, facilitating closed-loop manufacturing, product reuse, and recycling, further minimizing resource consumption and waste generation (Bag et al., 2023; Shabur, 2024; Delpla et al., 2022). However, potential rebound effects must be considered. Increased efficiency and lower production costs may lead to increased consumption and demand, potentially offsetting environmental gains. Addressing rebound effects requires a holistic approach that considers both the direct and indirect environmental impacts of Industry 4.0 technologies and promotes sustainable consumption patterns (Berg et al., 2021; Ching et al., 2022).

1.8.3 Social considerations

The social implications of Industry 4.0 are multifaceted, encompassing both opportunities and challenges. On the positive side, the automation of hazardous tasks and the use of collaborative robots can improve workplace safety and reduce the risk of injuries (Lee, Cameron, et al., 2019; Bragança et al., 2019). Advanced analytics and AI can also enhance decision-making in areas such as healthcare and disaster response, leading to improved social outcomes (Ragini et al., 2018; Sun et al., 2020). However, the rapid advancement of Industry 4.0 technologies is creating a skills gap, requiring a workforce equipped with digital literacy, data analysis skills, and the ability to work alongside intelligent machines. The automation of routine tasks may result in job losses, particularly for low-skilled workers, exacerbating economic disparities (Erer & Erer, 2020; Mehta & Awasthi, 2019; Ejsmont, 2021). Additionally, the digital divide could widen if access to advanced technologies and the associated benefits are not equitably distributed (Tiwari et al., 2024; Mhlanga & Dzingirai, 2023). Policymakers and industry leaders must develop inclusive strategies that ensure equitable access to Industry 4.0 technologies and provide support for workers transitioning to new roles.

1.8.4 Charting the path to sustainable Industry 4.0

Given the complex interplay between technological innovation and sustainable development, the deployment of Industry 4.0 technologies without a sustainability-oriented lens risks exacerbating existing inequalities, increasing rebound effects, and generating unintended environmental consequences. The successful implementation of Industry 4.0 for sustainability requires a multifaceted strategy that goes beyond mere technological adoption (Müller et al., 2018; Narula et al., 2020; Gadekar et al., 2022; Schumacher et al., 2019). It necessitates a comprehensive transformation encompassing workforce upskilling,

leadership commitment, and the integration of sustainability into core business strategies. A recent survey conducted by the World Economic Forum (WEF, 2023a) reveals a striking contrast in perspectives between industry leaders and nonleaders (companies that have not yet successfully implemented these technologies). While nonleaders identify a lack of leadership commitment and investment as the principal obstacle to scaling Industry 4.0 technologies, industry leaders consider the absence of a clear strategy as the primary challenge. Notably, industry leaders overwhelmingly recognize workforce engagement and dedicated transformation offices as critical enablers of digital transformation (WEF, 2023a).

Experts have identified four key areas where Industry 4.0 technologies can significantly drive sustainability: eco-efficiency (Ghobakhloo, 2020; Bai et al., 2020; Oláh et al., 2020), circular economy (Dantas et al., 2021; Rajput & Singh, 2019), supply chain management (Esmaeilian et al., 2020; Dutta et al., 2020), and product stewardship. These areas align with and expand upon the technological, cultural, and policy dimensions discussed in our framework, underscoring the multidimensional nature of the Industry 4.0-sustainability nexus. Eco-efficiency, enabled by technologies such as AI-driven process optimization and smart energy management systems, offers substantial potential for reducing resource consumption and emissions. For instance, data from real-world industries that have implemented Industry 4.0 technologies indicate a typical reduction in energy consumption in production processes by 30%–40% (WEF, 2023a, 2022) (WEF, 2019, 2021b). Advanced manufacturing techniques, such as additive manufacturing, can lower material waste and enhance production efficiency. However, realizing these benefits requires careful consideration of potential rebound effects and the need for complementary policies to ensure that efficiency gains translate into absolute reductions in environmental impact.

The circular economy concept is significantly enhanced by Industry 4.0 technologies. Advanced tracking and tracing capabilities, enabled by IoT and blockchain, facilitate the implementation of closed-loop systems and product lifecycle management. Digital twins and blockchain technology can provide detailed insights into the lifecycle of products, thereby supporting circular economy practices (Pagoropoulos et al., 2017; Alves et al., 2022; Preut et al., 2021). However, the transition to a circular economy also demands changes in business models, consumer behavior, and regulatory frameworks.

In supply chain management, Industry 4.0 technologies offer unprecedented visibility and control, enabling more sustainable and resilient supply chains. Blockchain technology, for example, can ensure the provenance of materials and products, thus supporting ethical sourcing and reducing the risk of supply chain disruptions. Additionally, AI and advanced analytics can optimize supply chain operations, leading to reduced emissions and improved resource efficiency. However, realizing these benefits requires addressing challenges related to data sharing, interoperability, and the digital divide between large corporations and smaller suppliers.

Product stewardship is revolutionized by Industry 4.0 technologies, enabling manufacturers to take greater responsibility for their products throughout their lifecycle. By integrating sustainability into product design, companies can reduce the environmental impact of their products and ensure they are easier to recycle or repurpose at the end of their lifecycle. Smart, connected products provide valuable data on usage patterns and performance, informing more sustainable design practices and enabling new service-based business models. Research indicates that such product-service systems could

reduce material consumption by up to 30% in certain industries (Sarasini et al., 2024; Product-as-a-service in the circular economy: the nine critical challenges and how to fix them et al., 2022; Matschewsky, 2019).

To chart a sustainable path forward, lessons can be drawn from the global leaders in Industry 4.0, which have demonstrated effective strategies for Industry 4.0 adoption. These companies employ a six-part approach (WEF, 2023b) to drive transformation to Industry 4.0 technologies: (1) setting a strategic roadmap that aligns the senior leadership team on the transformation vision, value and roadmap, (2) building delivery capabilities through talent acquisition and training, (3) adopting an agile operating model to enhance collaboration and speed, (4) establishing a robust technology backbone with scalable and distributed architecture, (5) creating a data architecture and governance framework for critical decision-making, and (6) implementing effective change management to ensure adoption and scaling. This approach ensures that technological advancements are seamlessly integrated and scaled across the organization, driving both innovation and sustainability.

To guide industries in adopting Industry 4.0 technologies sustainably, this study proposes a framework for the Sustainable Industry 4.0 Maturity Path (Fig. 1.11). The framework outlines key stages of maturity, from initial digitalization efforts to fully integrated, sustainable smart factories. It emphasizes the importance of strategic planning, continuous monitoring, and adaptive management to ensure that technological advancements align with sustainability goals. Each stage is characterized by specific technological implementations, organizational changes, and sustainability outcomes. The framework emphasizes that achieving sustainable Industry 4.0 is not merely about technological adoption, but also involves cultural transformation, skills development, and strategic alignment with sustainability goals. By following this maturity path, organizations can



FIGURE 1.11 Framework for sustainable Industry 4.0 Maturity Path.

systematically enhance their Industry 4.0 capabilities while simultaneously improving their sustainability performance.

1.9 Summary

The long-term viability of industrial production systems requires a holistic approach that integrates technological innovation, social responsibility, and environmental stewardship, which can be facilitated by the convergence of Industry 4.0 and sustainability. This study has explored the multifaceted interplay between Industry 4.0 and sustainability, highlighting the potential of advanced digital technologies to enable a paradigm shift toward more environmentally benign, socially equitable, and economically viable industrial production systems. By synthesizing insights from engineering, management, and social science perspectives, this study has elucidated the pathways through which Industry 4.0 can contribute to each pillar of sustainability, while also acknowledging potential risks and limitations.

A key takeaway of this study is the need to move beyond simplistic narratives that portray Industry 4.0 as either a panacea or a threat to sustainability. The reality is far more nuanced. The actual sustainability outcomes of Industry 4.0 implementation will depend on a multitude of factors, including specific technological choices, organizational contexts, policy frameworks, and societal values.

This analysis reveals that Industry 4.0 technologies, when strategically oriented and responsibly implemented, can significantly enhance sustainability across various dimensions. This potential is evident in the optimization of resource utilization and minimization of waste through intelligent automation and closed-loop manufacturing. Additionally, data-driven traceability can foster supply chain transparency and ethical sourcing practices. Furthermore, Industry 4.0 can contribute significantly to decarbonizing industrial activities and mitigating their environmental impact by enabling remote monitoring, predictive maintenance, and the design of eco-friendly products and processes. Empirical evidence already demonstrates significant eco-efficiency gains, with leading manufacturing sites achieving energy consumption and greenhouse gas emission reductions ranging from 30% to 40% through AI-powered process optimizations, predictive maintenance, and real-time data analytics.

However, realizing the sustainability potential of Industry 4.0 necessitates moving beyond a techno-centric perspective. This necessitates a holistic approach that considers the economic, social, and environmental dimensions of sustainability in tandem, rather than viewing technology as a standalone solution. This requires acknowledging the social and ethical implications of widespread automation, addressing potential job displacement through upskilling and reskilling initiatives, and ensuring equitable access to the benefits of technological advancements. While the technical capabilities of Industry 4.0, such as automation, data analytics, digital twins, and cyber-physical systems—are critical for improving efficiency and reducing environmental impact, they must be complemented by organizational, cultural, and policy shifts. Furthermore, robust governance mechanisms, including ethical guidelines for AI, data privacy regulations, and policies promoting circular economy principles, are essential to mitigate risks related to data privacy, algorithmic bias, and the potential exacerbation of existing inequalities.

To navigate this complex landscape, the proposed integrative framework, encompassing technological, cultural, and policy dimensions, provides a valuable roadmap. By aligning technological advancements with robust governance mechanisms and fostering a culture of sustainability within organizations and society at large, it is possible to harness the transformative potential of Industry 4.0 to drive positive environmental, social, and economic outcomes.

Nomenclature

AGVs	Automated guided vehicles
AI	Artificial intelligence
AR	Augmented reality
BIM	Building information modeling
CE	Circular economy
COBOTS	Collaborative robots
CPS	Cyber-physical systems
CRISPR	Clustered regularly interspaced short palindromic repeats
DT	Digital twins
GDP	Gross domestic product
GHG	Greenhouse gas
IoT	Internet of Things
IIoT	Industrial Internet of Things
IP	Intellectual property
IR	Industrial revolution
IT	Information technology
KYC	Know your customer
LCA	Lifecycle assessment
OEE	Overall equipment effectiveness
OEM	Original equipment manufacturer
PDP	Physical-digital-physical
PLM	Product lifecycle management
SDGs	Sustainable development goals
SMEs	Small and medium-sized enterprises
UN	United Nations
VR	Virtual reality

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Sustainability imperatives for manufacturing

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2.1 Introduction

In the current eco-conscious landscape, adopting sustainable production methods and engaging in environmentally responsible operations have become essential business strategies to ensure competitiveness in the manufacturing sector (Caniato et al., 2012; Ching et al., 2022; Margherita & Braccini, 2021). Sustainable manufacturing comprises a framework of techniques, strategies, and practices focused on producing goods through value creation processes that are economically sustainable. These processes are directed toward reducing environmental impacts, saving energy and natural resources, and ensuring the well-being and safety of employees, consumers, and communities (Ching et al., 2022; Garetti & Taisch, 2012; Machado et al., 2020; Sharma et al., 2020).

The concept of sustainable manufacturing prioritizes “doing better things” rather than merely “doing things better” (Khan, Ahmad, et al., 2021). This perspective seeks to improve the reputation of businesses by promoting greater social responsibility while simultaneously achieving environmental and economic objectives, collectively known as the triple bottom line (TBL) of sustainability (Agrawal et al., 2016). However, balancing the social, economic, and environmental aspects of a product throughout its design, manufacturing, and end-of-life stages is a challenging and resource-intensive endeavor. It demands significant investments in resources, information, integration and collaboration technologies, scenario planning, and process innovation at both the value chain and factory levels

(Ching et al., 2022; Kamble et al., 2020). The limited access to such tools, coupled with the lack of a cohesive policy framework, further exacerbates the difficulties in addressing TBL challenges, contributing to the currently low global adoption rate of sustainable manufacturing practices (Bhatt et al., 2020).

Despite these challenges, companies are increasingly drawn to the principles of sustainable manufacturing, as it not only aims for economic efficiency but also integrates the principles of the circular economy (CE). CE aims to achieve environmental resilience by recovering valuable materials from waste products and transitioning away from conventional fossil-based energy sources, providing social and economic benefits (Dev et al., 2020; Jones & Wynn, 2019; Tahir et al., 2024; Tseng et al., 2019). CE principles also focus on lowering product costs while continuously creating more value (Sarc et al., 2019) through advanced technologies like those offered by the Industry 4.0 (hereafter I4.0) that drive operational efficiency via automation (Huang et al., 2021).

I4.0 marks a significant digital transformation in industrial value creation, characterized by the adoption of advanced technologies and the development of innovative design principles. This transition introduces new methods for creating and delivering value across the entire product lifecycle. Both I4.0 and sustainable manufacturing seek to optimize the complete lifecycle of products, thereby enhancing value generation and delivery channels (Ching et al., 2022). Consequently, the scope of I4.0, which was previously limited to the digitalization of production processes within factories (Barata et al., 2019), has now expanded to encompass a more comprehensive, value chain-oriented perspective.

From an economic development perspective, I4.0 and its foundational digital technologies, such as cyber-physical systems (CPS), the industrial Internet of Things (IIoT), blockchain, digital twinning, among others, are projected to reduce operational costs in various manufacturing activities (Gouda & Saranga, 2020; Ngu et al., 2020). Numerous studies agree that the most evident benefit of the economic sustainability is the cost savings achieved through improved material, energy, and resource efficiency. I4.0 is also expected to contribute to environmental sustainability by minimizing waste in value creation processes and promoting the use of cleaner energy and materials (Machado et al., 2020). Moreover, the integrative, decentralized, and interoperable manufacturing ecosystem facilitated by 4.0 is anticipated to provide the agility required to effectively manage environmental uncertainties (Birkel & Müller, 2021; Ching et al., 2022; Margherita & Braccini, 2021).

As a matter of fact, Jacobs et al. (2016) argue that manufacturing profitability, environmental preservation, and workers' satisfaction can align through improved productivity and efficiency in manufacturing systems (Jena et al., 2020). This alignment is demonstrated through the implementation of automation, process monitoring, and enhanced supply chain visibility, which results in higher equipment reliability, reduced machine downtime, optimized inventory management, and increased employee engagement (Ivascu, 2020).

Similarly, Ching et al. (2022) identified several sustainability functions through which I4.0 enhances sustainable manufacturing. Their research indicates that I4.0 platforms, including sensor-equipped machinery, machine controllers, smart manufacturing execution systems, and cloud-based energy management systems, foster long-term sustainability and cost savings. This is achieved by enabling continuous, real-time monitoring of resource and energy consumption (Nascimento et al., 2019; Ren et al., 2019).

Regarding social sustainability, I4.0 is believed to enhance working conditions, improve customer experiences, and create new job opportunities (Sartal et al., 2020). However, I4.0 addresses human-centricity, sustainability, and resilience primarily from a technological perspective. Consequently, the broader social implications of I4.0 technologies (I4.0 T) on individuals and communities are often overlooked. In response to this oversight, Industry 5.0 (I5.0) has emerged, redirecting attention from isolated technologies to a more integrated and comprehensive strategy. This innovative concept aspires to fulfill societal objectives that go beyond mere job creation and economic expansion, with a strong emphasis on prioritizing the well-being of industry workers at the core of the production process (Xu et al., 2021).

Despite the numerous benefits that I4.0 and eventually I5.0 can offer in addressing the TBL challenges of sustainable manufacturing, several factors complicate the adoption and evaluation of these digital transformations. These factors include a lack of understanding, high implementation costs, the need for alterations to legacy systems, and potential energy drawbacks (Sharma et al., 2020). Authors such as Machado et al. (2020) support this view, emphasizing that the economic, environmental, and particularly social implications of adopting I4.0 tools in sustainable manufacturing are insufficiently explored and require more dedicated investigation.

This chapter aims to highlight the key benefits, challenges, and research opportunities associated with the adoption of I4.0 T at the social, economic, and environmental levels in sustainable manufacturing. Examining real-world case studies across various manufacturing sectors provides an overview of the current integration of I4.0 T into the routine operations of companies. This comprehensive analysis offers valuable guidance for future research and assists companies in navigating the path toward more sustainable manufacturing practices.

2.1.1 The technologies of Industry 4.0

I4.0 is heralded as a new era of smart and autonomous manufacturing, offering a deeper integration of manufacturing operations with communication, information, and intelligence technologies (Jeschke et al., 2016; Wang et al., 2017). This integration provides numerous benefits, including the development of profitable business models, increased efficiency, improved quality, and better workplace conditions (Hofmann & Rüsch, 2017). Due to these potential advantages, Industry 4.0 has attracted significant interest from both researchers and practitioners (Liao et al., 2017). However, challenges such as a lack of understanding, high costs, necessary alterations to legacy systems, and potential energy drawbacks complicate the adoption and evaluation process (e.g., Saberi et al. (2019), which addresses barriers to blockchain technology as an example).

I4.0 technologies can be categorized into physical and digital technologies. Physical technologies include manufacturing advancements like additive manufacturing (Gibson et al., 2021), as well as drones and sensors (Morrar & Arman, 2017). Digital technologies encompass modern information and communication tools, such as cloud computing, big data, blockchain analytics, and simulation (Liao et al., 2017). Table 2.1 provides a summary of various Industry 4.0 technologies (Dalenogare et al., 2018; Lu, 2017; Posada et al., 2015; Wan et al., 2015).

TABLE 2.1 Overview and definitions of various Industry 4.0 technologies.

Technologies	Definition
Additive manufacturing (3D printing)	A manufacturing process that builds three-dimensional objects by adding material layer by layer
AI and ML	A branch of computer science focused on creating machines capable of performing tasks that typically require human intelligence
AR	An interactive environment that overlays computer-generated enhancements, such as graphics and sounds, onto the real world to improve user experience
Autonomous robots (Robotics)	Robots designed to perform tasks autonomously, mimicking human actions in manufacturing settings
Mobile Technology	Wireless communication technologies integrated into mobile devices, enabling connectivity and data exchange
Big data and analytics	Techniques for analyzing large datasets that traditional methods cannot handle, to uncover hidden patterns and insights.
Blockchain	A decentralized database that securely records transactions across multiple computers using encryption and consensus mechanisms to ensure data integrity
RFID	A technology that employs radio waves to automatically detect and monitor tags attached to items, enabling efficient inventory and asset management
Cloud Computing	IT services provided and accessed over the internet from a cloud computing provider
Cobotic (Collaborative Robots)	Robots designed to work collaboratively with humans in a shared workspace
Cybersecurity	Measures and practices designed to protect data and systems from cyber threats such as theft, damage, or unauthorized access
Unnamed aerial vehicle (Drones)	Aircraft operated without a human pilot, usually known as drones, used for various applications, including surveillance and delivery
IIoT	A network of interconnected devices and sensors used to improve and optimize industrial and manufacturing processes
Digital Twin Technology	A digital replica of a physical asset, process, or system that can be used for real-time monitoring, simulation, and optimization
Nanotechnology	The process of controlling and altering matter at the atomic or molecular level to develop materials and devices with unique properties and functionalities
Advanced Sensors and actuators	Devices that detect physical changes (such as temperature, light, or motion) and respond with corresponding actions, often used in automated systems
GPS	A navigation system that relies on satellite signals to provide precise location, speed, and time information for GPS receivers
Simulation	Utilizing computer models to mimic and examine the behavior of real-world systems or processes for analysis and optimization

AI, Artificial intelligence; *AR*, augmented reality; *GPS*, global positioning system; *IIoT*, industrial internet of things; *ML*, machine learning; *RFID*, radio frequency identification.

2.2 Economic sustainability

In today's rapidly evolving, sustainability-driven, and interconnected global market, the traditional take-make-dispose model of the linear economy (LE) is under growing scrutiny for its harmful impacts on natural ecosystems, business models, and society (D'Adamo and Lupi, 2021). As a result, there is an urgent need to transform supply chains to be more innovative, resilient, and less wasteful (Groschopf et al., 2021), with a particular focus on reducing manufacturing costs through enhanced resource and energy efficiency. Authors like Ching et al. (2022) note that performing manufacturing activities at lower costs without compromising quality also enables manufacturers to invest in flexible manufacturing systems, meet client expectations through product customization, and achieve higher profit margins. This, in turn, supports sustainable value creation networks and eco-friendly product development.

Compared to traditional business models, I4.0 offers several ways to reduce manufacturing costs, including autonomous 24/7 production, increased production capacity, improved product quality, higher precision, fewer errors, and better equipment efficiency (Lim et al., 2021; Margherita & Braccini, 2021). Additionally, I4.0 supports sustainability goals by incorporating CE principles, which help extend product lifespans and maximize their value through practices such as maintenance, repair, reuse, and remanufacturing (Sarc et al., 2019). These practices directly contribute to various Sustainable Development Goals (SDGs) by creating jobs, promoting sustainable industrialization, reducing waste, and conserving natural habitats.

Moreover, technologies like CPS, artificial intelligence (AI), IoT, and big data analytics (BDA) enhance the integration of manufacturing operations, enabling real-time information sharing and coordinating physical and financial flows across the supply chain (Dhar Dwivedi et al., 2024; Strandhagen et al., 2022). This interconnected approach leads to more efficient resource use, increased productivity, and reduced waste in production processes.

Another significant advantage is that the extraction and sharing of real-time, accurate information allow managers to track, monitor, and make informed decisions on the efficient use of resources and the recycling of consumed products (Palsodkar & Koltharkar, 2024). This capability provides organizations with social, economic, and environmental benefits by promoting sustainability, longevity, and efficiency (Khan, Razzaq, et al., 2021). As a result, these advancements facilitate the transition from a linear production model to a CE, addressing the technical, economic, logistical, and regulatory challenges associated with the traditional LE system (Atif, 2023; Palsodkar & Koltharkar, 2024).

2.2.1 Industry 4.0 and its economic implications

The transition to I4.0 has created numerous profitable business opportunities, but it also presents significant challenges. One of the primary challenges is the substantial investment required in new technologies and infrastructure (Ching et al., 2022; Xu et al., 2021). Implementing tools such as CPS, IoT, AI, and big data analytics demands considerable capital, which can be especially burdensome for small and medium-sized enterprises (SMEs). This financial strain often limits smaller firms' ability to compete with larger corporations that have more substantial resources (Atif, 2023; Ching et al., 2022; Palsodkar & Koltharkar, 2024).

In the CE model, reverse logistics is a crucial stage for achieving sustainability in manufacturing and supply chains. This process focuses on recovering value from end-of-life (EOL) products through various methods that adhere to specific and stringent regulations (Shukla et al., 2022). Recycling practices enable the recovery of a significant portion of discarded products (Li et al., 2004), while remanufacturing EOL products returns them to their original functionality and performance (Aziz et al., 2021), often encompassing a combination of repair, refurbishment, and replacement of worn-out components to extend the product's lifecycle (Yu & Sun, 2024).

I4.0 T significantly impacts reverse logistics. The economic benefits include increased competitiveness, enhanced productivity, and higher revenue (Birkel & Müller, 2021). Automation, advanced analytics, and interconnected systems speed up and refine the processing of returned products, decreasing lead times and boosting customer responsiveness. These technologies provide real-time data, enabling identification of cost savings and supporting long-term growth (Barreto et al., 2017; Rajput & Singh, 2022). Additionally, continuously updated systems enable organizations to adapt to changing market conditions (Aziz et al., 2021) and are particularly useful for controlling process variables in small batch productions (Bag & Pretorius, 2022).

Remanufacturing plays a vital role in reverse logistics, contributing to the TBL of sustainable development (Ramezani et al., 2013). For some EOL products, remanufacturing has proven to be an economically viable and profitable method for value recovery. Remanufactured products can be up to 50% cheaper than new ones and require about 40% less energy compared to conventional manufacturing systems (Liu et al., 2017), which typically have energy efficiencies of less than 30% (Cai et al., 2019). Remanufactured, repaired, or recycled products can offer profitable opportunities by optimizing product usage and addressing customer needs (Agrawal et al., 2016).

Setting up a reverse logistics system for remanufacturing is a complex task that involves strategic, tactical, and operational decisions (Kannan et al., 2017). The variability in the quality of EOL products introduces uncertainty, which makes it difficult to effectively manage inventory, plan production schedules, and balance the disassembly lines (Bockholt et al., 2020). In addition, returned materials may be less reliable than new materials, increasing the risk of waste (Guide, 2000; Ke et al., 2020).

Fortunately, I4.0 T can help minimize the uncertainty in reverse logistics activities by using cloud-based digital twins that provide information throughout the entire product lifecycle (Wang & Wang, 2019). This capability enables smart and efficient planning and execution of remanufacturing operations (Linden et al., 2024). Furthermore, the increasing use of smart robots and additive manufacturing may also enhance the flexibility, reconfigurability, and efficiency of the remanufacturing process (Aziz et al., 2021; Liu et al., 2019). However, the critical connectivity between manufacturers, end-users, EOL product collectors, and remanufacturers is often overlooked by I4.0 T (Yu, 2022).

In this regard, I5.0 is gaining traction as a solution to the limitations of I4.0, yet it presents significant economic challenges (Chowdhury et al., 2021; Younis et al., 2023). A primary concern is the necessity for businesses to adopt new models that incorporate social and environmental responsibilities, compelling them to find a balance between profitability and sustainability. This shift often involves substantial upfront costs for implementing

sustainable practices and technologies, creating obstacles for businesses that prioritize short-term profits (Ghobakhloo et al., 2022; Nahavandi, 2019).

Furthermore, I5.0 targets on human-machine collaboration, requiring considerable investment in technologies designed to enhance human abilities, such as advanced human-machine interfaces and bio-inspired innovations. These technologies are not only expensive but also difficult to integrate into existing manufacturing systems, adding to the financial burden on companies (Husain et al., 2021; Leng et al., 2022; Palsodkar & Koltharkar, 2024; Xu et al., 2021).

Beyond economic challenges, the absence of a robust and practical policy framework hinders the widespread adoption of I4.0 and the transition to I5.0. Current sustainability regulations, rooted in an economic-centric model, attempt to legitimize trade-offs between the excessive exploitation of natural resources and the pursuit of profit maximization (Horst & Santiago, 2018). However, global and national agendas aimed at achieving carbon neutrality by mid-century or the end of the century frequently surpass the technical capabilities of companies. This misalignment can result in greenwashing practices as companies endeavor to meet stakeholder expectations and maintain competitive advantage (Delmas & Burbano, 2011; Terán-Cuadrado et al., 2024).

Rather than imposing sustainability goals on companies at any cost, regulatory bodies should prioritize increased investments in research and development projects and foster close collaboration with academia and industry (Esangbedo et al., 2024). This approach will strengthen the concept of corporate social responsibility (CSR), which holds that enterprises are accountable for the impacts of their operations on stakeholders—both positive and negative, direct, and indirect—while still aiming for profitability and growth (Sutherland et al., 2016). Building this collaborative relationship is crucial, as coordinated efforts among all stakeholders are essential for achieving data-driven, sustainable, and socially balanced industrial production.

2.2.2 Industrial applications

While important economic and operational benefits of I4.0 T in industrial activities have been recognized, few studies have combined I4.0 T with environmental modeling tools to assess the sustainability of digitalized processes. This gap has begun to close with recent research, such as the study by Astudillo et al. (Astudillo et al., 2024), who examined the potential effects of smart algorithms on optimizing production scheduling within a steel plant. Aiming to understand how optimization algorithms can reduce global warming (GW) and steel production costs, the researchers integrated CPS with open-source lifecycle assessment (LCA) software.

Their findings indicate that digitalization and smart algorithms may not lead to significant reductions in costs or climate change impacts but can offer incremental improvements rather than transformative changes. The simulations revealed that approximately 7.7% of the steel intended for casting would be scrapped under human scheduling, compared to 6.6% with the inclusion of sensors and algorithms. In terms of cost, results show modest reductions mainly due to decreased use of additives and electricity.

The authors also highlighted difficulties encountered during the study, particularly the planners' reluctance to trust or learn the algorithm. They suggested that while the immediate benefits for the industry may not be apparent, the long-term advantages could become more significant, especially as planning becomes harder to pass on with an aging workforce. This underscores the need to continue analyzing digitalized systems in industry to create compelling evidence of their benefits and gain insights on how to address their obstacles properly and holistically.

2.3 The sustainable environment in Industry 4.0

Industrialization is essential for production. Organizations that have not yet embraced information technology (IT) are finding it difficult to remain competitive. In the present-day business arena, companies across all sectors possess a common vision for the future and work to avoid being caught off guard. As a result, every industry is adopting I4.0 due to its ability to deliver high-quality, customized products. However, I4.0 also involves significant consumption of resources, raw materials, information, energy, and the management of electronic waste, which poses environmental sustainability challenges. Despite the numerous benefits of I4.0, these issues have heightened societal and public sector awareness and concern about the associated environmental risks and challenges (McWilliams et al., 2016; Oláh et al., 2020).

The environmental sustainability itself in I4.0 T has the potential to decrease the consumption of energy and resources by utilizing detection and data analysis throughout production and supply chain operations (Shrouf et al., 2014). These technologies can also help reduce waste and CO2 emissions through data-driven and traceable carbon footprint analyses (Gabriel & Pessl, 2016; Sarkis & Zhu, 2018). Additionally, products can be disassembled into their individual components for purposes such as remanufacturing, reuse, or recycling.

The topic of environmental sustainability within I4.0 has garnered significant attention in academic research. Although there are various perspectives on the relationship between I4.0 and environmental sustainability, a consensus on its long-term impact remains elusive (Oláh et al., 2020). Some research suggests that start-ups and new enterprises incorporate strategies that integrate I4.0 with sustainable production practices. For instance, studies by Ford and Despeisse (2016), as well as Jelonek and Urbaniec (2019), have highlighted the advantages of implementing technologies like 3D printing in manufacturing for environmental sustainability. However, these studies also identify challenges due to the nascent stage of these technologies.

Conversely, Stock and Seliger (2016) argue that industrial value should prioritize sustainability and that I4.0 offers significant opportunities to achieve this goal. According to Burritt and Christ (2016), comprehensive digitization within I4.0 positively influences environmental sustainability by enabling precise management and real-time event monitoring of the external environment.

In a different study by the authors of Müller and Hopf (2017), a model based on the TBL framework was proposed, which underscores the challenges and opportunities linked with

adopting I4.0. Their findings indicate a significant positive correlation between the adoption of I4.0 technologies and environmental benefits, suggesting that companies are more likely to embrace these technologies due to their advantages, regardless of company size or industry sector. Tim et al. (Stock et al., 2018) and Müller and Hopf (2017) also recommended a framework for encouraging the sustainable management of natural resources by incorporating CE principles within organizations. This approach emphasizes recycling and waste reduction within the framework of I4.0, which is beneficial for the environment. Furthermore, Junior et al. (Gobbo et al., 2018) explored the link between environmental protection and process safety in the context of I4.0, finding that there is more research focused on environmental protection than on process safety. Additionally, studies by Junior et al. (Gobbo et al., 2018), Carrillo et al. (2014), and Lingam (2018) have demonstrated that value creation in I4.0 contributes positively to sustainable development through innovative processes, lifecycle perspectives, and new business models. Kumar and Luthra (Luthra & Mangla, 2018) identified 18 challenges that I4.0 may face in developing sustainable supply chains, highlighting the complexity and multifaceted nature of integrating sustainability into modern industrial practices.

2.3.1 Dimensions in Industry 4.0 contributing to environmental sustainability

I4.0 significantly contributes to environmental sustainability through key dimensions like energy, materials, natural resources, and waste and emissions (see Fig. 2.1). These dimensions are further subcategorized into aspects such as land and water use, recyclability, energy loss rate, energy utilization, scrap rate, smart production, and impacts on ozone



FIGURE 2.1 Environmental sustainability dimensions in Industry 4.0

depletion and greenhouse gas (GHG) emissions (Abbasi & Kamal, 2020; Sajid et al., 2021; Stachová et al., 2019). Proper management of these dimensions supports sustainable environmental development.

Advancements in I4.0 have modernized manufacturing with smart machinery and technical equipment, emphasizing the importance of human roles in this evolving landscape. Additive manufacturing has expanded from prototyping to small and medium-scale production, while the Industrial Internet of Things (IIoT) promotes open-source technologies for greater efficiency (Garcia-Muiña et al., 2018; Lin et al., 2017; Manavalan & Jayakrishna, 2019; Prause, 2019).

In plastic packaging, essential for pharmaceuticals and medical fields, I4.0 T has reduced water use and wastewater discharge. Augmented reality (AR) and other immersive technologies streamline resource management, improve inventory control, and boost worker productivity (Ashima et al., 2021; Morrar & Arman, 2017; Müller & Voigt, 2018; Stock et al., 2018). Overall, I4.0 successful implementation reduces waste, time, and energy consumption, fostering smarter, more sustainable production systems and promoting a society that values diverse perspectives and sustainable practices.

2.3.2 Applications of Industry 4.0 in the sustainable environment

I4.0 is transforming manufacturing by merging physical operations with advanced digital technologies like IoT, machine learning (ML), and real-time data processing. This integration significantly enhances efficiency, streamlines processes, and drives innovation, leading to a new era of sustainable manufacturing characterized by increased productivity, flexibility, and reliability. These advancements contribute to long-term profitability and sustainability for businesses (Tortorella et al., 2021). Key applications of I4.0 include the development of sustainable smart factories that prioritize environmental friendliness and resource efficiency.

These factories utilize connected equipment, AI-powered energy systems, and IoT devices to manage resources more effectively, supporting global sustainability efforts through CE principles and climate-aware practices (Erboz, 2017; Tsai & Lai, 2018). Additionally, I4.0 T plays a pivotal role in lowering carbon footprints and controlling pollution across industries by minimizing the dependence on fossil fuels and optimizing energy use (Oztemel & Gursev, 2020). In the realm of sustainable building practices, I4.0 extends its influence from design to ongoing management, with technologies like building information modeling (BIM) software and IoT-enabled systems enabling real-time energy efficiency management. Sensors and IoT devices can automatically signal environmental control systems to turn off lights and air conditioning when a building is unoccupied (Kamble et al., 2018). Digital information and communication technologies further enhance the environmental impact of industries by improving operational productivity, occupational health and safety, and aligning product designs with sustainable manufacturing processes (Santos et al., 2017).

I4.0 T enhances sustainability in smart manufacturing by managing complex processes through 5G, IoT, ML, and augmented reality. These technologies improve business operations, sustainability, and integration among stakeholders (Takhar & Liyanage, 2020). In service management, I4.0 connects measurement tools with automation infrastructure, optimizing energy and data management (Fonseca et al., 2021). Focusing on enhancing

productivity and competitiveness leads to a virtuous cycle where better financial performance allows for reinvestment into further capacity and productivity improvements (Müller & Buliga, & Voigt, 2018).

Environmental innovation is further driven by I4.0, which facilitates the exchange of knowledge between people and machines, leading to more efficient and less wasteful manufacturing processes. Technologies like digital twins and CPS integrate computational, network, and physical processes, contributing to the overall environmental sustainability of industrial operations (Sołtysik-Piorunkiewicz & Zdonek, 2021). I4.0 also emphasizes the development of skills and flexible automation, ensuring that workers are prepared for new roles in a digitally driven industrial landscape. Robots, which play a central role in flexible automation, are used in various applications to enhance quality management, ensure worker safety, and increase overall efficiency (Mittal et al., 2018; Schalllock et al., 2018).

The environmental benefits of I4.0 extend to improved safety in operations, particularly in industries like mining, where remote control and haptic feedback technologies are used to manage heavy machinery. These advancements contribute to safer operations and a more environmentally friendly approach to industrial processes (Javaid et al., 2022; Salkin et al., 2018). I4.0 also offers practical tools for addressing climate change, fostering partnerships between technology innovators, scientists, and industries to create new, sustainable business models. This approach not only enhances economic viability but also promotes long-term environmental protection (Felsberger & Reiner, 2020).

Additionally, sustainable manufacturing practices, supported by I4.0 T, are key to minimizing waste and optimizing resource use. The adoption of low-cost sensors and big data analytics helps companies optimize their processes and supply chains, leading to cost reductions and improved customer experiences. These smart production practices are essential for reducing waste and GHG emissions (Ciliberto et al., 2021). In the automotive sector, additive manufacturing is being used to create lighter parts, improve fuel economy, and reduce material usage. As manufacturers face increasing pressure to reduce their environmental impact, I4.0 T is helping them implement the most effective eco-friendly practices (Vasco, 2021). The control of electronic machinery is revolutionized by I4.0, which builds independent factory networks capable of executing physical operations autonomously. By linking IoT infrastructures across multiple factories, these networks operate seamlessly on a global scale, breaking down geographical barriers (Javaid et al., 2022). Overall, I4.0 is driving the future of production toward greater environmental and economic sustainability.

2.4 The role of society in the context of sustainable manufacturing

2.4.1 Opportunities and challenges

The integration of I4.0 T into standard business models marks a transformative phase in the manufacturing domain, presenting both valuable opportunities but also significant challenges for advancing social sustainability. The concept of social sustainability in the manufacturing context emphasizes the well-being of stakeholders and communities within

the manufacturing value chain (Ghobakhloo et al., 2021). Typically, the industry has prioritized technological progress and economic benefits, often at the expense of social sustainability. This focus has led to adverse social impacts, including unsafe working conditions, community disruptions, and broader societal inequalities (Linden et al., 2024; Sutherland et al., 2016).

The insufficient attention to social factors can be attributed to the notion that manufacturers need to maintain profitability to achieve other sustainability objectives (Ndubisi et al., 2021). In this context, Ching et al. (2022) suggest that the socio-environmental impacts of I4.0 should be evaluated in terms of the economic opportunities presented by digital transformation in the manufacturing scenario. They argue that without economic sustainability, manufacturers cannot afford to prioritize environmental conservation and social progress, as ensuring corporate survival takes precedence. This perspective is supported by evidence showing that lower manufacturing costs and the resulting economic gains enable manufacturers to commit more effectively to socio-environmental initiatives (Kamble et al., 2020).

In contrast to Ching et al. (2022) and Kamble et al. (2020), Margolis and Walsh (2003) and Baron et al. (2011) point out that although there is some evidence indicating a positive relationship between social and financial performance, the exact nature of this relationship remains ambiguous, particularly within industrial markets. This ambiguity presents challenges for the broader adoption of CSR in the manufacturing sector. Nonetheless, companies that implement robust CSR practices often gain significant benefits, including easier access to capital, increased brand awareness, reduced costs and risks, enhanced competitive advantages, and the creation of synergistic value (Sutherland et al., 2016).

A solid regulatory framework is also crucial for companies to operate sustainably and socially responsibly while remaining profitable. In this regard, increased investments from both public and private organizations in sustainable industry digitalization, supported by an interconnected work involving the government, academia, and the industrial sector, can help companies view the well-being of workers, communities, and the environment from a new perspective.

Various I4.0 T are reshaping the manufacturing sector to address current and prospective social challenges. For instance, real-time monitoring of work environments enhances safety conditions, predictive maintenance prevents accidents before they occur, and smart wearables continuously monitor workers' health and safety. These advancements create safer and more humane workplaces (Torres de Oliveira et al., 2023), where people's consent and the protection of their identity are crucial elements for maintaining a harmonious relationship between humans and machines. I4.0 T also facilitates seamless connectivity between departments and optimizes production processes, thereby improving employee performance (Beier et al., 2017; Strandhagen et al., 2022). This increased productivity among employees leads to higher profit margins, better working conditions, and more robust business networks (Jacobs et al., 2016).

Regarding the common and latent issue of overworking, I4.0 T suggests integrating flexible work structures that promote greater engagement and skill development for all employees while maintaining a healthy work-life balance. Intelligent-assisted systems free employees from repetitive tasks, enabling them to focus on innovative and value-adding activities, and extend the productivity of older employees for longer periods (acatech, 2013; Xu et al., 2021).

Despite the aforementioned benefits, some authors emphasize that the transition to digital and automated manufacturing processes requires comprehensive retraining and upskilling programs to equip workers to thrive in a technologically advanced environment while maintaining safety and productivity (van Lopik et al., 2020). However, implementing these programs is costly and requires coordinated efforts among industry, government, and educational institutions (Ching et al., 2022).

Acquiring and continuously updating professional skills is seen as a valuable opportunity for workers' growth. Nevertheless, these initiatives imply significant changes for individuals, and resistance to change is common. Additionally, educational barriers can impede the acceptance of these strategies leading to a growing number of individuals lacking the necessary skills, which, in turn, increases unemployment rates (Biresselioglu et al., 2018; Ejsmont, 2021). This skills gap is likely to be more pronounced in regions with limited access to education and economic resources, potentially driving manufacturing operations offshore in search of a more cost-effective and efficient workforce. Such offshoring can destabilize domestic markets, further exacerbating unemployment and economic insecurity (Sutherland et al., 2016).

While many scholars acknowledge the inevitable job losses due to automation, others highlight that adopting I4.0 T can promote regional development by creating new types of jobs that previously did not exist (Ching et al., 2022). Manufacturers investing in digital transformation are compelled to create new professional roles in areas such as data analytics, problem-solving, sustainable innovation, digital twin technology, rapid prototyping, new product introductions, technological advancement, and product lifecycle evaluation (Gualtieri et al., 2020). If managed correctly, these new employment opportunities under I4.0 can help reduce occupational and income inequality (Sung, 2018). However, according to Ching et al. (2022), large-scale implementation of environmental sustainability strategies and new employment opportunities are among the most challenging aspects of I4.0, as their success heavily depends on economic factors that enable enterprises to innovate, develop sustainable products, and establish value networks. These efforts also require the synergistic, yet challenging, collaboration of all actors involved in the product lifecycle.

In the context of the CE, it is expected that many new jobs will require only entry-level skills, as they involve basic tasks such as sorting and cleaning (Yu & Sun, 2024). While these positions may promote job market equity by requiring less specialized skills (Matsumoto & Ijomah, 2013), numerous authors argue that the demand for high-skilled positions will be greater. These roles require access to advanced technologies and digital literacy, which can vary significantly across regions and socio-economic groups, potentially exacerbating social inequalities. Workers who lose their jobs may face prolonged unemployment, financial insecurity, and social displacement. The necessity for continuous learning and adaptation adds further pressure on the workforce, particularly for older workers who may struggle to acquire new skills (Ching et al., 2022; Sutherland et al., 2016). These challenges highlight the importance of developing comprehensive strategies that balance technological progress with social equity.

Particularly in reverse logistics, worker safety is a vital yet often undervalued issue, contingent on the type of items or materials being processed or remanufactured (Linden et al., 2024). In the chemical industry, safety is a heightened concern due to the considerable

risks posed by returned products (Ali et al., 2018). In such cases, safety concerns, working hours, and workplace climate emerge as social impacts created by reverse logistics within organizations (Sun et al., 2022). Additionally, the quality of materials returned may be less reliable than those leaving the system, increasing the risk of significant waste. This creates external impacts, as communities must manage waste that could have been disposed of elsewhere, potentially harming local populations (Presley et al., 2007).

Fortunately, tools from the fourth industrial revolution, such as automation and collaborative robots, offer solutions by relieving workers from hazardous and ergonomically challenging tasks (Atif, 2023; Taylor et al., 2020). The current challenge lies in ensuring a safe working environment as the global adoption of smart systems in industrial processes continues.

Addressing microsocial concerns such as enhancing customer experiences, ensuring fair employment opportunities and wages, and eradicating child labor across the supply chain represents some of the most challenging social issues. These concerns are inherently complex and multifaceted, requiring detailed attention to fully comprehend their underlying causes and impacts (Longoni & Cagliano, 2015; Mani et al., 2018; Sutherland et al., 2016). Proponents of industrial digitalization argue that technologies, like Blockchain and IoT, enable companies to engage in ethical sourcing of materials and resources. This, in turn, helps avoid extracting scarce minerals and promotes fair labor practices. They maintain that the ability to trace and verify the origins of materials ensures that supply chains remain free from unethical practices, including child labor and environmentally harmful sourcing methods (Asokan et al., 2022; Sutherland et al., 2016).

Nevertheless, the effectiveness of these technologies in mitigating issues such as child labor and unfair wages remains uncertain due to the intricate nature of these social impacts and the difficulty in accurately quantifying them. This complexity arises in part because analysts can select various social criteria, indicators, and assessment methods based on the specific needs of different stakeholder groups and the local conditions of the manufacturing facilities (Jørgensen et al., 2008). Moreover, the measurement of the social dimension of sustainability is influenced by the cultural, ethical, and moral norms of the involved social entities, as well as the internal conduct of companies, rather than solely the technical aspects of the processes themselves (Souza et al., 2015). These factors contribute to the lack of standardization in indicators related to the social dimension of sustainability.

Tackling the social impacts associated with manufacturing decisions necessitates a robust set of sustainability indicators. These indicators should cover the entire product lifecycle to account for the social consequences of a company's activities. They must guide decision-making, address relevant stakeholders, and enable objective comparisons between options (Sutherland et al., 2016).

Various frameworks, principles, and guidelines propose potential indicators and metrics to address social impacts within organizations (OECD, 2011; United Nations Global Compact, 2015, 2024). While these documents are valuable, they are often interpreted differently depending on the stakeholder and the specific context. As a standardized approach, many researchers recommend the use of social LCA (SLCA), which provides a comprehensive framework and methodology to help stakeholders assess and map the socio-economic impacts throughout the product lifecycle (SETAC, 2009). Despite the growing focus on SLCA methods, they still face challenges such as a lack of sufficient, specific, and

objective data, and no consensus on which impacts to include and how to model them (Sutherland et al., 2016).

Indicators like the third SDG and the 403-9 Global Reporting Initiative (GRI) standards aim to ensure worker well-being by disclosing health and safety metrics. However, the methodologies for measuring the societal impact of data-driven manufacturing are often inadequate. Many of these indicators are qualitative or binary (yes/no), which does not effectively measure policy impact (Sutherland et al., 2016). For example, a simple job satisfaction question cannot capture the complexity of work-related stressors such as mental fatigue or psychological pressures from changes in the work environment. These stressors can lead to severe issues, such as increased alcohol consumption or even suicide, as evidenced in the Foxconn tragedy (Buckheit & Maisto, 2023). The fear of job loss or the challenges employees face for not being up to the new work conditions can exacerbate these problems.

This discussion highlights the complexity of studying the effects of industrial digitalization on social systems. Therefore it is crucial to develop strategies that balance the social, environmental, economic, and political dimensions of sustainable manufacturing.

2.4.2 Evolution of Industry 4.0

The literature suggests that I4.0 has struggled to keep up with the rapidly evolving societal and geopolitical landscape (Xu et al., 2021). Consequently, it has been challenging to comprehensively analyze the socio-environmental aspects of sustainable development at a macroregional level. To address these limitations, the concept of I5.0, introduced in 2021, aims to enhance the social equity and sustainability dimensions that I4.0 lacks, while still leveraging the digital advancements achieved under I4.0. I5.0 is specifically designed to mitigate the adverse effects of I4.0, such as employment disruption, organizational and wage inequality, Technology gap, the rebound effect, and Resource overuse, by emphasizing human-centricity, adaptability, sustainability, and CE principles (Ching et al., 2022).

Industry 5.0 thus introduces a new paradigm, highlighting the need for research and innovation to ensure that industry serves humanity within the earth's ecological limits over the long term. Sustainability is central to this model, with I5.0 integrating CE practices as a fundamental component of its framework. At the same level of importance, I5.0 places the needs and interests of people at the forefront of industrial operations. This shift moves the emphasis away from purely technology-centric progress toward a perspective that is more aligned with societal well-being (Xu et al., 2021). It envisions a transformation in how industry workers are perceived (from being viewed as “costs” to being valued as “investments”). In I5.0, technology is designed to serve people and society, adapting to the diverse needs of industry workers (Lu et al., 2021).

Another critical pillar of I5.0 is resiliency, which focuses on developing robust supply chains and production processes capable of withstanding and quickly recovering from disruptions (Xu et al., 2021). This approach involves diversifying supply sources, strengthening local and regional capabilities, and adopting flexible manufacturing systems that can be reconfigured as needed. Recent global events, such as the COVID-19 pandemic, geopolitical shifts, and natural disasters, have underscored the necessity of resilient and adaptable manufacturing systems (Breque et al., 2024).

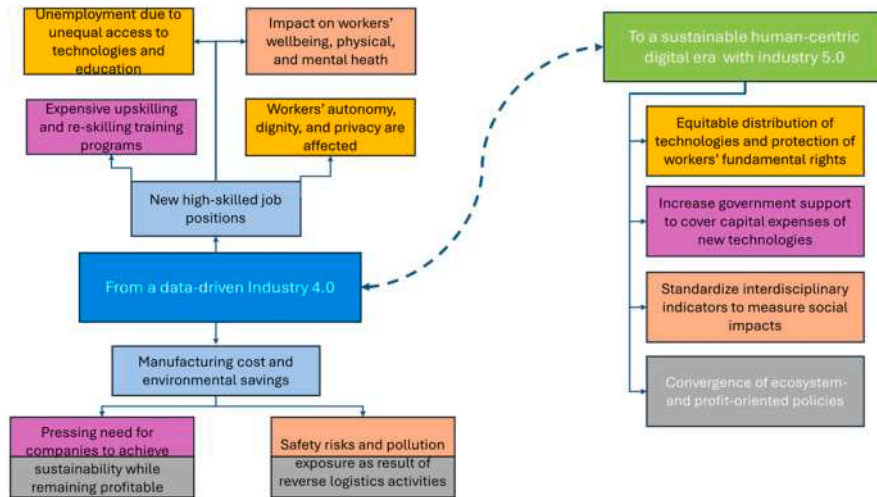


FIGURE 2.2 Socio-economic benefits and obstacles of Industry 4.0 and its transition to Industry 5.0. Boxes of the same color correspond to Industry 4.0 drawbacks (left) and the solution strategies (right) that Industry 5.0 should address. Multicolored boxes indicate links to multiple approaches. Source: *Information taken from Ching et al., 2022. Industry 4.0 applications for sustainable manufacturing: A systematic literature review and a roadmap to sustainable development. Journal of Cleaner Production, 334. <https://doi.org/10.1016/j.jclepro.2021.130133>.*

Fig. 2.2 succinctly presents the key socio-economic and environmental opportunities, as well as the associated challenges of I4.0, and illustrates how I5.0 addresses these shortcomings by focusing on specific areas. It can be observed that rather than replacing I4.0, I5.0 seeks to complement it by fostering a safe and inclusive work environment that prioritizes physical and mental health, well-being, and the protection of workers' fundamental rights, such as autonomy, dignity, and privacy, while enhancing collaboration between humans and machines (Xu et al., 2021). Furthermore, I5.0 encourages continuous upskilling and reskilling of industrial workers to improve career prospects and achieve a better work-life balance, in line with the principles of I4.0. This approach not only aims to enhance job satisfaction and workplace safety but also fosters innovation by leveraging the unique capabilities of both humans and machines (Breque et al., 2024)

Despite its goals, I5.0 faces significant social challenges. One major challenge, as depicted in Fig. 2.2, is ensuring the equitable distribution of technological advancements across society. The focus on personalized and decentralized production in I5.0 could lead to disparities if not managed carefully, with more affluent regions and individuals potentially benefiting more than disadvantaged ones (Ching et al., 2022; Xu et al., 2021) (Fig. 2.2).

Additionally, the widespread integration of advanced technologies raises concerns about privacy and data security. As I5.0 promotes the use of digital twins and extensive data sharing, ensuring the protection of personal and sensitive information becomes increasingly important. This requires the development of robust regulatory frameworks and technological safeguards to uphold individuals' rights and maintain public trust (Chiappetta Jabbour et al., 2020; Xu et al., 2021).

I5.0 also presents unique challenges not encountered previously in I4.0. Those include managing social diversity in values and acceptance, measuring environmental and social value generation, integrating SMEs across entire value chains, and handling the complexity of interdisciplinary research and systems (Xu et al., 2021). Additionally, Breque et al. (2024) emphasize that establishing an ecosystem-oriented innovation policy, characterized by agile and outcome-focused strategies, presents a considerable challenge. This challenge lies in the necessity of balancing productivity with the substantial investments required to support such initiatives (Breque et al., 2024).

2.4.3 What are companies doing?

The industrial sector recognizes that decarbonization efforts hinge on the adoption of new technologies, which are predominantly automated and digitized. However, the challenge remains in transitioning from traditional business models to data-driven, sustainable processes without undermining the core objective of profitability.

National initiatives and industrial projects are collaboratively advancing I4.0 principles. Notable examples include Germany's SmartFactoryKL initiative (SmartFactoryKL, 2024), France's Industrie du Futur project (Alliance Industrie du futur, 2024), Japan's Robot Revolution and Industrial IoT Initiative (Robot Revolution and Industrial IoT Initiative, 2024), the United States' Manufacturing USA program (United States' Manufacturing USA program, 2024), the European Union's Horizon Europe (European Union's Horizon Europe, 2024), and China's Made in China 2025 strategy (Made in China 2025, 2024). These initiatives aim to integrate advanced technologies, such as AI and IoT, to improve manufacturing efficiency, sustainability, and innovation.

In the industrial sector, companies are applying specific technologies to realize these objectives. Siemens, for example, employs the MindSphere IoT operating system for predictive maintenance and process optimization (Siemens, 2024). ABB's YuMi robot facilitates human-robot collaboration in manufacturing processes (ABB, 2024). GE utilizes the Predix platform for data analytics and asset performance management (General Electric, 2024), while Carbon's Digital Light Synthesis (DLS) technology is transforming 3D printing for personalized manufacturing (Carbon, 2024; Flores et al., 2020; Khan, Koç, et al., 2021). These examples demonstrate the growing embrace of I4.0 technologies by companies determined to modernize their manufacturing processes and remain competitive in the global marketplace.

In the same line, the manufacturing segment has started to actively utilize the I4.0 innovations to build new socio-technical infrastructures. These advancements are reshaping workplace dynamics, including wellness management, work structuring, learning methods, and knowledge governance, with the goal of providing workers with more responsibility and opportunities for personal and professional growth (acatech, 2013; Flores et al., 2020; Xu et al., 2021). The Factory2Fit project (Factory2Fit, 2024) in Europe exemplifies this approach by involving workers directly in the design of their tasks, acknowledging their expertise in their own work. This project leverages adaptive automation solutions, tailored to workers' physical and cognitive abilities, to provide continuous feedback that fosters ongoing learning and skill development. Additionally, virtual factory models and augmented reality tools are designed to enhance participatory design, knowledge sharing, and training.

Through a coordinated effort by government, industry, and educational institutions, it is anticipated that these initiatives will enable the development of smart factories distinguished by their high complexity, dynamism, and flexibility (Acatech, 2013). These factories will foster a work environment that promotes inclusive and participatory corporate governance, ensuring that employees are regarded as integral members of the system rather than as replaceable components.

2.5 Strategies for addressing sustainability in Industry 4.0

I4.0, characterized by the integration of CPS, IoT, and advanced data analytics, offers significant opportunities to enhance sustainability in industrial processes (Javaid et al., 2022). Implementing strategies to address sustainability within this framework is crucial for reducing environmental impact, improving resource efficiency, and fostering long-term economic growth. Here are some key strategies for achieving sustainability in I4.0:

2.5.1 Energy efficiency and management

The transition to I4.0 offers a significant opportunity to enhance energy efficiency through the integration of advanced technologies (Mohamed et al., 2019). One key strategy is the implementation of Smart Energy Grids, which leverage IoT and AI to optimize energy distribution, manage demand, and reduce wastage (Javaid et al., 2022). By using real-time monitoring systems equipped with sensors and data analytics, industries can continuously track energy consumption and swiftly identify inefficiencies (Mohamed et al., 2019). Additionally, the integration of renewable energy sources such as solar, wind, and hydro into industrial operations further supports sustainability efforts. These approaches collectively contribute to more efficient and environmentally friendly industrial processes (Javaid et al., 2022).

2.5.2 Resource optimization in Industry 4.0

In I4.0, optimizing resource use is critical for enhancing sustainability and operational efficiency. Implementing predictive maintenance systems helps reduce downtime, extend equipment life, minimize waste, and reduce the overall expenses of producing better quality components (Zonta et al., 2020). Additionally, by leveraging data analytics, industries can optimize the use of raw materials, reducing scrap rates and improving overall resource efficiency (Duan & Da Xu, 2021). Additionally, adopting CE practices involves designing processes and products that facilitate recycling, reusing, and refurbishing materials, thereby minimizing waste and promoting sustainable resource management. These strategies collectively contribute to a more sustainable and efficient industrial ecosystem (Ciliberto et al., 2021).

2.5.3 Smart manufacturing and production

I4.0 advancements in manufacturing efficiency are driven by several key technologies. Additive manufacturing, or 3D printing, reduces material waste and energy consumption by

producing components layer by layer only where needed (Peng et al., 2018). Flexible manufacturing systems, with adaptable production lines, quickly respond to changes in demand, reducing overproduction and associated waste (Florescu & Barabas, 2020). Additionally, the use of digital twins—virtual models of physical assets—optimizes design, monitors performance, and predicts maintenance needs. These innovations collectively enhance overall operational efficiency and improve safety for human employees, as robots can undertake dangerous tasks during the manufacturing process (Stavropoulos & Mourtzis, 2021).

2.5.4 Promoting supply chain sustainability in Industry 4.0

Supply chain sustainability in I4.0 can be significantly enhanced through advanced technologies and strategic practices. Utilizing blockchain and IoT enhances supply chain transparency and traceability, ensuring sustainable sourcing and reducing environmental impact (Matarneh et al., 2024). By applying data analytics, industries can optimize logistics and transportation, thereby reducing fuel consumption and emissions (Liu et al., 2023). Furthermore, prioritizing suppliers with sustainable practices and certifications supports sustainable procurement, promoting overall sustainability throughout the supply chain (Matarneh et al., 2024). These strategies collectively contribute to a more transparent, efficient, and environmentally responsible supply chain.

2.5.5 Effective waste management and reduction in Industry 4.0

Waste management and reduction are essential components of sustainability in I4.0. Implementing zero-waste production involves applying lean manufacturing principles to minimize waste at every stage of the production process (Veseli et al., 2024). Advanced recycling technologies play a crucial role in this strategy, enabling the efficient processing of waste materials. Integral to this is recycling 4.0, which incorporates smart systems and automation to enhance the recycling process. Recycling 4.0 leverages IoT, AI, and robotics to sort, process, and repurpose waste with high precision and minimal human intervention, significantly improving efficiency and reducing environmental impact (Blömeke et al., 2020). Additionally, identifying opportunities for by-product utilization—where by-products from one process serve as inputs for another—helps create closed-loop systems (Ciliberto et al., 2021; Sbahieh et al., 2023). These strategies work together to significantly reduce waste and enhance sustainability in industrial operations.

2.5.6 Employee training and engagement in Industry 4.0

Employee training and engagement are vital for achieving sustainability in I4.0. Investing in training programs gives employees the needed skills to operate and maintain advanced technologies sustainably (Stachová et al., 2019). Fostering a culture of sustainability within the organization is achieved through awareness programs and incentives, encouraging employees to prioritize environmentally friendly practices (Javaid et al., 2022). Additionally, promoting collaborative innovation by encouraging cross-functional teams to work together on sustainability initiatives and innovative

solutions further enhances the organization's overall sustainability efforts (Aguilar-Rodríguez et al., 2021). These strategies ensure that employees are well-prepared and motivated to contribute to the organization's sustainable goals.

Employee education is an ongoing process that involves adapting and changing work behaviors and enhancing knowledge, skills, and motivation. This continuous development is achieved through various learning methods, ensuring that employees remain proficient and motivated in their roles. These strategies ensure that employees are well-prepared and motivated to contribute to the organization's sustainable goals (Stachová et al., 2019).

2.5.7 Regulatory compliance and standards in Industry 4.0

Ensuring regulatory compliance and adhering to standards are crucial for sustainability in I4.0. Organizations must ensure compliance with environmental regulations and standards, such as ISO 14001, to maintain sustainability credentials (Bravi et al., 2020). Proactive engagement in the development of new sustainability standards and regulations allows companies to stay ahead of compliance requirements and influence future policies (Aguilar-Rodríguez et al., 2021). Additionally, implementing robust reporting systems to track and disclose sustainability performance enhances transparency and accountability. These practices help organizations maintain regulatory compliance, improve sustainability performance, and build trust with stakeholders (Javaid et al., 2022).

2.5.8 Data-driven decision-making in Industry 4.0

Data-driven decision-making is a cornerstone of sustainability in I4.0. Leveraging big data analytics provides valuable insights into environmental impacts and helps identify areas for improvement (Kumar et al., 2018). AI and ML technologies are used to predict and optimize sustainability outcomes, enhancing efficiency and reducing resource consumption (Jamwal et al., 2021). Additionally, developing decision support systems that integrate sustainability metrics into business decision-making processes ensures that sustainability is a key consideration in strategic planning and operations (Marques et al., 2017). These approaches enable organizations to make informed, data-driven decisions that support their sustainability goals.

2.6 Industry 4.0 and sustainable development goals

The SDGs are a set of 17 goals and 169 targets introduced by the United Nations (UN) in 2015 as part of the "Transforming our World: The 2030 Agenda for Sustainable Development" initiative (United Nations Transforming Our World: The 2030 Agenda for Sustainable Development, 2015). These goals are designed to enhance global well-being by addressing challenges related to social, environmental, and economic sustainability (United Nations Transforming Our World: The 2030 Agenda for Sustainable Development, 2015). The seventeen goals are categorized into social, environmental, and economic

categories. The SDGs offer a unified framework and set of objectives that all countries, industries, businesses, and individuals can work toward to achieve sustainable development for society as a whole (Griggs et al., 2013).

The technological advancements in I4.0 enhance productivity and efficiency and play a crucial role in achieving the United Nations' SDGs. The relationship between I4.0 and the SDGs is comprehensive, as the technologies in I4.0 significantly contribute to various global sustainability objectives.

One of the key goals, No Poverty (SDG 1), can be addressed by I4.0 through the provision of access to critical resources such as education, healthcare, and economic opportunities, especially for vulnerable populations. By enabling broader economic inclusivity through digital platforms and smart systems, these technologies help reduce poverty and mitigate economic losses during disasters (Ajaj et al., 2024). Zero Hunger (SDG 2) is supported by I4.0 T in agriculture, such as precision farming and automated distribution systems. These innovations ensure food security and improve nutrition, even in the most vulnerable regions, by enhancing sustainable agricultural practices and efficient food distribution (Hassoun et al., 2022).

In the realm of health, good health, and well-being (SDG 3), I4.0 is transforming healthcare through digitalization. AI-driven diagnostics, telemedicine, and wearable health devices improve preventive care and treatment options, contributing to healthier lifestyles and better health outcomes for all (Zengin et al., 2021). Quality Education (SDG 4) benefits from I4.0 by expanding access to education through digital learning platforms, augmented reality, and AI-powered personalized education tools. These technologies make education more inclusive and equitable, overcoming geographic and economic barriers (Bai et al., 2020). When it comes to Gender Equality (SDG 5), I4.0 technologies play a vital role in providing equal opportunities for both men and women in the workforce. Automation and digital tools help to dismantle traditional gender roles, creating a more inclusive work environment (Bai et al., 2020). In addressing Clean Water and Sanitation (SDG 6), I4.0 contributes significantly by improving water management and sanitation through IoT sensors and AI algorithms. These technologies monitor water quality, optimize usage, and manage wastewater treatment, ensuring the availability of clean water and sanitation (Bai et al., 2022).

The role of I4.0 in advancing Affordable and Clean Energy (SDG 7) is profound. Through smart grids, energy-efficient manufacturing, and the integration of renewable energy sources, these technologies make energy more affordable, sustainable, and accessible to all (Jayachandran et al., 2022). In promoting Decent Work and Economic Growth (SDG 8), I4.0 enhances economic productivity and creates new job opportunities while fostering sustainable growth. The shift toward digital economies supports inclusive development without compromising environmental sustainability (Dantas et al., 2021). Industry, Innovation, and Infrastructure (SDG 9) are directly bolstered by I4.0 through the modernization of infrastructure and the promotion of sustainable industrialization. The widespread deployment of digital technologies drives innovation and strengthens the resilience of critical infrastructure (Dantas et al., 2021). Reduced Inequalities (SDG 10) are addressed by I4.0 through bridging the digital divide. By connecting the unconnected and providing equal access to technology and economic opportunities, these advancements help reduce disparities within and among countries (Bai et al., 2020).

In urban development, Sustainable Cities and Communities (SDG 11) benefits from I4.0 T that enables the creation of smart cities. These cities are characterized by efficient resource management, smart transportation, and enhanced public safety, making urban areas more inclusive, safe, and sustainable (Bai et al., 2022).

The goal of Responsible Consumption and Production (SDG 12) is advanced by I4.0 through the optimization of supply chains and production processes. Technologies like IoT and AI help minimize waste, improve resource efficiency, and promote sustainable consumption patterns (Dantas et al., 2021). Climate Action (SDG 13) is supported by I4.0 through the reduction of GHG emissions and the optimization of energy use. Data-driven insights and real-time monitoring allow for effective carbon management and climate impact mitigation (Bai et al., 2020). In marine conservation, Life Below Water (SDG 14) is enhanced by I4.0 T that improves resource management and reduces pollution. Automated systems monitor marine resources and environmental changes, ensuring the sustainable use of ocean ecosystems (Alhammadi et al., 2024).

On land, Life on Land (SDG 15) benefits from Industry 4.0 through the sustainable management of terrestrial ecosystems. These technologies support conservation efforts, combat desertification, and protect biodiversity, ensuring the sustainability of life on land (Bai et al., 2022). Peace, Justice, and Strong Institutions (SDG 16) are strengthened by Industry 4.0 through the promotion of transparency, accountability, and inclusivity in institutions. Digital tools help uphold human rights, ensure justice, and foster peaceful societies (Bai et al., 2020).

Finally, Partnerships for the Goals (SDG 17) are facilitated by I4.0, enabling global collaboration and sharing of knowledge and resources. These technologies are crucial in driving sustainable development initiatives forward by connecting stakeholders across borders (Bai et al., 2020). I4.0 is intricately linked with the SDGs, offering powerful tools to address global challenges. By leveraging these technologies, industries and governments can accelerate progress toward a more sustainable, equitable, and prosperous world.

2.7 Future work

- Future research in I4.0 should address challenges and enhance sustainability by focusing on critical areas such as deepening understanding through standardized frameworks, reducing implementation costs to increase accessibility, especially for SMEs, and developing strategies for seamless integration with legacy systems. Strengthening cybersecurity, creating supportive policies, and fostering workforce development through continuous retraining are essential.
- Additionally, research studies into sustainable business models and ongoing environmental impact assessments are needed to ensure positive contributions to sustainability.
- To fully leverage I4.0 to achieve the SDGs, future efforts should focus on bridging the digital divide and ensuring access to necessary technologies and infrastructure, especially in developing regions. This requires investments in digital literacy and workforce training. Promoting inclusive innovation through policies that equitably distribute technological benefits, enhancing international collaboration for sharing best practices,

and ensuring sustainable implementation that prioritizes environmental goals are also essential.

- Continuous research is needed to assess the long-term impacts of I4.0, including automation's socio-economic effects and potential environmental benefits. Addressing these areas will align I4.0 with sustainable development, fostering a more equitable and prosperous global society.

2.8 Conclusion

- The transition to I4.0 presents an unparalleled opportunity to drive sustainability in industrial operations. By implementing sustainable strategies, industries can achieve significant environmental benefits, improve resource efficiency, and ensure long-term economic viability. The successful integration of sustainable practices within I4.0 requires a holistic approach, encompassing technology, processes, people, and regulatory frameworks.
- Employee training and engagement are critical, with continuous education and a culture of sustainability ensuring that employees are equipped and motivated to support sustainable goals. Regulatory compliance and proactive engagement in developing new standards help maintain sustainability credentials and build trust.
- Data-driven decision-making, leveraging big data analytics, AI, and decision support systems, provides valuable insights and optimizes sustainability outcomes. Collectively, these strategies form a comprehensive approach to achieving sustainability in I4.0, emphasizing the integration of advanced technologies, sustainable practices, and regulatory adherence to support long-term environmental and economic goals.
- The intersection of I4.0 and the SDGs offers significant opportunities to advance global sustainability in economic, social, and environmental areas. Technologies like IoT, AI, and robotics enhance productivity and resource efficiency, contributing to goals such as eradicating poverty, promoting sustainable agriculture, improving health, and fostering industrialization. However, challenges include the digital divide, high implementation costs, the need for substantial investment in education and training, and the risk of increased unemployment due to automation. Ensuring these technologies are accessible and equitable across all regions is also a critical obstacle.
- I4.0 offers significant potential to enhance production efficiency and product customization across various sectors, but it also presents environmental sustainability challenges due to its resource-intensive nature. While the adoption of I4.0 T can decrease energy consumption, reduce waste, and lower CO₂ emissions through advanced data analysis and CE practices, the long-term environmental impact remains a topic of ongoing research. Studies indicate that integrating sustainable practices with I4.0 can lead to positive environmental outcomes. However, challenges such as the nascent stage of certain technologies and the complexity of developing sustainable supply chains must be addressed.
- I4.0 is transforming manufacturing by integrating advanced technologies like AI, IoT, and 5 G to enhance environmental sustainability. It enables more efficient resource

management, reduces carbon footprints, and supports sustainable practices in production and building management. By optimizing processes and promoting flexible automation, I4.0 minimizes waste and GHG emissions while fostering the development of sustainable business models. This technological shift is paving the way for a more sustainable, globally connected, and economically viable future in industrial operations.

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Cyber-physical security and sustainability: foundations for a resilient Industry

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3.1 Introduction

The integration of digital and physical systems under the Industry 4.0 paradigm, driven by advanced technologies such as artificial intelligence (AI), Big Data, Internet of Things (IoT), Cloud Computing, and cyber-physical systems (CPSs), has significantly transformed industrial operations (Khan et al., 2025). CPS serves as the backbone of Industry 4.0 by enabling seamless interactions between computational systems and physical processes through interconnected sensors, actuators, control systems, and communication networks. This integration facilitates real-time monitoring, intelligent decision-making, and autonomous control, enhancing productivity, efficiency, and sustainability across various domains, including smart manufacturing, smart grids, and smart buildings. The deployment of CPS allows for efficient resource management, predictive maintenance, and optimized operational control, contributing to economic growth and improved environmental performance (Information security, cybersecurity and privacy protection, 2025).

Despite the benefits, the increased connectivity and complexity of CPS expose them to various security challenges that can undermine their potential to contribute to sustainability. Unlike traditional IT systems, CPS integrates physical processes with digital networks, making them susceptible to a broader range of threats that target both cyber and physical domains. Cyberattacks on CPS can result in operational disruptions, data integrity

violations, safety hazards, and environmental damage. For instance, a successful attack on a smart grid could lead to power outages, resource wastage, and even catastrophic safety failures. As CPS continues to be implemented across various critical infrastructures, ensuring that their security is paramount to achieving sustainability goals (Osazuwa et al., 2023).

The primary objective of CPS security is to maintain Confidentiality, Integrity, Availability, and Reliability (CIAR) of systems, which is essential for their sustainable operation. Effective CPS security extends beyond protection against cyber threats; it also involves enhancing resilience to withstand adverse conditions and ensuring reliable performance. The importance of CIAR is particularly evident in sustainability contexts, where compromised CPS can lead to resource inefficiencies, increased emissions, financial losses, and potential harm to human life.

While various frameworks and standards such as NIST SP 800-82, IEC 62443, and ISO 27001 provide guidelines for securing CPS, they often lack specificity in addressing sustainability-related requirements. Ensuring CPS security within the Industry 4.0 framework requires developing solutions that align with economic, environmental, and social sustainability objectives. For instance, enhancing the efficiency of CPS components can reduce energy consumption, while robust security mechanisms can prevent economic disruptions caused by cyberattacks. Furthermore, addressing social concerns such as job displacement and privacy issues is crucial for ensuring a fair and inclusive transition towards CPS-enabled systems (Stouffer et al., 2013).

This chapter provides a comprehensive exploration of CPS security within the context of Industry 4.0, emphasizing its relevance to achieving sustainability. The discussion will cover the unique vulnerabilities of CPS, existing frameworks for securing these systems, and the integration of security mechanisms with sustainability goals. Additionally, the role of CPS security in promoting economic, environmental, and social sustainability will be analyzed, highlighting the need for resilient architectures capable of withstanding evolving threats. The subsequent sections will examine the challenges and opportunities associated with CPS security and outline future directions for developing more robust and sustainable CPS frameworks.

3.2 Overview of cyber-physical security

CPS refers to the protection of systems where physical processes are integrated with digital computation and communication networks. Unlike traditional IT systems, CPS comprises interconnected hardware and software components responsible for real-time monitoring, control, and automation of industrial processes. The primary objective of CPS security is to ensure Confidentiality, Integrity, Availability, and Reliability (CIAR), which is critical for maintaining operational resilience, efficiency, and sustainability in Industry 4.0 systems.

CPS consists of various components that interact cohesively to enable efficient and sustainable operations. Sensors play a crucial role by collecting real-time data from the physical environment, including parameters such as temperature, pressure, motion, and

vibration. These data are essential for accurate decision-making and efficient resource utilization. However, sensors are often exposed to external environments, making them vulnerable to tampering, unauthorized access, and data integrity attacks. Compromised sensor data can significantly impact economic productivity, environmental monitoring, and social safety, thereby undermining sustainability objectives.

Actuators are another essential component of CPS, converting digital commands into physical actions to control processes such as manufacturing, energy distribution, and infrastructure management. Their primary purpose is to enhance economic efficiency by automating operations and reducing operational costs. Despite their benefits, actuators are susceptible to unauthorized access, which can result in hazardous outcomes such as equipment damage, safety risks, and inefficient resource utilization. Such disruptions can have detrimental effects on sustainability by compromising system reliability, productivity, and resource optimization.

Communication networks form the backbone of CPS by facilitating data exchange between sensors, actuators, control systems, and human-machine interfaces (HMIs). Technologies such as Ethernet, Wi-Fi, Zigbee, and Industrial IoT protocols provide the infrastructure necessary for CPS connectivity (Kassan et al., 2018). However, increased connectivity also broadens the attack surface, making CPS systems vulnerable to attacks like Denial-of-Service (DoS) and Man-in-the-Middle (MitM). Disruptions to communication networks can compromise data integrity, hinder real-time monitoring, and degrade system reliability, leading to significant economic losses and environmental inefficiencies. Ensuring the integrity and availability of communication networks is essential for achieving economic efficiency, environmental performance, and social safety.

Control systems are responsible for analyzing sensor data and providing appropriate commands to actuators to maintain optimal system performance. Modern control systems often incorporate advanced technologies such as AI and machine learning (ML) algorithms to enhance predictive maintenance, anomaly detection, and adaptive control (Olowononi et al., 2021). However, these systems are increasingly targeted by malicious actors aiming to manipulate control algorithms, inject malicious code, or alter decision-making processes. Such attacks can compromise operational reliability, productivity, and sustainability by disrupting essential industrial functions. Effective protection of control systems is crucial to ensuring continuous and efficient operations.

HMIs provide an interactive platform for operators to monitor, control, and visualize CPS processes. While HMIs enhance usability, they also present significant security risks if unauthorized access allows attackers to alter system parameters, disable essential functions, or manipulate operational processes (Mourtzis et al., 2023). Implementing robust access control mechanisms is essential to safeguard social sustainability by protecting privacy and ensuring ethical data usage. Moreover, user-friendly HMIs can enhance productivity and job satisfaction by promoting efficient human-machine interactions.

The interconnectedness of these CPS components highlights the complex security challenges associated with Industry 4.0. The economic dimension of CPS security focuses on enhancing operational efficiency, reducing costs, and ensuring business continuity. Environmentally, CPS security aims to improve resource utilization, reduce emissions, and build resilient infrastructure capable of withstanding evolving threats. The social aspect of CPS security involves ensuring safety, privacy, inclusivity, and ethical data usage.

Addressing these challenges requires developing integrated frameworks that combine technical security measures with sustainability metrics. Emerging technologies such as blockchain, AI, and resilient control algorithms have the potential to enhance CPS security and contribute to achieving sustainability goals across economic, environmental, and social dimensions.

3.2.1 Security concerns and importance of cyber-physical systems security in sustainability

CPSs present unique security challenges due to their complex integration of physical components and digital networks. Unlike conventional IT systems, CPS involves tightly coupled interactions between sensors, actuators, control systems, communication networks, and HMI, making them particularly vulnerable to a broad range of cyber threats that can undermine operational reliability, data integrity, and sustainability. As Industry 4.0 increasingly relies on CPS to enhance productivity, efficiency, and sustainability, addressing these challenges becomes essential for ensuring resilient and sustainable operations ([Industrial communication networks, 2025](#)).

One of the critical concerns in CPS security is maintaining communication integrity. CPS relies heavily on low-latency, high-reliability communication channels for seamless monitoring, control, and decision-making processes. However, this dependency makes CPS systems susceptible to various attacks, such as DoS and MitM, which can degrade performance, disrupt communication links, and compromise decision-making ([Sharma et al., 2022](#)). The high connectivity of CPS systems also broadens their attack surface, increasing the likelihood of adversaries exploiting communication networks to disrupt data exchange, manipulate operational processes, and cause severe operational, economic, and environmental consequences.

Ensuring system reliability is another essential aspect of CPS security, particularly for critical infrastructure applications where operational continuity, efficiency, and safety are paramount. Cyberattacks targeting control systems in smart manufacturing or smart grids can result in equipment damage, operational downtime, safety hazards, and inefficient resource utilization, leading to increased resource consumption and negative environmental impacts ([Anitha et al., 2024](#)). Moreover, CPS architecture often involves heterogeneous devices and protocols, increasing the risk of interoperability issues. Incompatible components or outdated protocols create vulnerabilities that attackers can exploit, disrupting system functionality and undermining sustainability objectives. Comprehensive frameworks and robust testing mechanisms are necessary to ensure compatibility, resilience, and security across all CPS components ([Acharya et al., 2024](#)).

Furthermore, data integrity plays a fundamental role in achieving sustainability through CPS. Accurate, real-time data collection is essential for effective decision-making and optimized resource utilization. However, unauthorized manipulation of sensor data can result in malfunctioning processes, incorrect control commands, and cascading failures that compromise efficiency, productivity, and safety. Data integrity attacks can have far-reaching consequences, including degraded system performance, resource wastage, and increased emissions. Therefore, ensuring data integrity throughout the entire life cycle of CPS—from

acquisition to processing and storage—is crucial for achieving resilient and sustainable industrial operations ([Herrero, 2025](#)).

The importance of CPS security in promoting sustainability cannot be overstated. Ensuring a secure CPS architecture directly contributes to achieving sustainability goals by enhancing operational reliability, optimizing resource use, and improving environmental performance. Effective CPS security is essential for maintaining the integrity of data used for decision-making, improving operational efficiency, and enhancing system productivity. A compromised CPS can lead to inefficiencies, resource wastage, and increased emissions, undermining the fundamental objectives of sustainability. Additionally, operational resilience plays a critical role in maintaining uninterrupted processes, minimizing downtime, reducing energy consumption, and enhancing productivity. By protecting CPS from evolving cyber threats, industries can enhance efficiency and reliability, contributing to reduced environmental impact, improved social safety, and economic growth ([Ballarino et al., 2017](#)).

Developing resilient CPS architectures capable of withstanding evolving threats is essential for future sustainable industrial practices. Integrating security mechanisms with sustainability metrics and resource optimization tools provides a holistic approach to enhancing CPS performance. Furthermore, the adoption of advanced technologies such as blockchain, AI, and ML can strengthen CPS security by enhancing predictive maintenance, anomaly detection, and adaptive control. The subsequent sections will explore existing frameworks, solutions, and research directions aimed at improving CPS security for achieving sustainable Industry 4.0 operations.

3.3 Security challenges in Industry 4.0

The adoption of CPS in Industry 4.0 has significantly transformed industrial operations by enhancing automation, connectivity, and intelligence. This integration enables seamless communication between physical processes and computational infrastructure, facilitating optimized decision-making and operational efficiency ([Lee et al., 2015](#)). However, as these systems become increasingly interconnected, they also become more vulnerable to sophisticated cyber threats. The attack surface expands as more devices, platforms, and networks converge, exposing industrial infrastructure to a wide range of security challenges that threaten not only performance but also the long-term sustainability of smart ecosystems ([Humayed et al., 2017](#)).

3.3.1 Common threats and attacks

The primary security risks in CPS are data manipulation. In many industrial settings, sensor data serve as the foundation for real-time decisions across control systems, energy optimization platforms, and predictive maintenance modules. When these data are maliciously altered, the resulting control actions can become flawed, leading to cascading failures across the system. These attacks impact not just operational functionality but also environmental goals by increasing carbon emissions and energy wastage

(Huzzat et al., 2025). Equally concerning are DoS attacks, which seek to overwhelm system resources and render critical services unavailable (Wang et al., 2023). In CPS environments where low latency and high availability are essential, such as in automated production lines or robotic assembly stations, a temporary loss of communication can result in halted operations and considerable material waste. These service interruptions are not merely technical failures, and they have direct implications for economic sustainability by affecting throughput, productivity, and profitability (Adetunla et al., 2024).

Supply chain security has also emerged as a critical concern. Malicious actors increasingly exploit these supply chains by injecting vulnerabilities or malware into components during manufacturing or distribution. Such embedded threats can remain dormant for extended periods and be difficult to detect, increasing the risk of widespread disruptions once activated (Hezam et al., 2024). Malware presents another persistent threat to CPS environments. Unlike traditional IT malware, which mainly targets user data and computer systems, cyber-physical malware known as Stuxnet specifically aims to disrupt physical processes. This type of malware achieves its goals by directly attacking industrial control systems, potentially leading to severe physical damage or operational disruption within critical infrastructure. These attacks can reprogram logic controllers, disrupt automation protocols, and cause real-world damage to equipment or infrastructure. In sectors like water treatment, power generation, or chemical processing, the stakes of such manipulation are especially high, with consequences that may include environmental contamination, safety breaches, or system downtime (Warbhe et al., 2025). Unauthorized access to HMIs is also a growing concern. These interfaces allow operators to monitor and control industrial processes, but if inadequately protected, they can become entry points for cyber intrusions. Attackers with access to HMIs can alter system parameters, disable alarms, or shut down essential functions (Idrus, 2024).

3.3.2 Sector-specific challenges

Security challenges in CPS often manifest differently across industrial sectors as shown in Fig. 3.1 In smart manufacturing environments, real-time synchronization among robotics, sensors, and actuators is paramount. Any latency or miscommunication induced by cyberattacks can lead to misalignments, equipment collisions, or product defects. These failures contribute to resource wastage, increase the environmental footprint of production, and disrupt economic efficiency (Mitra et al., 2024). Smart grids, by contrast, must handle highly dynamic load profiles and integrate distributed energy sources. Cyberattacks that target energy management algorithms or inject false consumption data can destabilize the grid, reduce energy efficiency, and hinder decarbonization efforts. Similarly, smart buildings incorporate IoT-based systems for lighting, heating, ventilation, and access control. Breaches in these systems can lead to overconsumption of energy, reduced occupant safety, and violations of privacy norms (Kufre et al., 2024).

The sustainability implications of security flaws in CPS are profound. Attacks that degrade process reliability or data accuracy can compromise resource management strategies, increase operational inefficiencies, and erode stakeholder trust. For instance, a single compromised sensor feeding erroneous data into a smart manufacturing system can derail entire production cycles, wasting materials and energy. The comparison of security

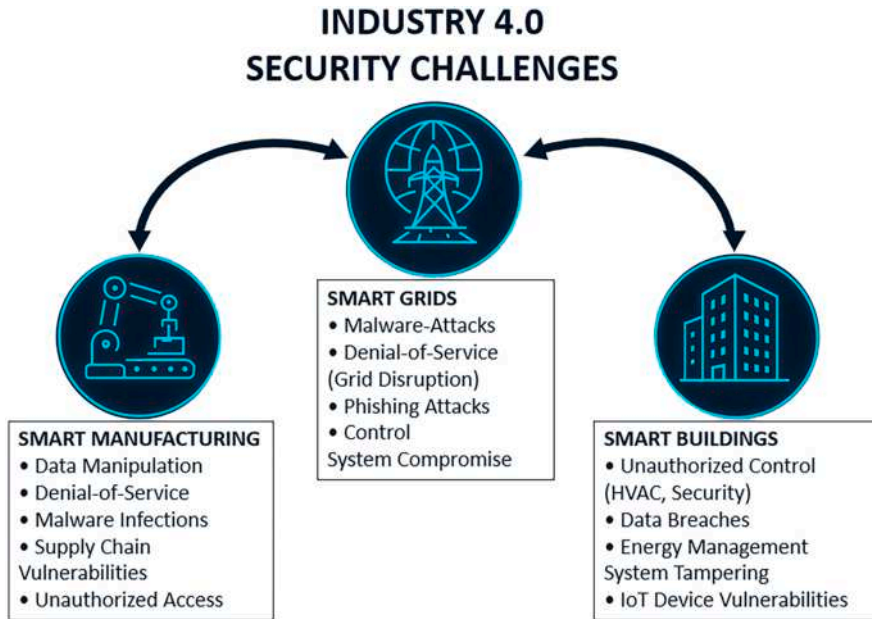


FIGURE 3.1 Overview of Industry 4.0 security challenges across smart ecosystems.

TABLE 3.1 Comparison of security challenges across smart environments.

Sector	Common security threats	Specific vulnerabilities	Potential impact on sustainability
Smart Manufacturing	Production disruption, IP theft, data manipulation	Insecure industrial protocols, vulnerable IoT devices, legacy systems	Resource wastage, energy inefficiency, increased scrap
Smart Grids	Blackouts, grid instability, control system compromise	Lack of grid segmentation, vulnerable communication protocols, remote access points	Energy inefficiency, potential environmental damage from outages
Smart Buildings	BMS compromise, unauthorized access, data breaches	Outdated BMS software, weak access controls, insecure network configurations	Energy wastage, compromised environmental controls, data leaks

challenges across smart environments are shown in [Table 3.1](#). In smart infrastructure, inadequate cybersecurity measures may result in environmental impacts such as uncontrolled emissions or inefficient HVAC operations, undermining long-term goals for energy conservation and carbon neutrality ([Chandra Sekhar et al., 2024](#)).

The reputational damage from security breaches affects not only individual enterprises but also public confidence in Industry 4.0 technologies as a whole. A secure CPS

environment is essential for maintaining operational continuity, protecting environmental resources, and ensuring the social legitimacy of digital innovation. The complexity and criticality of CPS in Industry 4.0 demand not only advanced technical solutions but also a holistic understanding of how security interacts with broader sustainability.

3.4 Security frameworks and solutions

As Industry 4.0 accelerates the integration of CPS into industrial infrastructure, the need for comprehensive and scalable security frameworks has become increasingly evident. The heterogeneous nature of CPS, which combines software, hardware, human interfaces, and physical systems, demands multilayered security protocols that extend beyond traditional IT solutions. This section examines the key international standards and emerging technologies that guide CPS security implementation, alongside real-world case studies that illustrate how these approaches support resilience and sustainability in critical infrastructure.

3.4.1 Existing standards and frameworks

One of the most widely referenced guidelines in the domain of industrial cybersecurity is the NIST SP 800-82, which provides tailored recommendations for Industrial Control Systems (ICS). Unlike conventional IT frameworks, NIST SP 800-82 emphasizes system availability and safe operation in time-sensitive environments, making it particularly applicable to CPS in sectors like energy, water, and manufacturing. The standard highlights threat modeling, incident response planning, and segmentation strategies to minimize lateral attack propagation within CPS architectures ([Henriques et al., 2023](#)). Also, the IEC 62443 series address security across the entire industrial automation and control systems (IACS) life cycle. This includes asset identification, threat assessment, and system hardening through defense-in-depth principles. These standards are crucial for ensuring compliance while also enhancing trust in automated industrial environments ([Triantafyllou et al., 2020](#)).

Another widely adopted standard is ISO/IEC 27001, which provides a framework for managing information security through risk assessment, access control, and continuous improvement mechanisms. While initially designed for IT systems, its flexibility allows for adaptation within CPS environments, particularly in organizations where digital twins, cloud services, and edge computing introduce new privacy and integrity risks ([Cirne et al., 2022](#)). Despite that, it is important to note that CPS security requires a hybrid strategy that unifies IT and Operational Technology (OT) governance. This convergence poses challenges but also creates opportunities for harmonized regulatory compliance and centralized monitoring.

3.4.2 Technological solutions

In parallel with these structured frameworks, technological solutions are evolving rapidly to address dynamic threat landscapes as shown in [Fig. 3.2](#). One of the most promising

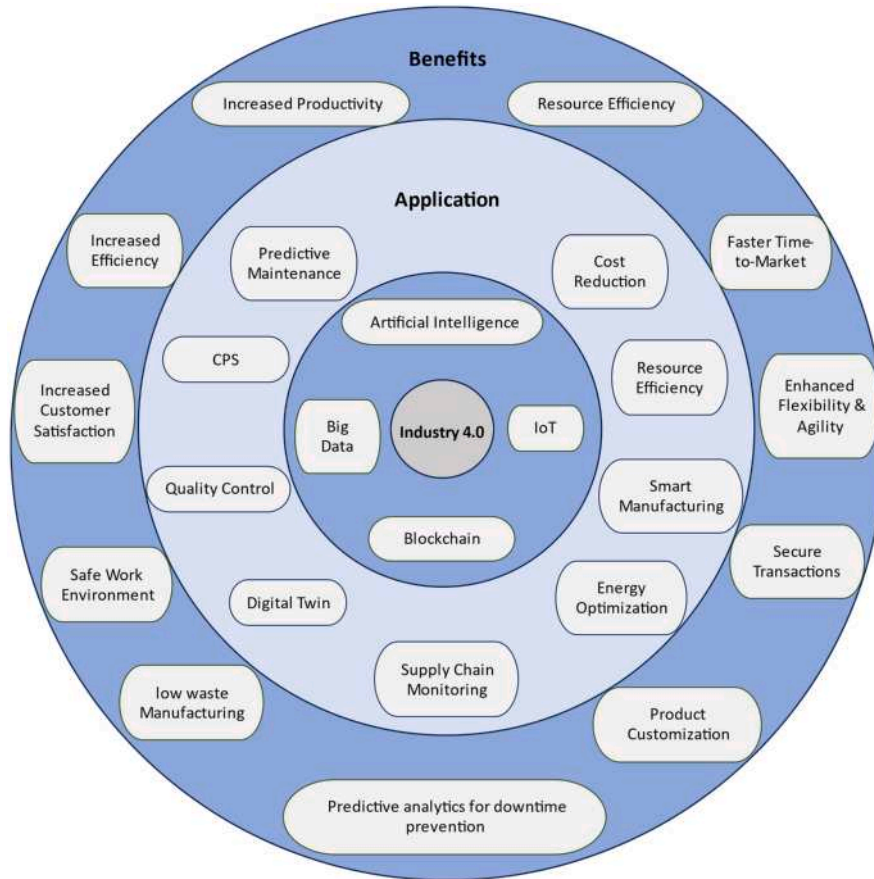


FIGURE 3.2 Layered model showing how core Industry 4.0 technologies drive applications and deliver benefits like productivity, efficiency, and customer satisfaction.

approaches involve the deployment of intrusion detection systems (IDS) tailored for CPS environments. CPS-specific IDS can analyze patterns across both digital signals and physical process behaviors. This dual-domain detection enhances anomaly identification and reduces false positives, thus improving operational continuity (Abdelkader et al., 2024). These systems can be integrated with ML algorithms to enable adaptive defense mechanisms that evolve with system usage and attack trends. Blockchain technology has also emerged as a compelling tool for CPS security. By decentralizing data storage and validation, blockchain can help protect control system logs, sensor data, and access records from tampering. Blockchains have shown promise in maintaining data integrity and nonrepudiation within energy grids and supply chains (Dong et al., 2022).

Another growing field is the use of AI, IoT, and Big Data analytics to develop predictive and self-healing security mechanisms in CPS. AI models, particularly those leveraging deep

learning, can be trained to recognize abnormal behavior within control systems, forecast attack surfaces based on historical patterns, and orchestrate automated mitigation actions (Mansour, 2022). When integrated with Big Data platforms, AI algorithms benefit from vast and diverse datasets collected across industrial environments, enabling more robust threat detection and system optimization. The IoT layer, which connects physical assets like sensors and actuators to the digital environment, serves as a critical data source but also introduces significant attack vectors due to its heterogeneity and scale (Gupta et al., 2020). To secure IoT-based CPS, AI-driven threat detection must be paired with real-time analytics and anomaly detection frameworks that can process vast volumes of data with low latency (Tang et al., 2023). Also, the convergence of AI, IoT, and Big Data enables continuous system learning and adaptation. When embedded within digital twin architectures, these technologies can simulate potential cyberattack scenarios, evaluate system responses under stress, and proactively mitigate vulnerabilities before they are exploited in live environments (Al-Abassi et al., 2020). This synergy contributes significantly to system resilience, reduces downtime, and supports sustainability through uninterrupted and optimized operations.

Real-world case studies underscore the practicality and necessity of integrated security frameworks. The deployment of blockchain for secure peer-to-peer energy trading has been piloted in Germany and South Korea, enabling decentralized verification of consumption and supply records (Nguyen et al., 2024). Meanwhile, AI-enhanced IDS systems are being actively deployed in smart factories across Europe and Asia to secure programmable logic controllers (PLCs) against malware and unauthorized configuration changes. These implementations not only deter cyberattacks but also improve operational transparency and compliance with international shipping regulations. Similarly, in the healthcare sector, AI-powered anomaly detection integrated with ISO 27001-compliant systems is helping secure CPS devices such as robotic surgical tools and smart patient monitoring systems (Gaspar et al., 2023).

3.5 Enhancing sustainability through cyber-physical security

CPSs have become the digital backbone of Industry 4.0, interlinking sensors, actuators, computing units, and data analytics in real time. These intelligent infrastructures not only drive operational efficiency but are critical enablers of sustainable industrial ecosystems (Broo & Schooling, 2021). As CPSs grow more complex and pervasive, their ability to support sustainability goals hinges on their resilience to cyber threats. Cyber-physical security ensures that decision-making processes based on sensor data remain uncompromised, system operations remain uninterrupted, and sustainability metrics remain verifiable and trustworthy (Tan & Li, 2024). The literature highlights that secure CPS architectures correlate strongly with sustainable performance indicators, including energy efficiency, emissions control, and infrastructure durability (Malagnino et al., 2021). CPS security enhancements in sustainability domains are shown in Table 3.2.

Cyber-secure communication channels, anomaly detection algorithms, and authenticated access protocols safeguard such infrastructures, thereby minimizing downtime and

TABLE 3.2 Cyber-physical system (CPS) security enhancements in sustainability domains.

Application area	Sustainability focus	Cyber-physical security contribution	Tools used
Smart grids (Hernández et al., 2024), (Kabir et al., 2024)	Energy efficiency, reduced emissions	Prevent load manipulation, data spoofing, unauthorized control	Digital Twins, AI Anomaly Detection
Smart buildings (Ohueri et al., 2024), (Desogus et al., 2021)	Energy conservation, occupant safety	Prevent unauthorized access to control systems	BIM + CPS integration, Real-Time IDS
Industrial automation (Desmond & Salama, 2024)	Waste reduction, productivity, emission reduction	Maintain uptime, detect anomalies, optimize material flows	Predictive CPS, Resilient Robotics
Urban infrastructure (Sharma et al., 2024), (Arsiwala et al., 2023)	Resource efficiency, carbon accounting	Secure data for urban LCA, planning, and compliance reporting	LCA platforms, Secure BIM-Digital Twin Synchronization

reinforcing environmental sustainability (Hernández et al., 2024). As well, operational resilience enabled by CPS security supports economic sustainability by reducing maintenance costs and extending asset life cycles (Sharma et al., 2024). In smart buildings, CPSs are used to regulate HVAC systems, lighting, and occupancy control. Still, unsecured systems are vulnerable to unauthorized access and control signal manipulation, which can cause energy waste or reduce occupant comfort. Security measures like multilayered encryption, real-time intrusion detection, and secure device authentication enhance system reliability and ensure that energy-saving goals are met without compromising safety or privacy (Ohueri et al., 2024). Industrial automation similarly benefits from CPS security by supporting predictive maintenance, anomaly detection, and synchronized robotic operations. These capabilities collectively contribute to lean manufacturing, waste minimization, and emission control that key pillars of sustainability (Desmond & Salama, 2024).

The integration of life cycle assessment (LCA) methodologies into CPS provides a holistic view of environmental impact over time. LCA quantifies emissions, energy consumption, and waste across stages from raw material acquisition to disposal. Ever so, the accuracy of these assessments depends on secure data streams. Cyber-physical security ensures that LCA inputs often derived from real-time sensors or industrial databases are not manipulated, thereby preserving the validity of sustainability decisions and carbon accounting (Arsiwala et al., 2023). Building Information Modeling (BIM) also benefits from CPS integration. BIM serves as a digital representation of a building's structure and systems, enabling simulation of operational scenarios and optimization of energy use. When merged with sensor inputs from CPS and protected via cybersecurity mechanisms, BIM transforms into a dynamic management platform for sustainability. Techniques like encrypted data exchange, secure APIs, and access control help protect BIM integrity while facilitating adaptive control strategies (Desogus et al., 2021).

Digital Twins, representing the most advanced convergence of CPS and simulation, mirror real-world systems in real time. When secured, they enable predictive diagnostics, real-time optimization, and proactive fault detection. In the context of smart cities or energy systems, digital twins that incorporate AI and cybersecurity controls allow continuous improvement of energy management, material flows, and urban services—all without risking data exposure or system disruption (Kabir et al., 2024).

CPSs play a pivotal role in enhancing sustainability by integrating real-time sensing, intelligent decision-making, and dynamic actuation through a closed-loop architecture as shown in Fig. 3.3 Core technologies such as embedded systems, IoT, and ML enable CPS to optimize energy usage, reduce emissions, and support applications like smart grids and sustainable manufacturing (Lee et al., 2015). The feedback loop of CPS drives predictive maintenance and resource efficiency, improving operational performance while minimizing waste. As sustainability challenges intensify, CPSs offer a promising pathway for informed policy-making and resilient infrastructure (Wollschlaeger, Sauter and Jasperneite, 2017) (Fig. 3.4).

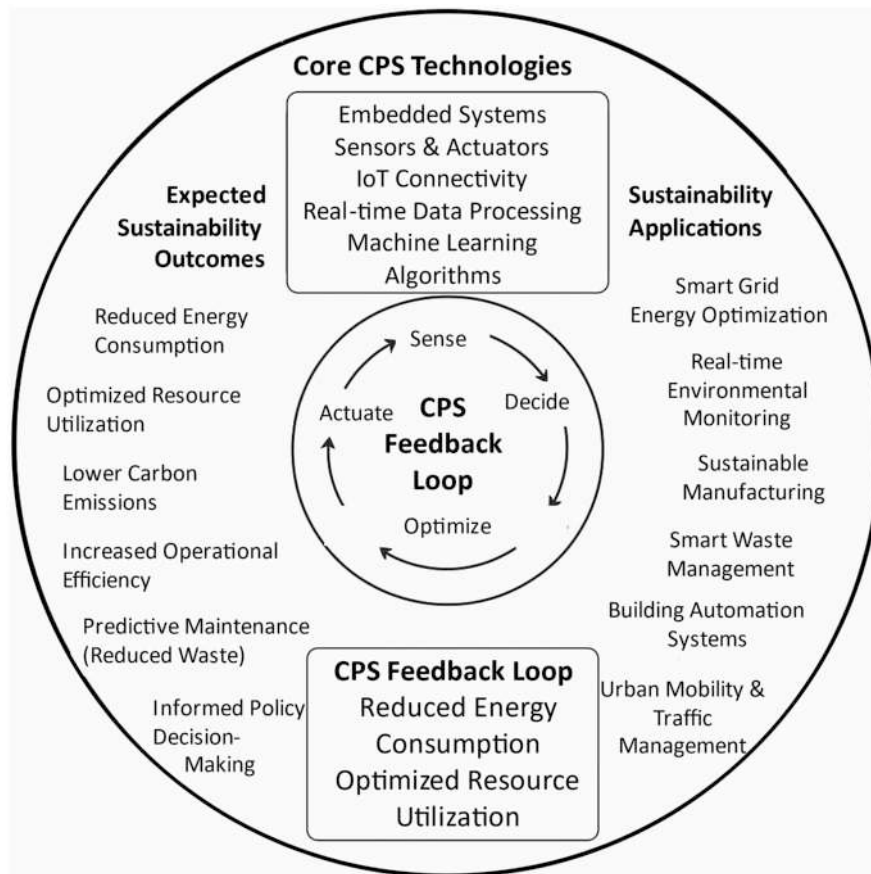


FIGURE 3.3 CPS feedback loop enabling sustainability through real-time sensing, decision-making, and optimization for energy, resource, and emission efficiency. CPS, Cyber-physical systems.

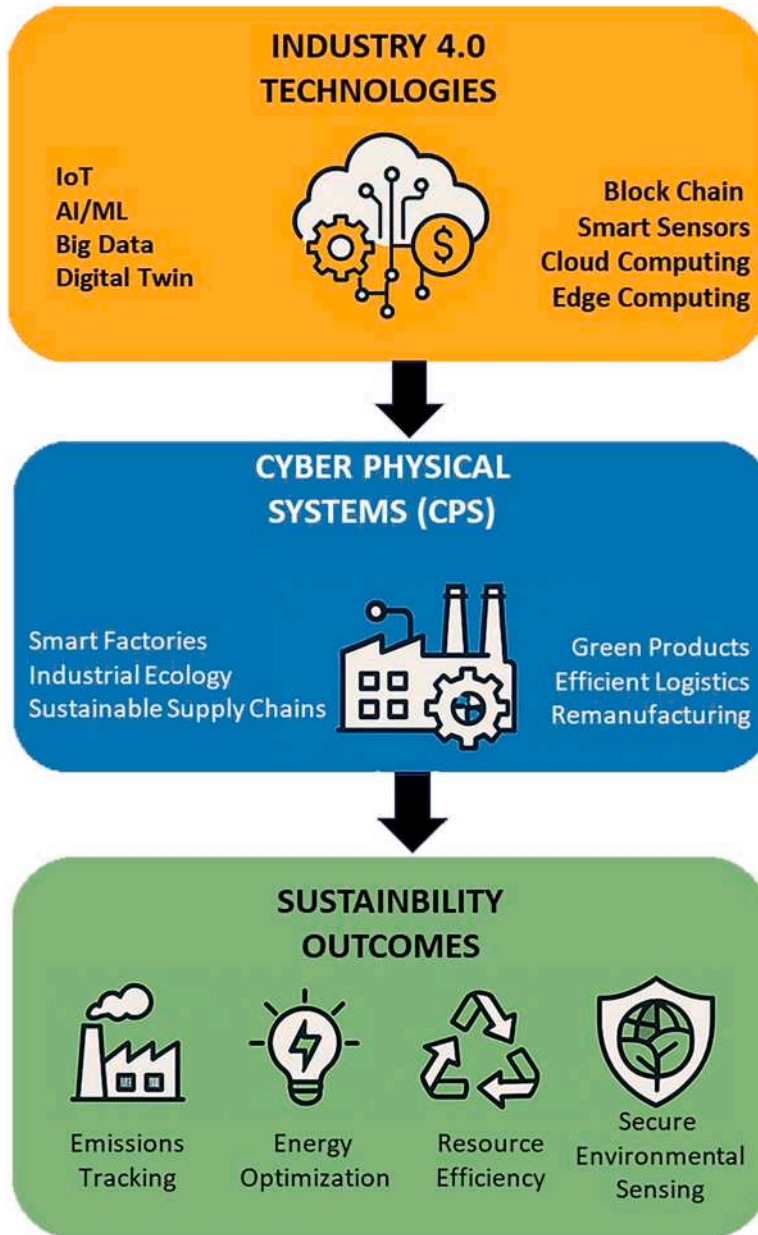


FIGURE 3.4 Flowchart illustrating the relationship between Industry 4.0 technologies, CPSs, and sustainability outcomes. *CPS*, Cyber-physical systems.

3.6 Future research directions and challenges

The future of CPSs security lies at the convergence of technological complexity and sustainability imperatives. CPSs, as the operational core of Industry 4.0 infrastructures, uniquely enable intelligent, autonomous, and resource-optimized industrial environments. However, the same interconnectedness that enhances efficiency also magnifies security vulnerabilities and sustainability risks. Traditional cybersecurity frameworks, largely designed for static IT environments, are insufficient for dynamic, distributed, and energy-sensitive CPS networks. This section identifies key CPS-specific challenges and proposes strategic research directions to create resilient, energy-aware, and sustainability-aligned CPS security architectures.

3.6.1 Emerging threats and systemic complexity in cyber-physical systems

Modern CPSs are increasingly characterized by heterogeneous devices, decentralized data processing, and real-time control loops. Such environments are vulnerable to sophisticated cyber threats, including adversarial ML attacks, data poisoning, and model manipulation. These attacks can not only disrupt operations but also indirectly escalate energy usage and material waste, undermining sustainability targets. For example, [Hassoun et al. \(2024\)](#) highlight how data-centric vulnerabilities in CPS used for food manufacturing can increase system emissions and lead to resource inefficiencies ([Hassoun et al., 2024](#)).

The expansion of digital twins, edge computing, and IoT telemetry further complicates CPS security. Digital twins, in particular, are critical in smart city CPS but remain inadequately protected, offering potential entry points for malicious interventions that could affect mobility control, energy distribution, and emissions tracking ([Huzzat et al., 2025](#)). Also, quantum computing represents a looming threat, with the capability to break classical encryption protocols. [Thirupathi et al. \(2024\)](#) emphasize the urgency of designing quantum-resilient CPS frameworks and embedding architectural redundancy to withstand potential future decryption attacks ([Thirupathi et al., 2024](#)).

3.6.2 Toward resilient, energy-aware, and sustainable cyber-physical systems architectures

To ensure both security and sustainability, future CPS designs must incorporate specific capabilities that enhance resilience, minimize energy consumption, and provide real-time feedback for sustainability analytics.

3.6.2.1 Resilience-enhancing cyber-physical systems architectures

Next-generation CPS must be designed with fault-tolerant and self-healing properties. Fault tolerance enables CPS to maintain operations despite localized failures or cyber intrusions, while self-healing architectures detect, isolate, and autonomously recover from anomalies without major service interruptions. This is crucial for minimizing operational downtime and associated environmental impacts such as excess emissions or resource wastage during system recovery ([Johnphill et al., 2023](#)).

3.6.2.2 Energy-aware security protocols for cyber-physical systems

Traditional cybersecurity solutions often impose significant computational and energy burdens. In resource-constrained CPS environments, particularly at the edge, lightweight security measures are necessary. Future research should focus on energy-aware cryptographic protocols, context-sensitive anomaly detection, and adaptive authentication mechanisms that dynamically adjust their security postures based on threat levels and energy availability. [Hussain et al. \(2025\)](#) advocate for integrating energy optimization into smart ecosystem cybersecurity, illustrating how intelligent resource management can support both resilience and sustainability ([Hussain et al., 2025](#)).

3.6.2.3 Resilience-enhancing cyber-physical systems architectures

CPS systems offer a unique opportunity to enable real-time emissions and waste monitoring. Embedded sensor networks within CPS can provide granular environmental data that, when secured and analyzed correctly, inform immediate corrective actions. This feedback loop can enhance operational sustainability by identifying and mitigating inefficiencies caused by system malfunctions or cyberattacks. Integration with sustainability KPIs, as suggested by [Hassoun et al. \(2024\)](#), ensures that CPS not only optimize performance but also contribute directly to corporate sustainability goals.

3.6.2.4 Integration with life cycle assessment, Building Information Modeling, and circular economy analytics

Secure CPS infrastructures should also be seamlessly integrated with external sustainability assessment tools like LCA, Building Information Modeling (BIM), and circular economy platforms. Such integration enables a comprehensive evaluation of the environmental footprint of security measures and system designs. For instance, linking CPS operational data with LCA models can help quantify the trade-offs between enhanced security and additional energy use, allowing for more informed, sustainability-conscious design choices ([Desmond & Salama, 2024](#)). [Razaque et al. \(2022\)](#) have proposed human-centric CPS designs that prioritize usability, data privacy, and ethical AI alignment in mission-critical contexts ([Razaque et al., 2022](#)).

3.6.3 Strategic research directions for sustainable cyber-physical systems security

The convergence of Industry 4.0 technologies with sustainability goals presents a critical opportunity for innovation. As depicted in flowchart illustrating the relationship between Industry 4.0 technologies, CPS, and sustainability outcomes ([Fig. 3.1](#)), technologies such as AI, IoT, Big Data, Digital Twins, and blockchain intersect with sustainability practices like LCA, resource optimization, and green supply chains. Future CPS security architectures should leverage this convergence to enhance not only resilience but also sustainability intelligence. Promising research directions include the development of AI-based IDS that are energy-aware, context-sensitive, and designed for real-time adaptive defense. Another direction is the creation of secure digital twins capable of simulating cyberattack impacts not just on performance, but on emissions, energy usage, and waste generation ([Desmond & Salama, 2024](#)).

Similarly, quantum-resilient CPS frameworks, as discussed by Thirupathi et al. (2024), must become a priority. This includes exploring neuromorphic computing, entropy-based key management, and decentralized consensus algorithms that align with green IT principles.

3.7 Conclusion

The transition to Industry 4.0 has catalyzed the integration of CPS into nearly every sector of modern industry, from manufacturing and logistics to energy and urban infrastructure. This integration has unlocked transformative capabilities such as real-time monitoring, automation, and data-driven optimization. However, it has also introduced significant security challenges. As demonstrated throughout this manuscript, the goals of resilience and sustainability in CPS are not distinct but deeply interdependent, requiring unified approaches rooted in technological innovation, strategic policy, and interdisciplinary collaboration. The discussion highlighted a wide range of emerging threats such as data manipulation, supply chain attacks, and adversarial AI, affecting smart grids, buildings, and automated production systems. These threats not only compromise system functionality but also undermine sustainability by increasing energy consumption, material waste, and operational risk.

The study also examined global security standards, including NIST SP 800-82, ISO/IEC 27001, and IEC 62443, along with advanced technologies such as AI-based intrusion detection, blockchain, and quantum-resilient infrastructures. These tools, when integrated into CPS, support critical sustainability objectives like energy efficiency, emissions reduction, and resource optimization. Future CPS development must embrace secure-by-design principles, adaptive AI, and ethical frameworks. Integration with tools like LCA, BIM, and Digital Twins will be key in enabling secure, predictive, and sustainable infrastructure. In the end, cyber-physical security is a cornerstone for realizing a sustainable, intelligent, and resilient Industry 4.0.

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Artificial intelligence and sustainability: unlocking the potential of smart industrial transformation

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Highlights

- AI enhances energy efficiency, reduces emissions, and minimizes waste in smart manufacturing.
- It drives innovation and cost savings but requires policies to address job displacement and inequality.
- AI improves workplace safety and decision-making but raises concerns about bias, privacy, and social impact.
- Sustainable AI adoption needs energy-efficient systems, recycling programs, and ethical frameworks.

4.1 Introduction

Manufacturing activities place significant pressure on both the environment and society. They are responsible for approximately 25%–28% of human-induced greenhouse gas (GHG) emissions, contribute to 20% of global water pollution, and are the source of about 85% of plastic waste found in oceans (IRENA, 2022). Industry 4.0 offers considerable potential to advance sustainability across environmental, economic, and social dimensions. According to Stock and Seliger (2016), this potential can be realized through several key strategies. These include the creation of data-driven business models that integrate product-service systems,

fostering closed-loop lifecycles and industrial symbiosis. Industry 4.0 also enables decentralized, resource-efficient organizations and promotes sustainable process design using technologies like additive manufacturing, which support cradle-to-cradle and circular economy principles.

Artificial intelligence (AI) is rapidly transforming the industrial landscape, offering powerful tools to enhance operational efficiency, precision, and innovation. By simulating human intelligence through advanced algorithms, machine learning, and data analytics, AI systems can process vast amounts of information, detect patterns, and make informed decisions in real time. This capability allows industries to optimize processes, reduce waste, and improve overall productivity (Khan et al., 2025; Peres et al., 2020). The significance of AI extends beyond operational improvements. In the context of sustainability, AI catalyzes change by enabling smarter resource management, supporting cleaner production methods, and facilitating real-time environmental monitoring. It fosters innovation and new business models, driving competitiveness and growth. Furthermore, AI has the potential to improve workplace safety, support public health initiatives, and enhance citizen engagement. As industries embrace digital transformation under the framework of Industry 4.0, the role of AI becomes increasingly central to achieving sustainable development goals (SDGs). However, realizing its full potential requires thoughtful integration, ethical oversight, and investments in human capital (Jan et al., 2023). When aligned with sustainability principles, AI offers a transformative pathway toward building smarter, more resilient, and inclusive industrial systems for the future.

From an environmental perspective, AI plays a crucial role in reducing energy consumption, minimizing waste, and cutting GHG emissions (Ti Chui et al., 201). Intelligent control systems optimize resource allocation, predictive analytics improve maintenance schedules, and AI-powered sensors enhance environmental monitoring and pollution control (Uriarte-Gallastegi et al., 2024). Additionally, AI facilitates the development of sustainable materials and eco-friendly manufacturing techniques (Hardian et al., 2020). Despite these advantages, AI systems require significant computational power, leading to high energy consumption. Furthermore, frequent hardware upgrades contribute to electronic waste (e-waste), and concerns over AI-driven decision-making in environmental policies raise ethical questions. Addressing these issues requires the development of energy-efficient AI algorithms, responsible hardware recycling programs, and life cycle assessments to minimize AI's environmental footprint (Khan et al., 2025).

Economically, AI drives innovation, enhances productivity, and reduces operational costs. It enables better decision-making, improves supply chain management, and supports new business models. However, AI's economic benefits are not evenly distributed (Hardian et al., 2020). Job displacement due to automation poses risks to workers, and economic inequalities may widen if AI adoption primarily benefits large corporations while leaving smaller businesses and workers vulnerable. To mitigate these risks, policymakers must promote inclusive business models, invest in reskilling and upskilling programs, and implement regulations that ensure AI-driven economic growth benefits society as a whole.

Socially, AI has the potential to improve workplace safety by automating hazardous tasks, enhancing citizen engagement in environmental monitoring, and supporting decision-making in critical sectors such as healthcare and disaster management. However, ethical concerns such as algorithmic bias, privacy risks, and reduced human autonomy must be

addressed (Hagerty & Rubinov, 2019). AI systems can reinforce existing social biases, leading to discrimination in areas like hiring, lending, and law enforcement. Moreover, overreliance on AI can lead to social isolation and reduced critical thinking. Ensuring ethical AI development, designing human-centered workplaces, and fostering collaboration between technologists, policymakers, and society is crucial for maximizing AI's social benefits. Hence, it is of paramount importance to analyze AI's multidimensional impacts on sustainability covering all three of its dimensions: environment, economics, and social. Therefore this chapter identifies both opportunities and challenges while proposing strategies to ensure AI contributes to a responsible, equitable, and sustainable industrial transformation in the era of Industry 4.0.

4.2 Role of artificial intelligence in revolutionizing industrial sector

AI is at the forefront of a new era in industrial transformation. As industries worldwide confront the challenges of efficiency, sustainability, and resilience, AI offers powerful tools to address these issues through automation, data analytics, and real-time decision-making. The integration of AI across the industrial sector has moved beyond isolated applications to become a foundational element of the smart factory concept within Industry 4.0 (Lee et al., 2018). One of the most significant contributions of AI is its ability to enhance operational efficiency. Machine learning algorithms, when trained on historical and real-time production data, enable predictive analytics that optimizes manufacturing processes. These algorithms can dynamically adjust variables such as temperature, pressure, and feedstock rates to maximize output while minimizing energy consumption and raw material waste. The result is not only a boost in productivity but also a marked reduction in operational costs and environmental impact.

Real-time monitoring and adaptive control systems powered by AI allow manufacturers to respond swiftly to changes in production conditions (Arinez et al., 2020). For example, computer vision integrated with AI can identify defects on production lines, enabling instant corrections and reducing material waste. This shift from reactive to proactive operations significantly improves quality assurance and supports lean manufacturing goals. Predictive maintenance is another key area where AI has revolutionized industrial operations. Traditional maintenance strategies are either reactive or scheduled, both of which can result in unnecessary downtime or unexpected failures. AI changes this paradigm by analyzing sensor data from machinery to detect anomalies and predict potential failures before they occur (Chen & Das, 2023). This allows companies to plan maintenance activities more efficiently, avoid costly breakdowns, extend equipment lifespan, and reduce unplanned downtime.

AI-powered digital twins—virtual models of physical assets and systems—enable simulations and scenario planning that drive innovation. Engineers can use digital twins to test process modifications, design changes, or new production configurations in a risk-free virtual environment. This enhances decision-making, speeds up development timelines, and supports continuous process improvement without interrupting actual production. AI has also transformed supply chain management. Algorithms analyze market trends,

customer behavior, and supplier data to improve demand forecasting and inventory management (Helo & Hao, 2022). Furthermore, AI helps detect supply chain disruptions early, allowing companies to reconfigure logistics networks and maintain service levels. Additionally, AI supports end-to-end visibility in supply chains, promoting transparency and agility, which are crucial in an increasingly volatile global market.

The role of AI in sustainability is growing rapidly. By identifying patterns in energy use, emissions, and resource flows, AI facilitates responsible resource consumption. It supports circular economy models by analyzing waste streams and suggesting reuse and recycling strategies. For instance, plastic and organic waste recycling have proven to lower the environmental impacts (Saleem et al., 2024, 2025a, 2025b); however, the reductions strongly depend on the recycling of chemicals and water recirculation. AI can help optimize these processes to minimize the associated environmental impacts. Other examples include the process optimization of green steel production (Nurdiawati et al., 2025), additive manufacturing (Al Rashid et al., 2020), cooling requirements (Belaid et al., 2024; Tahir et al., 2024), low-carbon cement and concrete production (Tahir et al., 2024; Terán-Cuadrado et al., 2024), energy–water–food nexus (Shubbar et al., 2024), etc., where AI can greatly impact the resource allocation and energy conservation.

AI also accelerates the development of sustainable materials and cleaner production methods by analyzing complex datasets beyond the scope of traditional tools. However, its implementation in the industry brings several challenges. High energy consumption during model training and operation can undermine environmental gains if unmanaged (DeCost et al., 2020). Additionally, increased reliance on connectivity makes AI systems vulnerable to cyber threats, raising critical cybersecurity concerns. The integration of AI also transforms the workforce, shifting job demands toward new skills in areas like data analysis, AI system management, and cybersecurity. While some routine roles may be displaced, reskilling and upskilling programs can help workers transition into emerging roles. In addition, the use of autonomous AI in decision-making requires robust ethical and governance frameworks to ensure transparency, accountability, and fairness—especially in areas like production planning, quality control, and workforce management (Mäntymäki et al., 2022).

4.3 Environmental aspects

AI holds great promise for improving environmental sustainability within the industrial sector. By enabling intelligent control systems, AI can significantly reduce energy consumption and associated emissions through smarter and more adaptive process management (Ti Chui et al., 2018) (Fig. 4.1). It also strengthens environmental monitoring efforts, using advanced sensors and data-driven insights to detect and manage pollution more effectively (Ye et al., 2020). Moreover, AI facilitates better resource utilization and waste minimization by predicting needs and optimizing material flows (Challoumis, 2024). AI can assist employees in sorting waste more accurately and effortlessly by simplifying the often confusing process. With multiple bins, complex plastic types, and unclear labels, disposal can be stressful (Wilts et al., 2021). An AI-powered app that scans items and offers

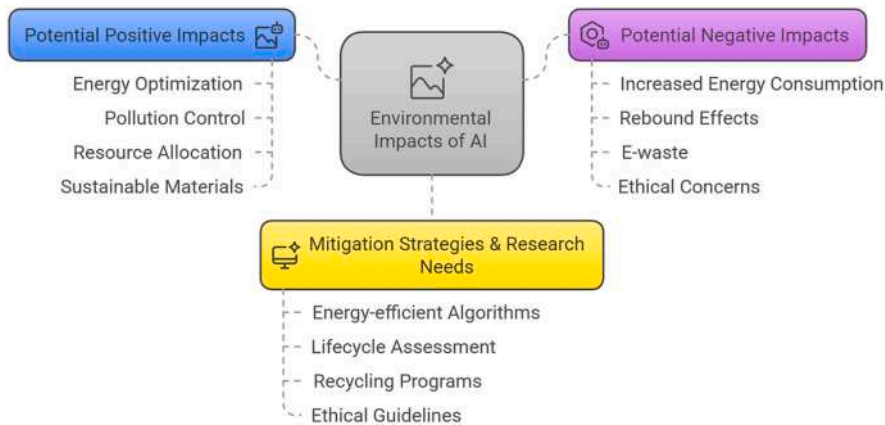


FIGURE 4.1 Environmental aspects of employing AI in the industrial sector. *AI*, Artificial intelligence.

real-time visual guidance—enhanced with gamified elements—can make sorting intuitive and engaging, improving waste management wherever sorting stations are present.

Though still emerging, generative AI can support businesses in advancing sustainability by enabling faster, more accurate data tracking and environmental, social, and governance reporting across regions, enhancing transparency and progress monitoring (Burnaev et al., 2023). Its role in supporting the discovery of eco-friendly materials and greener production methods further enhances its value in building a more sustainable industrial future (Lodhi et al., 2024). Furthermore, AI-powered inventory and logistics optimization helps minimize excess stock, streamline transportation, and strengthen coordination between factories and suppliers. This alignment boosts production efficiency, ensures timely deliveries, and ultimately reduces waste, supporting greater sustainability across the supply chain (Boute & Udenio, 2022).

However, the environmental benefits of AI must be carefully weighed against its drawbacks. The technology's reliance on large-scale data processing and high-performance computing can lead to increased energy use, potentially undermining the very efficiencies it aims to create (de V, 2023; Pimenow et al., 2024). Additionally, as AI systems evolve, the frequent need for hardware upgrades may contribute to the growing issue of electronic waste (Wang et al., 2024). Ethical concerns also emerge when AI is used in environmental decision-making, particularly regarding transparency, accountability, and fairness (Ahmad et al., 2021).

To fully realize the environmental benefits of AI while minimizing its unintended consequences, targeted mitigation strategies and focused research are essential. Developing energy-efficient algorithms and hardware can significantly reduce the carbon footprint of AI technologies, making their deployment more sustainable. Equally important is conducting comprehensive life cycle assessments to understand and address the environmental impacts associated with AI systems from production to disposal. Establishing robust recycling and reuse programs for outdated or obsolete AI hardware can help mitigate the growing challenge of e-waste (Chen et al., 2021). Moreover, the integration of clear ethical guidelines is vital to ensure that AI applications in environmental contexts are transparent, equitable,

and just. By embedding sustainability principles into the design, implementation, and governance of AI, the industrial sector can harness its full potential as a transformative tool for environmental stewardship.

4.4 Economic aspects

AI serves as a powerful catalyst for economic transformation in the industrial sector, with the potential to unlock substantial gains in innovation, efficiency, and competitiveness (Fig. 4.2). One of its most promising contributions lies in enabling data-driven insights that drive the development of innovative products, services, and business models (Ibarra et al., 2018). By analyzing vast datasets in real time, AI helps industries identify market trends, streamline operations, and explore new revenue streams. It enhances decision-making by offering predictive insights and intelligent recommendations, leading to faster, more informed choices that optimize productivity. Furthermore, AI is reshaping supply chain management through automation and real-time optimization, enabling industries to reduce operational costs, improve demand forecasting, and respond swiftly to market fluctuations.

Despite these promising benefits, the widespread integration of AI in the industrial economy brings challenges that must be addressed thoughtfully. A major concern is the potential for job displacement as automation replaces certain tasks, particularly those involving routine or manual labor (Cazzaniga et al., 2024; Hunter et al., 2023). This can lead to economic instability for workers whose roles become obsolete, especially in regions heavily dependent on traditional industries. Additionally, there is a growing risk that the economic advantages of AI may be unevenly distributed, benefiting large corporations and

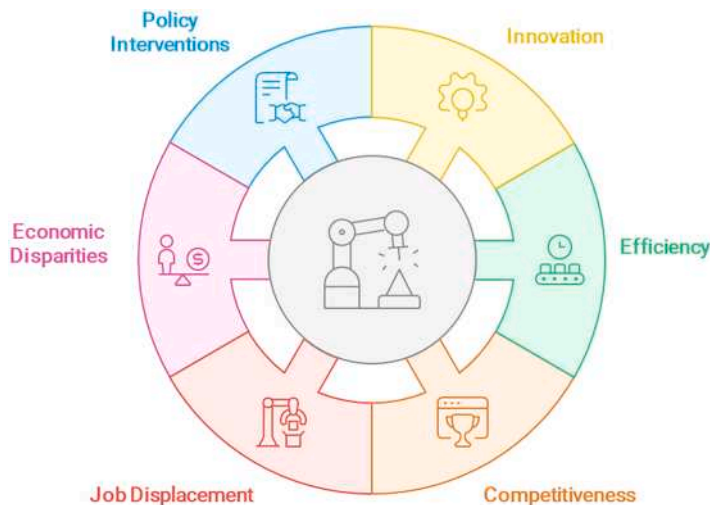


FIGURE 4.2 AI's impact on the industrial economy. AI, Artificial intelligence.

technologically advanced regions while leaving behind small enterprises and marginalized communities (Zhao et al., 2024). Such disparities can exacerbate existing economic inequalities and create long-term socioeconomic divides.

To mitigate these risks and ensure AI contributes to inclusive economic development, proactive policy and institutional interventions are necessary. Governments and industry leaders must develop forward-looking labor policies that anticipate shifts in the job market and support displaced workers through retraining, upskilling, and social protection measures. Investing in education systems that emphasize digital literacy and AI competencies will also help build a resilient workforce prepared for the evolving industrial landscape. Furthermore, fostering inclusive business models that prioritize shared value creation can ensure that the economic gains of AI are distributed more equitably (Lu & Zhou, 2021). These models should involve stakeholders at all levels—including workers, communities, and smaller enterprises—so that AI technologies serve broader societal interests rather than narrow profit motives. In summary, while AI holds immense promise for enhancing economic sustainability in the industrial sector, realizing this potential requires a balanced approach. By coupling technological innovation with inclusive policies and responsible governance, AI can become a powerful engine for equitable and sustainable economic transformation.

4.5 Social aspects

Across industries and communities, rapid technological advancement is reshaping how people live, work, and interact. Among these changes, the rise of intelligent systems is having a profound impact on the social fabric of society. When examined through the lens of social sustainability—especially within the industrial sector—these developments present a complex mix of opportunities and challenges that must be thoughtfully addressed (Fig. 4.3). On one hand, AI has immense potential to contribute positively to societal well-being. It can enhance citizen participation in environmental governance by enabling real-time monitoring through mobile applications and sensors, empowering individuals and communities to take part in local decision-making processes (Kar et al., 2022). In workplaces, AI-driven automation can help minimize exposure to hazardous environments by handling dangerous tasks, thus improving occupational health and safety standards. Moreover, AI is proving valuable in sectors such as healthcare and disaster management, where intelligent systems support faster diagnosis, personalized treatment, and timely responses to emergencies—ultimately saving lives and improving public health outcomes.

Despite these advantages, the unchecked or irresponsible deployment of AI may lead to serious social challenges. A pressing concern is algorithmic bias, where AI systems unintentionally reproduce or even exacerbate social inequalities (Menard & Bott, 2025). This has been observed in several real-world scenarios, such as recruitment tools unintentionally favoring certain demographic groups over others, thereby reinforcing existing biases (Dastin, 2022). In addition, as AI systems increasingly take over decision-making roles, there is a risk of diminishing human autonomy and critical thinking

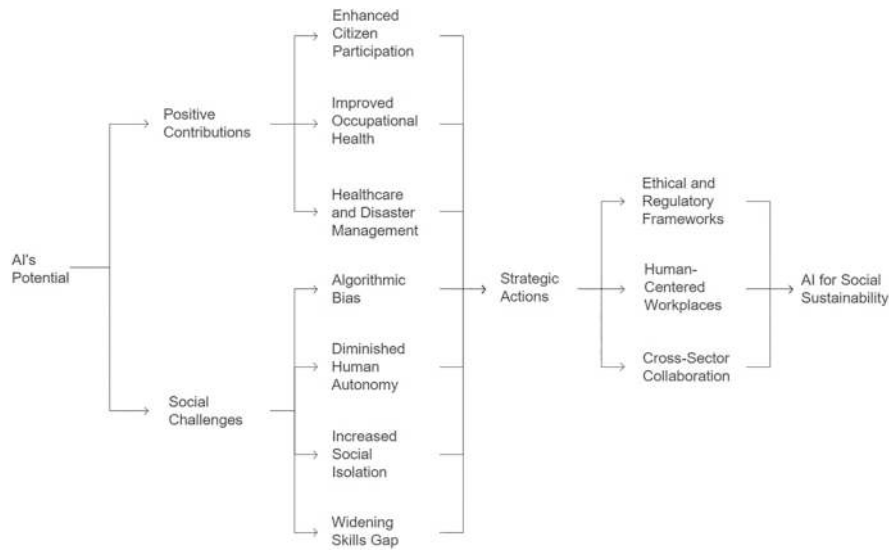


FIGURE 4.3 AI's impact on social sustainability. *AI*, Artificial intelligence.

(Ghosh et al., 2019). Overreliance on machine judgments may erode people's capacity to assess information independently, affecting democratic processes and social dynamics. Furthermore, the rise of AI-powered automation is changing the nature of human interaction within workplaces and society at large. As machines take on roles traditionally filled by humans, the potential for increased social isolation grows—especially in sectors where interpersonal relationships have been a key part of the work culture (Khakurel et al., 2018). At the same time, rapid technological changes are widening the skills gap, making it harder for certain segments of the workforce to keep pace. This can lead to job displacement and social inequality, particularly for low-skilled workers and marginalized communities, increasing the risk of societal unrest and exclusion (Cazzaniga et al., 2024; Hunter et al., 2023).

To ensure that AI contributes to social sustainability rather than undermining it, several strategic actions are necessary. Implementing robust ethical and regulatory frameworks is essential to guide the design and deployment of AI systems in ways that respect human rights, equity, and diversity. These frameworks should prioritize transparency, accountability, and fairness to prevent harmful biases and discrimination (Yadav et al., 2020). Additionally, workplaces must be reimagined with a human-centered approach, where AI complements rather than replaces human capabilities. Cross-sector collaboration among technologists, policymakers, educators, and civil society is also crucial to address broader societal impacts, build trust in AI systems, and foster inclusive participation in shaping their development. In sum, while AI holds transformative potential to improve social conditions, this promise can only be realized through deliberate, ethical, and inclusive governance. Balancing technological advancement with human values will be key to ensuring that AI strengthens, rather than fractures, the social foundations of sustainable development.

4.6 Discussion

The convergence of AI and sustainability in the industrial sector marks a critical turning point in our pursuit of a more resilient, equitable, and low-carbon future. As industries globally undergo digital transformation under the umbrella of Industry 4.0, the integration of AI technologies offers a unique opportunity to accelerate progress across the three pillars of sustainability: environmental, economic, and social. AI holds significant promise in mitigating the impacts of industrial operations. Intelligent control systems can optimize energy consumption, reduce emissions, monitor pollution in real time, and minimize resource waste. Additionally, AI contributes to the development of sustainable materials and cleaner production methods. However, these benefits must be weighed against the environmental drawbacks, including the high computational energy demands of AI systems, electronic waste from frequent hardware upgrades, and ethical concerns surrounding the deployment of AI in environmentally sensitive contexts. Therefore a balanced approach is required—one that includes the adoption of energy-efficient AI algorithms, application of circular economy principles to hardware design, and integration of life cycle thinking in AI development. A truly sustainable AI ecosystem must not only advance environmental goals but also minimize its ecological footprint.

AI facilitates smarter decision-making, fosters innovation, and creates new business models by leveraging the power of large-scale data analytics. It enhances productivity, optimizes supply chains, and lowers production costs—contributing to industrial competitiveness and broader economic growth. However, automation-driven disruptions pose serious risks, such as job displacement and widening income inequality. If left unaddressed, these challenges could lead to greater economic disparity. To mitigate these effects, it is crucial to implement inclusive and adaptive economic policies, invest in workforce reskilling, and develop AI-driven business models that distribute benefits equitably across stakeholders, especially workers and local communities.

From the social aspect, AI can enhance workplace safety by automating hazardous tasks, enabling citizen engagement in environmental monitoring, and improving decision-making in public health and disaster response. These applications have the potential to significantly elevate social well-being. Yet, the misuse or irresponsible design of AI systems introduces risks: algorithmic bias, social isolation, overreliance on automation, and threats to individual autonomy and privacy. These concerns must be addressed through strong ethical frameworks, regulatory protections, and inclusive governance mechanisms. Ensuring that AI systems are transparent, accountable, and human-centered is essential to fostering trust and maintaining societal cohesion.

To fully harness the transformative potential of AI in the industrial sector, a strategic and balanced approach is required. This involves not only investing in advanced technologies but also fostering collaboration between AI developers, industrial engineers, policymakers, and social scientists. Regulations should ensure the responsible development and use of AI, while incentives can encourage the adoption of energy-efficient and ethically aligned technologies. AI is a cornerstone of modern industrial evolution. It enables industries to become smarter, more efficient, and more sustainable. By leveraging AI for real-time optimization, predictive maintenance, supply chain resilience, and sustainable innovation, the industrial sector can achieve significant advancements. However, to truly revolutionize the industry, AI must be deployed responsibly, with attention to its environmental footprint,

social implications, and governance requirements. When balanced with thoughtful policy and human-centered design, AI will not only revolutionize industrial systems but also drive the global agenda for sustainable development and economic prosperity.

4.7 Concluding remarks

In essence, the responsible integration of AI into industrial systems offers a powerful tool to advance sustainability goals—if implemented thoughtfully and inclusively. To fully realize AI's transformative potential, development and deployment must be guided by interdisciplinary collaboration and a long-term vision that centers on sustainability. This requires rethinking innovation not simply as a means to maximize efficiency or profit, but as a collective endeavor aimed at securing a just, inclusive, and sustainable future. AI represents not only a technological revolution but also a sustainability opportunity. The industrial sector—one of the largest contributors to economic prosperity and environmental impact—stands at the forefront of this transformation. By embedding sustainability principles into AI system design, deployment, and governance, it will ensure that innovation serves people, communities, and the planet. To achieve this, several key takeaways should inform future strategies:

- AI can drive substantial gains in energy efficiency, emissions reduction, and environmental monitoring, but its environmental footprint must be actively managed through sustainable design and life cycle assessments.
- Economic transformation through AI must be inclusive and supported by policies that encourage skills development, workforce transition, and fair value distribution.
- The social impacts of AI demand attention to ethical governance, data privacy, human autonomy, and the mitigation of bias and discrimination.
- A sustainable AI future relies on interdisciplinary collaboration across sectors, strong institutional frameworks, and a shared commitment to the United Nations SDGs.

Looking ahead, more research is needed to assess the full life cycle impacts of AI technologies, particularly as they become deeply embedded within complex industrial ecosystems. Building cross-sectoral coalitions can help set global standards, share best practices, and align innovation with global sustainability objectives. Ultimately, aligning AI development with sustainability values offers a rare and powerful opportunity: to shape a future where technological advancement supports environmental stewardship, inclusive economic development, and social well-being in equal measure.

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Additive Manufacturing (AM): the future of sustainable manufacturing

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5.1 Introduction to additive manufacturing

Additive manufacturing (AM) technologies are the contemporary manufacturing technologies that produce parts using a highly flexible digital process using additive technique, that is, adding the material where it is required, in a sequential layer-by-layer manner. AM is one of the core pillars and only manufacturing technology of Industry 4.0 (Elnagar et al., 2024; Leong et al., no date). The major advantage of AM technologies over conventional manufacturing technologies is its flexibility of being tool-less manufacturing, independent of the complexity of the design, and less material wastage (Javaid et al., 2021). The process is independent of the design's complexity, meaning that concerns about the design introducing major issues with selecting processes and tools are minimal.

The AM process is shown in Fig. 5.1. The process starts with Computer-Aided Design (CAD) model development (part or assembly) using any of the available software followed by the translation into AM file (AMF) file format (ISO/ASTM 52915:2020 - Specification for additive manufacturing file format (AMF), 2025), which is more advanced than the previous Standard Tessellation Language (STL) file format. AMF format has a greater level of detail as compared to the STL file, and it is expected to be adopted by the AM industry as it grows in the years to follow. This file is sent to the machine where the material is loaded, and the

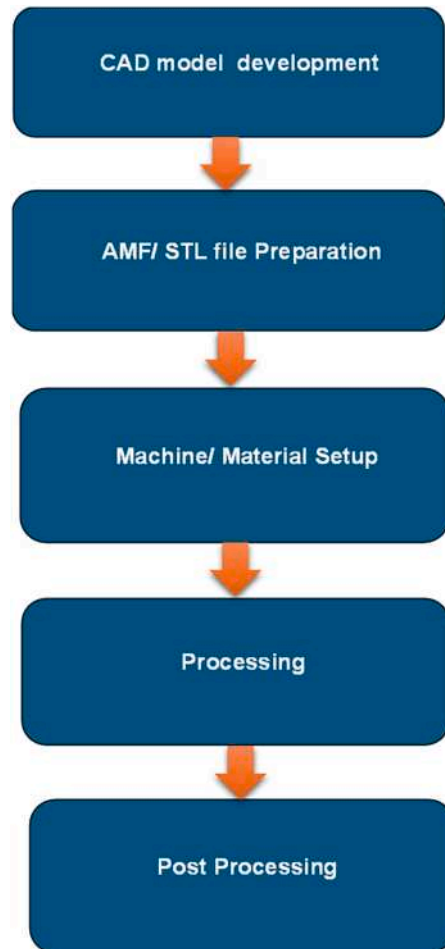


FIGURE 5.1 General processing steps for additive manufacturing processes. *AMF*, AM file; *CAD*, Computer-Aided Design; *STL*, Standard Tessellation Language.

machine is calibrated for processing. After the required input from the user related to the processing parameters (orientation and layer quality, etc.), the processing is started. Once the model is manufactured, it is followed by the required postprocessing steps (cleaning, cutting, grinding, finishing, painting, etc.).

AM technologies are capable of processing various materials using various energy sources, for applications ranging from automotive to aerospace and biomedical, etc. According to Wohler's associates, the AM industry grew by 11.1% to 20.035 billion USD in 2023, whereas metal AM grew by 24.4% ([Wohlers Report 2024 - Just Released! Latest 3D Printing Trends, 2025](#)). This analysis is based on the data received from hundreds of companies worldwide. The future growth of AM is associated with several factors, which are highlighted in [Section 5.4](#), later in this chapter.

The American Society for Testing and Materials (ASTM) has placed all the AM processes in seven basic categories for Standardization ([Additive manufacturing - General principles - Fundamentals & vocabulary, 2025](#)). These processes are as follows: Binder Jetting, Direct Energy Deposition (DED), Material Extrusion, Material Jetting, powder bed fusion (PBF), Sheet Lamination, and Vat Photopolymerization. This categorization can be considered the nonhybrid categorization of the AM processes, where hybrid processes such as additive–subtractive processes ([Dai et al., 2025](#); [Qian et al., 2024](#); [Wang et al., 2025](#)) or additive–additive processes ([Kumaran & Ravi, 2024](#)) are not considered. An elaborate categorization based on the type of process, type of materials used, material deposition/feed mechanism, and type of energy is detailed in [Fig. 5.2](#). For example, the metal PBF Process utilizes “melting of material” as the process, “metals/alloys or polymers, etc.” as the material, uses “powder bed” for material deposition mechanisms, and utilizes a “laser energy” source for processing of the material.

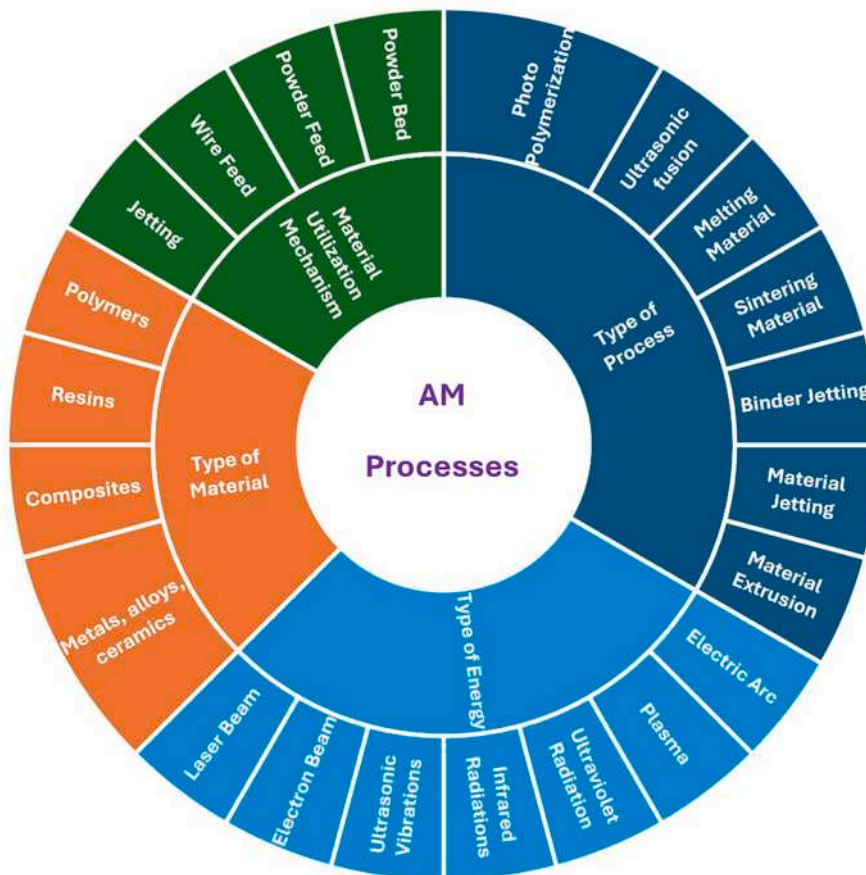


FIGURE 5.2 Process categorization based on types of process, type of material, material utilization mechanism, and energy utilized. AM, Additive manufacturing.

5.2 Sustainability in additive manufacturing

AM and subtractive manufacturing (SM) differ from each other in the ways the parts are manufactured, that is, AM uses the addition of material as per requirement, while the SM removes material from the material stock to give it the required shape. The core sustainability elements for SM processes include energy consumption, cost, waste material management, resource utilization, environmental impact, design for reuse and remanufacturing, and health and safety (Bonilla Hernandez et al., 2019; Mohammad & Ibrahim, 2017).

To compare sustainability in AM and SM, let's first consider the example of a part being manufactured by an SM process like machining (milling operation). In SM, several factors must be considered, such as part features (pocket, holes, etc.), selection of cutting tools based on the features (can be more than one tool for each feature depending on the feature size), part setup, sequencing of operation, and finishing. Here, the complexity of the design is constrained by the manufacturing technology, where simple geometries and features can be manufactured by 3-axis milling machine; however, higher axis or degree of freedom systems may be required for complex geometries and features. Therefore the hardware (machine tool) limits the design that can be manufactured on the system, which compromises the overall flexibility and design freedom. However, if the same part is to be manufactured through an AM process like the selective laser melting (SLM) process, the focus is on the design like design optimization for minimum material and energy utilization, build orientation of the part (the correct orientation will save material and time), etc. The SLM machine can produce any design, without any concern for the design complexity, as there is no tool selection, sequencing of operation, part setup, etc. Therefore the design can be complex, and it is tailored to the functionality of the product without the worry of manufacturing intricacies. The design of the part is the initial step in the product development, and to enhance product sustainability, efforts should begin at the design phase. However, if the design is constrained by the manufacturing process, as in the case of SM, then the initiative toward true sustainability is lost. Based on the above discussion, it can be argued that sustainability in SM processes is primarily driven by the process, rather than by the design. Consequently, if the design is inherently not sustainable (e.g., in terms of minimizing material usage), then true sustainability cannot be achieved.

Therefore the journey toward sustainability in AM processes starts from the design phase, and it is much more design-driven rather than process-driven. Once the optimum design is selected (through topology optimization, generative design, lattice structures, biomimetic designs, etc.), then the other process factors are considered such as quantity of raw material, energy utilization, wastage, and health and safety considerations. It must be highlighted that the material utilization and wastage in the AM processes are much lower than in conventional manufacturing processes due to the adoption of new design techniques (Chouhan & Gunji, 2023; Li et al., 2024). Contemporary design techniques/approaches have introduced a new dimension into the design for sustainable additive manufacturing (DfSAM), which is discussed in detail in Section 5.2.1.

Fig. 5.3 shows the six elements of the AM sustainability ecosystem, that is, DfSAM, material, process, human factor, life cycle (LC) and end-of-life (EoL) assessment and circular economy. All these elements are strongly interconnected and interdependent for the overall sustainability of the AM processes. At the design stage, for the parts produced through AM

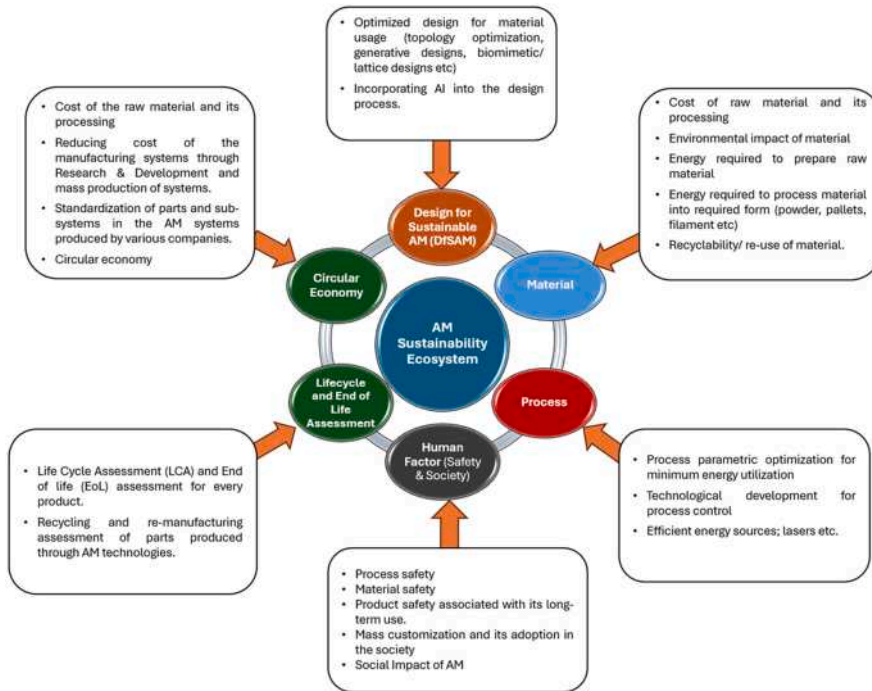


FIGURE 5.3 The AM sustainability ecosystem. AI, Artificial intelligence; AM, additive manufacturing; DfSAM, design for sustainable additive manufacturing.

technologies, all aspects of the material, process, economics, environmental impact (through material impact, Life Cycle Assessment (LCA), and EoL assessment), health and safety, and society must be considered. This comprehensive approach at the design stage is crucial to attaining a truly sustainable design for AM. Considering only one factor at a time, which is the focus of research these days, does not capture the essence of sustainability for AM. It can be reasoned that the advantage gained through design freedom, less material utilization, and low material waste in AM is lost due to this discrete approach toward sustainability.

Analyzing all these elements at the design stage and performing analysis to optimize every element of sustainability is very difficult without an artificial intelligence (AI) driven model. In this regard, a comprehensive AI model for AM, which integrates all the above factors, is a need of the hour and is the future of true sustainability through AM.

The environmental impact is one of the core aspects of the sustainability of any manufacturing process, whether conventional or nonconventional. The environmental impact should be assessed at every stage, and it is embedded into every element of the AM sustainability ecosystem. During the design stage, choosing an optimized design, whether through topology optimization, generative design, or biomimetic design approaches, minimizes the material usage, thereby reducing the environmental impact. Similarly, during the material selection stage, material with minimum environmental impact or environmentally friendly material must be selected. At the process stage, the selection of

the energy-efficient AM process, optimum process parameters, and low carbon footprint of the process will result in a low impact on the environment. Similarly, when the human factor is under consideration, health and safety are associated with material hazards, and any environmental hazards arising due to processing. In the EoL and LC assessment of the product, the environmental impact is also an important factor. Therefore when we assess the sustainability of AM, the environmental impact will always be at the core of the discussion and decisions taken for product development.

5.2.1 Design for sustainable additive manufacturing

Manufacturing sustainability has emerged as a fundamental issue because it combines both environmental impact reduction and production efficiency improvements. The manufacturing industry must adopt sustainable practices, now that operational activities continue expanding and customers demand environmentally responsible production methods. The design phase sets the foundation for sustainability in AM as detailed before. When designers make poor choices, they create systems that produce excessive waste together with energy inefficiency and unrecyclable final products. The application of sustainable design principles results in structure optimization that reduces resource demand while maintaining maximum functionality and extended durability.

Although AM processes produce near-net-shape parts, reducing scrap and material and energy consumption and lowering carbon emissions ([Thompson et al., 2016](#)), there are still challenges. For example, high energy consumption in the production of raw materials (such as metal powders and wires), especially in PBF processes, and reliance on virgin materials are still a hurdle to sustainability ([Gibson et al., 2015](#)).

DfSAM is the process of designing the product for AM capabilities and is based on sustainable design principles that optimize material use and enable creative structural configurations. The application of these structures in AM results in both structural integrity and significant weight reduction, thus making it more sustainable. Research activities have been undertaken in the design and assessment of various lattice structures for the improvement of mechanical properties and manufacturability. The lattice structures provide high-strength-to-weight ratios, which make them suitable for lightweight applications resulting in both structural integrity and significant weight reduction for the material. [Pham et al. \(2019\)](#) studied damage-resistant architected materials that mimic crystal microstructures and presented enhanced mechanical properties and potential usage for lightweight structures. Recently, [Armanfar et al. \(2024\)](#) proposed a novel approach to embedding lattice structures into the shipbuilding process through AM. The developed lattice structure-supported ship models outperformed conventional support elements in their application.

Biomimetic designing is the practice of using natural designs to develop more sustainable and efficient products and systems. Biomimetic designs use natural examples to create structures that are both strong and lightweight. [Gu et al. \(2020\)](#) studied the mechanical properties of spider silk bionic materials for potential AM applications to create strong and lightweight components. [Islam et al. \(2021\)](#) researched biomimetic armor design methods for AM, showing how natural design patterns create protective structures with reduced material requirements and improved performance. [Leary et al. \(2014\)](#) presented a

methodology that used topology optimization to enable the AM of support-free optimal structures, as well as addressed issues concerning support material consumption and build orientation. The method helps achieve sustainability through both reduced material usage and decreased need for additional manufacturing steps. [Barbieri and Muzzupappa \(2022\)](#) performed a comparative analysis between performance-driven engineering design methods that used generative design and topology optimization tools to develop efficient sustainable designs for AM. Generative design employs AI to search through an extensive design area and produce various design options that fulfill specified requirements and limitations. The application of AI generative design at the design stage results in innovative structures, which provide both high performance and minimal material requirements. [Wang et al. \(2021\)](#) presented a constructive solid geometry-based generative design method for AM that incorporated manufacturing constraints to verify the manufacturability of designed models. The method improves sustainability through the generation of structures that need reduced materials and are compatible with AM process requirements. Recent progress in deep learning technology enabled a better understanding and representation of heterogeneous hierarchical bioinspired structures using generative deep learning to develop spider web-inspired structures that could be used for lightweight and strong components ([Lu et al., 2023](#)).

Triply periodic minimal surface (TPMS) structures can improve process sustainability by optimizing material distribution without compromising strength and improving certain characteristics such as energy characters. Inspired by natural geometries, TPMS enables superior load distribution, high-strength-to-weight ratios, and enhanced mechanical performance. Studies have shown that TPMS lattices can reduce material consumption by up to 50%, while improving elastic modulus (18.9%–42.2%), yield strength (19.2%–29.5%), and compressive strength (2%–36.6%) compared to conventional designs ([Li et al., 2024](#)). Shell and lattice infill approach was used to reduce weight by over 50% without sacrificing structural integrity, making TPMS ideal for aerospace, automotive, and biomedical applications ([Ngo et al., 2018](#)). Other than saving material for sustainability, TPMS also improves energy efficiency. Due to its periodic structure and uniform stress distribution, TPMS components can be as porous as 86%, which requires at least 50% less energy during printing than fully dense parts. This is particularly useful in energy-intensive metal AM processes like laser powder bed fusion (LPBF) and electron beam melting (EBM). Other than its manufacturing, TPMS can improve sustainability during its lifetime by improving device efficiency and lowering environmental impact. For example, TPMS enhances heat dissipation and fluid flow, making it valuable for heat exchangers, where a 60% increase in heat transfer efficiency has been demonstrated compared to traditional metal foams ([Broughton & Joshi, 2020](#)). The lower manufacturing energy, materials usage, and higher process efficiency make TPMS ideal for making AM sustainable ([Broughton & Joshi, 2020](#)).

Since TPMS can produce parts with much lower weight, it is used in industries such as aerospace and automotive; TPMS-based lightweight components contribute to fuel efficiency, reducing fuel consumption by up to 10%, which directly lowers carbon emissions ([Ngo et al., 2018](#)). In biomedical applications, TPMS lattices mimic natural bone structures, enhancing osseointegration and reducing the need for secondary surgeries, thus minimizing medical waste ([Li et al., 2024](#)). The interconnected porous geometry also improves impact resistance, extending component lifespan and reducing replacement needs. Therefore TPMS

structures could be produced at much lower energy and material consumption, while offering enhanced functional performance. Also, with advancement and research on TPMS designs and with a better understanding of their behavior for AM parts and different materials, AM is expected to further enhance the efficiency of the designs as well as become more sustainable. Optimum design not only contributes toward the efficiency of the product/system that it is designed for but also reduces environmental effects during service (lifecycles) and at EoL.

5.2.2 Material sustainability

The most commonly used polymers are polylactic acid (PLA) and acrylonitrile butadiene styrene (ABS) because they are both easy to work with and inexpensive (Lu et al., 2023). Titanium and aluminum alloys show high-strength-to-weight properties that explain their use in the aerospace and automotive sectors (Colorado et al., 2020). Ceramics and composites exhibit excellent thermal stability and mechanical strength making them suitable for specific applications (Lakhdar et al., 2021). The selection of sustainable materials implies the consideration of the environmental, economic, and social aspects. The environmental effects are throughout the lifecycle and EoL of the material, which includes the use of resources, the use of energy in the manufacturing process, and the ultimate disposal (Hegab et al., 2023). Renewable resource-based materials or biodegradable materials like PLA are used frequently due to their better sustainability properties (Tripathi et al., 2021). Economic factors involve assessing material availability, cost, and the feasibility of recycling or reusing materials to minimize waste (Cruz Sanchez et al., 2020). The social factors include the health and safety risks to the workers, consumers, and the environment, so that the materials do not cause any harm during processing and use. Most recently, the Örebro University (Sweden) launched a research project Synergi22 NanoSafety2, which aims to analyze the presence of nanoparticles in AM process and their health and safety assessment (Alijagic et al., 2024; What are the health & safety concerns in additive manufacturing, 2025). Such research efforts highlight the importance of unexplored hazards associated with AM processing of different materials. Therefore sustainable AM practices require a holistic approach to material selection criteria to integrate health and environmental concerns during processing and the use of the products.

AM has major benefits; however, it has certain disadvantages in terms of material reuse and energy efficiency. The reuse of metal powders particularly titanium and nickel alloys is very important for both the economic and environmental points of view. Nevertheless, the same material used several times can reduce the performance of the part, and therefore it is necessary to carry out a strict testing procedure (Jung et al., 2023). Powder contamination and oxidation are the other factors that make the recycling process more difficult and less efficient (Lanzutti & Marin, 2024).

The high energy requirement for the manufacture of metal powders further increases the overall environmental impact of AM. According to Jung et al. (2023), AM can be less energy efficient than traditional processes in high-volume production, only if the process parameters are not optimized. The situation can only be improved by the development of more efficient powder recycling methods, as well as the development of standard protocols for powder reuse and optimization of AM processes for energy efficiency. Other steps that

can also be taken to enhance the sustainability of AM comprise the use of renewable energy sources and enhancing machine operations (May & Psarommatis, 2023).

Although AM offers some environmental advantages such as material advancement and local production, the environmental impact of AM materials is not the same. The use of AM is also associated with a reduced amount of material waste as compared to other manufacturing processes such as subtractive manufacturing. The lifecycle assessments have shown that AM can help in the reduction of carbon dioxide emissions, and the capacity to create lightweight components leads to energy conservation (Huang et al., 2016).

5.2.3 Process sustainability

Sustainability in manufacturing is now a concern as industries strive to reduce their effects on the environment, without compromising on the production rates and costs. Sustainability of the AM process also implies optimization of the manufacturing parameters, the reduction of the quantity of material wasted, the increase of the recyclability of the material, and the integration of environmentally friendly postprocessing techniques. As AM technologies are still developing, sustainability can only be achieved by considering process factors such as powder reuse, in situ monitoring, and postprocessing techniques. Recent studies are aimed at improving the environmental performance of AM processes without compromising on productivity. An approach that has been adopted toward enhancing the sustainability of the AM processes is the optimization of the processing parameters. The efficiency of the AM processes is a function of parameters like laser power, scan speed, layer thickness, and cooling rate, which affect the energy consumption, material use, and the environmental impact of the process in general. Recent studies have indicated that it is possible to optimize these parameters to achieve faster build times, reduced energy consumption, and fewer defects, all of which lead to sustainability (Gharghabi et al., 2011; Khalid & Peng, 2021; Obeidi et al., 2024). Machine learning (ML) and AI are starting to be used for the prediction and real-time control of AM process parameters to reduce the number of experiments and the consequent material waste (Charles et al., 2021; Mondal & Shubhra Goswami, 2024; Qin et al., 2020).

Also, the use of hybrid manufacturing systems that integrate AM with subtractive or other conventional manufacturing processes has been found to reduce overall energy consumption. Hybrid processes are characterized by the capacity to build components closely to their final shape and size, hence reducing or eliminating the need for postprocessing (Grguraš & Kramar, 2017; Wüst et al., 2020).

Postprocessing in AM includes part cleaning, surface finishing, and heat treatment. Postprocessing is necessary to achieve the required quality of the metal parts produced by AM. The methods presented here tackle problems such as poor surface finish, unfavorable microstructure, and low mechanical properties (Khan et al., 2020; Mahmood et al., 2022). Different approaches, including laser shock peening, laser polishing, conventional machining, and thermal treatments, have been reported to enhance the surface properties and performance of the AM metal components (Mahmood et al., 2022). Other methods like sandblasting in Multi Jet Fusion processes have also been evaluated for sustainability (Mele et al., 2020). One interesting application is the use of ultrasonic cleaning systems for metal AM parts (Tan et al., 2022). These systems use less energy and require fewer chemical

solvents, which are bad for the environment. Bioinspired designs, including tree-like and fractal topologies, are green alternatives to conventional support structures, which may enhance mechanical functions and material usage (Díaz Lantada et al., 2017).

5.2.4 Human factor (safety and society)

AM is changing the societal mindset toward decentralized production, creating new jobs, and enhancing the economic and community development of society. With the new material and applications of AM, the possibility of mass adaption is not far-fetched, and there have recently been many start-ups and home-based enthusiasts that are working on the application of AM. In recent times, AM has proven its usefulness in healthcare through personalized prosthetics, medical devices, and bioprinting, and sustainability by reducing waste and carbon footprint. The AM education provides hands-on Science, Technology, Engineering and Mathematics (STEM) education and skill development.

At the same time, it must be realized that there are significant societal impacts and health and safety implications of AM. Despite the benefits of AM in product customization and local manufacturing (Naghshineh et al., 2021), there are concerns about environmental sustainability and occupational safety. Matos et al. (2019) have identified both positive and negative health and safety impacts and while physical hazards are generally reduced, risks from hazardous substances may be increased. In terms of environment, energy consumption is higher than conventional manufacturing, but AM is more beneficial for small batches or redesigns that enhance product efficiency (Kellens, Baumer, et al., 2017a). The social impacts of technology are also active in areas like working conditions, economic prosperity, and innovative employment types (Matos et al., 2019). Nevertheless, comprehensive lifecycle assessments and quantitative data on AM's environmental performance are limited (Buranská et al., 2019; Kellens, Baumer, et al., 2017a).

Research has consistently shown that fused filament fabrication (FFF) 3D printers emit ultrafine particles (UFPs) and volatile organic compounds (VOCs) during operation (Byrley et al., 2020). Particle emission rates vary significantly depending on filament material, with some materials producing up to 1013 UFPs per minute (Seeger et al., 2018). Common VOCs emitted include styrene, caprolactam, and lactide, with emission rates varying by filament type (Azimi et al., 2016). Notably, filament extruders used to create 3D printer feedstock also emit UFPs and VOCs at levels comparable to 3D printers (Byrley et al., 2020). These emissions raise concerns about potential health risks, especially in poorly ventilated spaces.

Inhalation of very fine metal particles, including nanoparticles, during metal AM, poses a health concern. These particles may contain hazardous metals like chromium, cobalt, and nickel (Dugheri et al., 2022). The handling and disposal of metal powders also present challenges (Arrizubieta et al., 2020). Additionally, there are potential fire and dust explosion hazards associated with these processes. Despite AM being considered environmentally friendly compared to conventional manufacturing, a comprehensive assessment of its environmental impact should include resource use, pollution, and effects on human health and society (Arrizubieta et al., 2020). Researchers suggest implementing protective measures such as filtration systems and proper ventilation to mitigate exposure risks (Gu et al., 2019).

5.2.5 Lifecycle and end-of-life assessment

The sustainability assessment of AM has been the focus of research for some years. It is of utmost importance that the environmental implications of a product's lifecycle are analyzed at the design stage, with accurate data and analysis. Most of the published research in this regard is based on the framework of Life Cycle Assessment (LCA) and standard ISO 14040 (2006) ([ISO 14040:2006 - Environmental management—Life cycle assessment—Principles & framework, 2025](#)). While LCA covers the lifecycle assessment, life cycle costing (LCC) provides the economic assessment of the process and product ([Pusateri & Olsen, 2024](#)). [Pusateri and Olsen \(2024\)](#) performed the cradle-to-grave LCA for part manufactured through multimaterial wire Arc AM (WAAM) and conventional manufacturing processes. It was concluded that the multimaterial WAAM process has significant advantages over conventional manufacturing, including reduced repairs, reduced material usage, and reduced electricity consumption. Similarly, [Kokare et al. \(2023\)](#) performed the LCA and LCC analysis for the environmental and economic impact of marine propeller manufactured through Computer Numeric Control (CNC) milling along with WAAM and SLM processes. Based on the analysis, WAAM was found to be the most environmentally friendly and cost-effective. Only the environmental impact of WAAM was 2.5 and 3.4 times lower than the CNC milling and SLM processes, primarily associated with the material utilization and energy efficiency of the process.

AM enhances sustainability by minimizing material waste and enabling on-demand production, reducing the need for large inventories and associated resource depletion. In PBF processes, particularly with metals, only a small fraction of the powder is melted and fused into the final part, while the remaining powder is sieved and reused. This significantly improves material efficiency, making the process both economical and environmentally sustainable ([Moghimian et al., 2021](#)).

Recycling AM metal powders provides substantial environmental and economic benefits, including energy and cost savings. [Carrion et al. \(2019\)](#) analyzed that powder recycling has negligible effects on material properties. The microstructure remains stable, with no noticeable changes in grain size or morphology, and the tensile and fatigue performance of Ti-6Al-4V specimens remains unaffected in the as-built surface condition. This confirms the viability of reusing AM powders multiple times before degradation impacts their usability ([Carrion et al., 2019](#)). Efficient recycling and reuse strategies are essential for enhancing AM process sustainability. By optimizing powder handling, refining sieving techniques, and ensuring strict quality control, manufacturers can maximize the lifecycle of AM materials while maintaining performance standards. These practices support resource conservation and reduce environmental impact, reinforcing AM's role in sustainable manufacturing.

Among AM processes, polymers are widely used, with fused deposition modeling (FDM) being a common material extrusion technique. As FDM production grows, effective recycling and reuse strategies are essential for sustainability. FDM relies on thermoplastic polymers, extruded into filaments as feedstock. Common materials include ABS, polypropylene (PP), polylactide (PLA), polyether ether ketone, and polyamide. PLA is particularly popular due to its low printing temperature (190°C–230°C) and its ability to print without a heated bed ([Shanmugam et al., 2020](#)). Integrating polymer recycling into AM

can minimize waste and support a circular economy (CE). By adopting sustainable material management, manufacturers can reduce environmental impact while maintaining material performance and economic viability. Research confirms the feasibility of polymer recycling in AM. Studies on recycled polymers show minor variations in properties but no major deterioration. For example, PLA exhibited a 10% reduction in elongation at break after five recycling cycles (Mohammed et al., 2017). Other research studies have reported similar results as well (Shanmugam et al., 2020).

Although many materials used in AM are recyclable, hazardous substances can limit the EoL recycling potential. Current recycling rates for AM materials remain significantly lower than what is theoretically achievable. Chea et al. (2024) conducted an extensive study with an estimated annual EoL material rate of 104,400 kg (with an average of 1.04 million kg) based on an estimated 870,000 annual AM operational units in the United States. It was concluded that recycling, incineration, and landfilling account for 9%, 58%, and 33% of AM EoL materials by weight, respectively. These figures highlight inefficiencies in existing waste management infrastructure, as a substantial proportion of recyclable materials, including polymers, metals, and glass, still end up in landfills. Improving material recovery processes and implementing better sorting mechanisms could significantly enhance recycling rates and minimize environmental impact. Further enhancing the study, Chea et al. (2024) also analyzed the theoretical occupational hazards associated with AM. In this study, hand-based exposure was considered the primary source of exposure, though other exposures such as facial and ocular dermal cannot be ruled out and need further analysis/review. In exposures related to EoL material management, primary sources may be volatile resins, plastics, heavy metals, incinerator ashes, leachates, etc. Therefore appropriate personal protective equipment during the processing or EoL material management is essential for responsible and sustainable AM, safeguarding the well-being of the people involved at all levels (Chea et al., 2025).

5.2.6 Circular economy

The CE is a transformative approach to manufacturing that aims to decouple economic growth from resource consumption by promoting the continuous use of materials, reducing waste, and minimizing environmental impact. AM is uniquely positioned to advance CE principles due to its inherent characteristics, such as material efficiency, waste reduction, design flexibility, and localized production (Kravchenko et al., 2020; Sauerwein et al., 2019). Unlike the traditional linear economy, which follows a “take-make-dispose” model, which results in excessive resource consumption and environmental degradation, the CE seeks to create a regenerative system by emphasizing reuse, repair, remanufacturing, and recycling. Furthermore, AM supports the development of sustainable supply chains by incorporating recycled materials and bio-based polymers, which contribute to the circularity of industrial ecosystems (Voet et al., 2018). The relationship between AM and CE is multifaceted, offering numerous benefits while also facing key challenges that must be addressed for widespread adoption. As illustrated in Fig. 5.4, AM contributes to CE through multiple avenues, aligning with the six ReSOLVE principles (Regenerate, Share, Optimize, Loop, Virtualize, Exchange) by facilitating waste reduction, remanufacturing, recycling, and supply chain optimization. However, barriers such as high material costs, slow production speeds, and

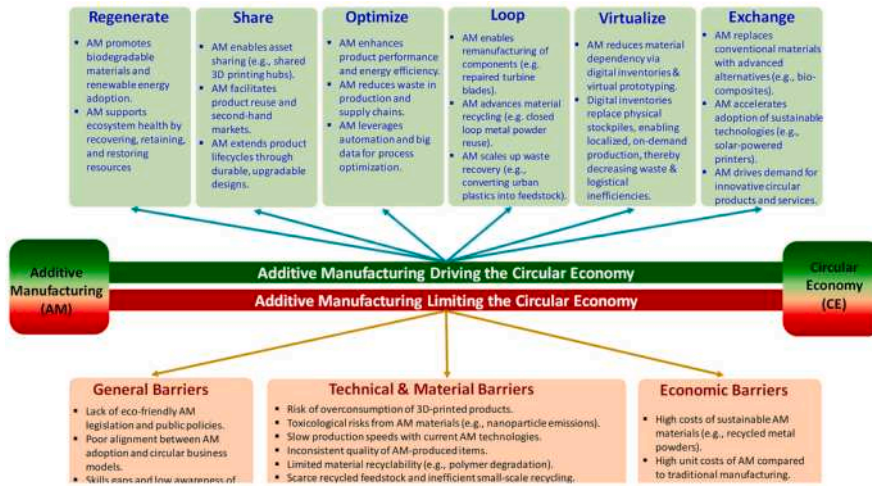


FIGURE 5.4 Systemic relationship between AM and the CE, mapping AM-driven benefits (e.g., material efficiency, design flexibility, and localized production) to CE principles while identifying barriers (e.g., energy intensity and material degradation) that require resolution to advance circularity. AM, Additive manufacturing; CE, circular economy. Source: Modified from Tavares, T. M., Ganga, G. M. D., Godinho Filho, M., & Rodrigues, V. P. (2023). *The benefits and barriers of additive manufacturing for circular economy: A framework proposal*. Sustainable Production and Consumption, 37, 369–388.

energy-intensive processes can limit its circularity potential. The integration of AM with CE strategies holds the potential to revolutionize production methods in industries such as aerospace, automotive, healthcare, and consumer goods by reducing environmental footprints and enhancing resource efficiency (Khan et al., 2025). AM contributes to CE in multiple ways, some of which are outlined below, by facilitating.

5.2.6.1 Material efficiency and waste reduction

One of the core principles of the CE is optimizing material usage to minimize waste. Traditional manufacturing methods, such as machining and casting, often result in high material losses, particularly when producing complex geometries. In contrast, AM significantly reduces material waste by depositing material only where needed. For example, in aerospace applications, where high-value materials like titanium are used, AM can reduce material waste by up to 90% compared to conventional methods (Kunovjanek & Reiner, 2020; Walter & Marcham, 2020). The efficiency of AM in resource utilization is further enhanced by its ability to process recycled materials. Polymer-based filaments derived from postconsumer waste and recycled metal powders used in PBF can be repeatedly reprocessed into printable feedstock, thereby closing the material loop and enhancing circularity (Cruz Sanchez et al., 2020; Hassan et al., 2024).

Recent advancements in material science have expanded the possibilities for AM sustainability. Researchers have explored bio-based and biodegradable materials for AM, such as natural polymers derived from renewable sources, which provide an environmentally friendly alternative to petroleum-based plastics (Mazurchevici et al., 2020; Skrodzka

et al., 2024). Additionally, innovations in metal alloy formulations now allow for greater tolerance of impurities in recycled metal powders, extending the usability of materials in repeated manufacturing cycles (Raabe, 2023; Yakubov et al., 2024). The ability to recycle and reuse materials during AM processes further reinforces its role in CE. For example, excess powder from LPBF jobs can be sieved and reused, lowering overall material waste and improving production efficiency (Rahmani et al., 2025; Warner et al., 2024). Furthermore, closed-loop recycling strategies in AM have been successfully implemented in industries such as construction, where AM-produced concrete components incorporate recycled aggregates, thereby reducing reliance on virgin raw materials (Irshidat et al., 2024; Mengistu & Nemes, 2024; Valera et al., 2023).

5.2.6.2 Product life extension: repair, remanufacturing, and spare parts

AM contributes significantly to CE by enabling product life extension through repair, remanufacturing, and refurbishment. One of the biggest challenges in conventional manufacturing is product obsolescence due to a lack of spare parts. AM addresses this challenge by allowing on-demand production of replacement components, reducing the need for large inventories and preventing unnecessary disposal of otherwise functional products (Dey et al., 2025; Thomas & Gilbert, 2014). This approach has been particularly beneficial in industries such as aerospace and automotive, where AM is used to fabricate complex replacement parts that are no longer available through traditional supply chains.

DED is a notable AM technology that plays a crucial role in product remanufacturing (Saboori et al., 2019; Svetlizky et al., 2021). DED allows for the restoration of worn or damaged components by selectively adding material to critical areas, thereby extending the service life of high-value parts in aerospace, heavy machinery, and defense applications (Shanmugam et al., 2020). This capability reduces the demand for new material extraction and manufacturing, aligning with the CE principle of keeping products and materials in use for as long as possible. The remanufacturing potential of AM has been further demonstrated in case studies on urban infrastructure, where obsolete or damaged parts have been successfully reproduced to extend the usability of city assets (Valera et al., 2023).

Beyond spare parts and remanufacturing, AM facilitates modular product design, allowing for easy disassembly and component replacement instead of complete product disposal. This modularity is especially relevant in the electronics industry, where AM can be used to fabricate circuit board components and enclosures that enable repairability rather than product replacement (Dhinesh et al., 2022; Dong et al., 2018). The medical sector has also benefited from AM's ability to enhance product longevity, with the production of customized prosthetics and implants designed for long-term use, minimizing medical waste and improving patient outcomes.

5.2.6.3 Resource efficiency and material circularity

AM plays a pivotal role in advancing resource efficiency and material circularity by integrating recycled and bio-based materials into production cycles, thereby reducing reliance on virgin resources. AM processes, such as fused deposition modeling (FDM) and PBF, enable the reuse of postconsumer plastics, industrial by-products, and recycled metal powders, transforming waste into valuable feedstocks (Sola & Trinchi, 2023). For instance,

urban waste streams, including discarded plastics, are increasingly repurposed through AM into functional products like construction components and consumer goods, supporting sustainable urban development. However, challenges persist in maintaining the mechanical integrity of recycled materials, as polymers degrade over successive recycling cycles, compromising their performance. To address this, innovations in material processing such as hybrid feedstock systems and chemical recycling are critical to ensuring the reliability of recycled AM materials.

A key strength of AM lies in its capacity to optimize material usage through lightweight, structurally efficient designs. Techniques such as topology optimization and generative design allow engineers to eliminate superfluous material while enhancing mechanical performance. For example, Airbus's 3D-printed cabin brackets are 45% lighter than conventionally manufactured counterparts, significantly reducing aircraft fuel consumption (Airbus, 2016). Similarly, lattice structures and biomimetic geometries unachievable with traditional methods minimize raw material demand without sacrificing strength, making these designs indispensable in weight-sensitive sectors like aerospace and automotive (Khan & Riccio, 2024; Ramakrishna & Bala Murali, 2023).

5.2.6.4 Customization and decentralized manufacturing

Unlike traditional mass production, which requires economies of scale for cost-effectiveness, AM enables the economically viable production of customized, small-batch products (Katsigiannis et al., 2024; Khan et al., 2017). This capability is essential in reducing overproduction, which often leads to excessive waste. AM's digital nature facilitates on-demand production, allowing manufacturers to produce only what is needed, thereby preventing unsold inventory from becoming waste (Sauerwein et al., 2019). AM's decentralized nature enhances sustainability by minimizing transportation emissions and logistical inefficiencies, as localized production shortens supply chains and reduces carbon footprints associated with globalized manufacturing (Maisano et al., 2022; Prasad et al., 2024). Decentralization also fosters localized recycling loops, where discarded AM products are reprocessed into new feedstock, closing material cycles and enhancing circularity (Khajavi et al., 2014). For example, agricultural by-products such as sawdust and grape skins have been incorporated into AM biocomposites, reducing waste and creating high-value products (Rahman et al., 2023). This approach strengthens circularity by transforming waste into a valuable resource, aligning with CE principles. Decentralized manufacturing is particularly advantageous in remote areas, where AM can enable the production of critical components without the need for extensive transportation infrastructure. The COVID-19 pandemic highlighted this benefit, as AM was rapidly deployed to produce medical supplies, such as face shields and ventilator components, locally, thereby mitigating supply chain disruptions.

5.2.6.5 End-of-life considerations: recycling and reuse

The effective management of products at the EoL is a critical component of the CE, and AM offers transformative solutions to address the challenges of recycling, remanufacturing, and material recovery. Unlike traditional linear systems, where products are discarded as waste, AM enables innovative strategies to extend material utility and minimize

environmental harm. A key opportunity lies in remanufacturing and repair: AM can restore worn or damaged components—such as turbine blades or machinery parts—by selectively adding material to degraded areas, thereby prolonging their service life and reducing demand for virgin resources. For example, Siemens Energy uses AM to repair gas turbine blades, extending their service life by decades (Nilsson, 2024). When recycling is unavoidable, AM processes can integrate recycled feedstocks, such as metal powders from previous builds or postconsumer plastics, into new products, effectively closing material loops. However, challenges persist, particularly in multimaterial AM components, where incompatible material combinations complicate separation and recycling, often leading to contamination or downcycling. To overcome this, researchers are advancing design-for-disassembly principles, embedding features such as snap-fit joints or mono-material architectures to simplify material recovery.

5.2.6.6 Enhancing design innovations for circularity

AM has introduced transformative design innovations that directly support CE principles by enabling efficient material utilization, extending product lifespans, and facilitating repairability. Unlike conventional methods constrained by geometric limitations and subtractive processes, AM empowers designers to create complex, lightweight, and material-efficient structures that inherently minimize waste while maximizing functionality. Techniques such as topology optimization, generative design, and lattice structures allow engineers to algorithmically refine components by eliminating excess material while maintaining structural integrity, thereby creating lightweight, high-strength designs that minimize raw material consumption and reduce energy requirements throughout a product's lifecycle. For instance, General Electric's 3D-printed fuel nozzles consolidate 20 traditionally manufactured parts into a single lightweight unit, reducing assembly steps, material consumption (by 25%), and operational energy demands, a breakthrough exemplifying AM's capacity to harmonize performance with sustainability (Lu et al., 2015; [Manufacturing Milestone: 30,000 Additive Fuel Nozzles. GE Aerospace, Ohio, United States, 2018](#)). These innovations are particularly transformative in weight-sensitive industries like aerospace and automotive, where light weighting directly correlates with energy efficiency and emissions reduction over a product's lifecycle.

The integration of digital inventories and decentralized production models amplifies AM's circular potential. By storing designs digitally and manufacturing parts locally, companies eliminate the need for physical stockpiles, reducing storage costs and overproduction. This approach not only streamlines supply chains but also empowers localized repair ecosystems, where damaged components are swiftly reproduced on-site, minimizing transportation emissions and fostering community-level sustainability. Moreover, AM supports biomimetic and lattice-based design methodologies that enhance mechanical performance while reducing material consumption. These structures, which mimic naturally occurring patterns, improve strength-to-weight ratios and optimize energy dissipation, making them particularly valuable in high-performance applications. Traditional manufacturing techniques often struggle to produce such intricate geometries, but AM allows for their seamless integration, further advancing sustainability objectives. By leveraging these advanced design strategies, manufacturers can create products that require fewer raw

materials, consume less energy during operation, and remain in use for extended periods through easy repair and upgrades.

5.2.6.7 Challenges in implementing additive manufacturing for circular economy

While AM holds transformative potential for advancing CE principles, its integration into sustainable industrial systems faces significant technical, regulatory, and economic challenges. A primary concern lies in the energy intensity of certain AM processes, particularly laser-based metal printing and PBF techniques, which demand high power inputs that can offset environmental gains from material efficiency (Chen et al., 2025; Jung et al., 2023; Rinaldi et al., 2021; Yadegari et al., 2025). For instance, metal AM systems often consume up to 100 times more energy per unit mass than conventional manufacturing, raising questions about their net sustainability benefits (Kellens, Baumers, et al., 2017a; Kellens, Mertens, et al., 2017b; Yoon et al., 2014). While advancements in process optimization and renewable energy integration are being explored to mitigate these impacts, achieving energy parity with traditional methods remains a critical hurdle. Material limitations further complicate AM's alignment with CE goals. Although AM theoretically supports recycled feedstocks, the availability of high-quality, recyclable materials remains constrained. Polymers, for example, degrade after multiple recycling cycles, leading to diminished mechanical properties and printability (Vidakis et al., 2021). Metal powders face similar challenges, as oxidation and contamination during reuse compromise structural integrity. Innovations in hybrid materials and bio-based additives such as polymers blended with agricultural waste show promise in extending material lifespans, but scalability and cost-effectiveness remain barriers. Additionally, the lack of standardized certification processes for recycled AM materials hinders industrial confidence, as manufacturers grapple with inconsistent quality and performance (Seifi et al., 2017; Sharma et al., 2025).

Regulatory gaps compound these challenges. Existing frameworks for traditional manufacturing often fail to address AM-specific considerations, such as material traceability, safety protocols for recycled feedstocks, and end-of-life disposal (Gazeau et al., 2024). For example, certification requirements for aerospace or medical components produced via AM lack uniformity, slowing adoption in high-stakes sectors. This regulatory ambiguity stifles innovation, as companies face uncertain compliance landscapes when integrating recycled or bio-based materials. The lack of standardized certification processes for AM materials poses a significant hurdle in ensuring traceability, compatibility, and safety compliance, making it difficult for companies to confidently integrate sustainable materials into their production cycles (Jin et al., 2022; Why Additive Manufacturing Needs Traceability to Succeed. AMFG - Autonomous Manufacturing London, UK, 2018). Addressing these gaps requires collaboration between policymakers, industry leaders, and researchers to develop clear guidelines for material sustainability, environmental impact assessments, and quality assurance standards (Valera et al., 2023). Additionally, supply chain constraints and limited consumer awareness regarding the sustainability potential of AM further hinder its adoption within CE frameworks. Many industries still rely on conventional supply chains that do not prioritize circularity, creating resistance to transitioning toward AM-driven manufacturing systems. Educating stakeholders on the

long-term environmental and economic benefits of AM in CE contexts is crucial for driving broader acceptance and adoption of the technology.

Economic barriers also impede the integration of AM into CE systems, particularly for small- and medium-sized enterprises deterred by high upfront costs for specialized equipment and sustainable feedstocks (Abdulhameed et al., 2019; Thompson et al., 2016; Tofail et al., 2018). Unlike traditional manufacturing, AM lacks economies of scale due to its slower production speeds and limited build capacity (Calignano & Mercurio, 2023). Although AM minimizes material waste, the high cost of recycled metal powders and bio-composites often exceeds that of virgin materials, making adoption less financially viable. Additionally, supply chain constraints, such as limited access to localized recycling infrastructure, further increase costs, especially in regions lacking industrial symbiosis networks. Achieving economic viability in AM-driven CE applications requires advancements in cost-effective material formulations, process optimizations that reduce energy consumption, and scalable manufacturing solutions that enhance production efficiency.

In conclusion, while AM offers a transformative pathway to circularity by minimizing waste and enabling innovative design, its full integration into CE frameworks requires overcoming energy consumption, material sustainability, regulatory gaps, and economic viability. By addressing these barriers, AM can drive the transition toward a more regenerative and resource-efficient industrial ecosystem, minimizing environmental impact while maximizing long-term economic benefits.

5.3 Integrating pillars of Industry 4.0 with additive manufacturing

AM is one of the core technologies of Industry 4.0 (Elngar et al., 2024; Leong et al., no date) and, in fact, the only technology that directly pertains to the physical manufacturing of products. Being the core manufacturing technology of the industries of the future or manufacturing of the future, it will heavily rely on the technological developments in the other pillars of Industry 4.0 such as augmented reality, digital twin, cloud computing and big data analytics, and last but not the least advancements in the system automation (sensors, etc.) and control. The future focus areas for AM regarding research and development are detailed in the following section, “Future Direction of Additive Manufacturing”. The focus at this point is the overall integration of these pillars into the AM ecosystem, which is deliberated below.

Considering all manufacturing technologies, AM can be easily classified as the most adaptable to the industries of the future, starting with the freedom of design and having no worries about the manufacturing constraints to the multimaterial processing and ease of in-process control. With this point of view, Fig. 5.5 provides a conceptual layout of integrating all pillars of Industry 4.0 into the AM ecosystem for the true industry of the future. To fully integrate these systems, the AM systems must be smart AM systems, incorporating advanced sensors to measure every aspect of the process, starting with the raw material, to machine calibration and in-process inspection, leading to cloud computing, big data analytics, and artificial intelligence (AI).

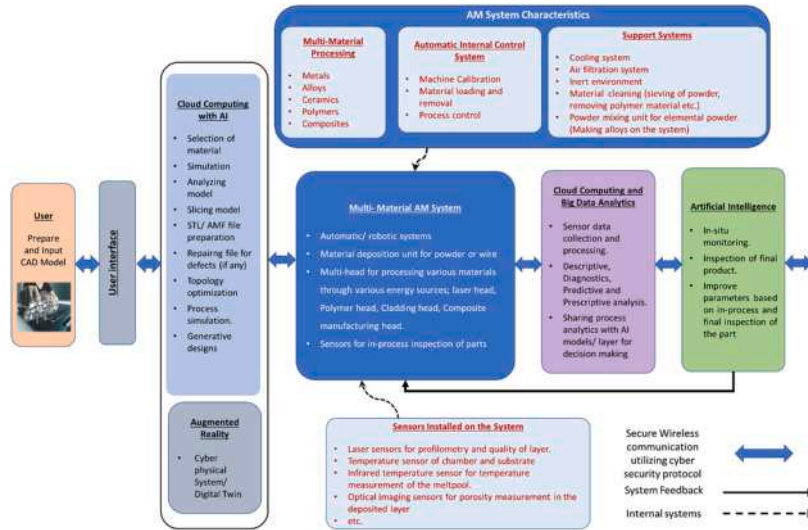


FIGURE 5.5 The AM system incorporating other Industry 4.0 technologies. AI, Artificial intelligence; AM, additive manufacturing; AMF, AM file; CAD, Computer-Aided Design; STL, Standard Tessellation Language.

The layout and features of the advanced AM system are detailed here. The process starts with the user providing basic information about the design through a simplified user interface, with minimal Computer-Aided Design (CAD) and Computer-Aided Engineering knowledge required from the user side. At this stage, the design is optimized through various techniques such as topology optimization or generative design, and the design parameters are finalized using AI. It is followed by the preparation process; selection of material and process, slicing the model, etc. The required information will be provided to the system to start manufacturing/printing, where all sensors will record the data and share it with the ML and AI model for decision-making at every stage of the manufacturing process. All the data are shared through high-speed secure communication channels that can be wireless or wired, incorporating the latest cybersecurity protocols. The integration of ML and AI into AM processes is ever-growing, paving the path for a universal AI model for AM processes (Soori et al., 2025).

5.4 The future of Additive manufacturing

The future directions of research in AM are summarized in Fig. 5.6, prioritized into eight areas. The product design phase is the most important phase for sustainable AM, as elaborated in previous sections. Material development and qualification for AM processes are the key to its use in various applications. Optimizing design for material use and product performance is essential to the sustainability of AM processes in comparison with conventional manufacturing processes. Multimaterial AM processes coupled with functionally graded capability will further enhance the application of AM processes. Significant

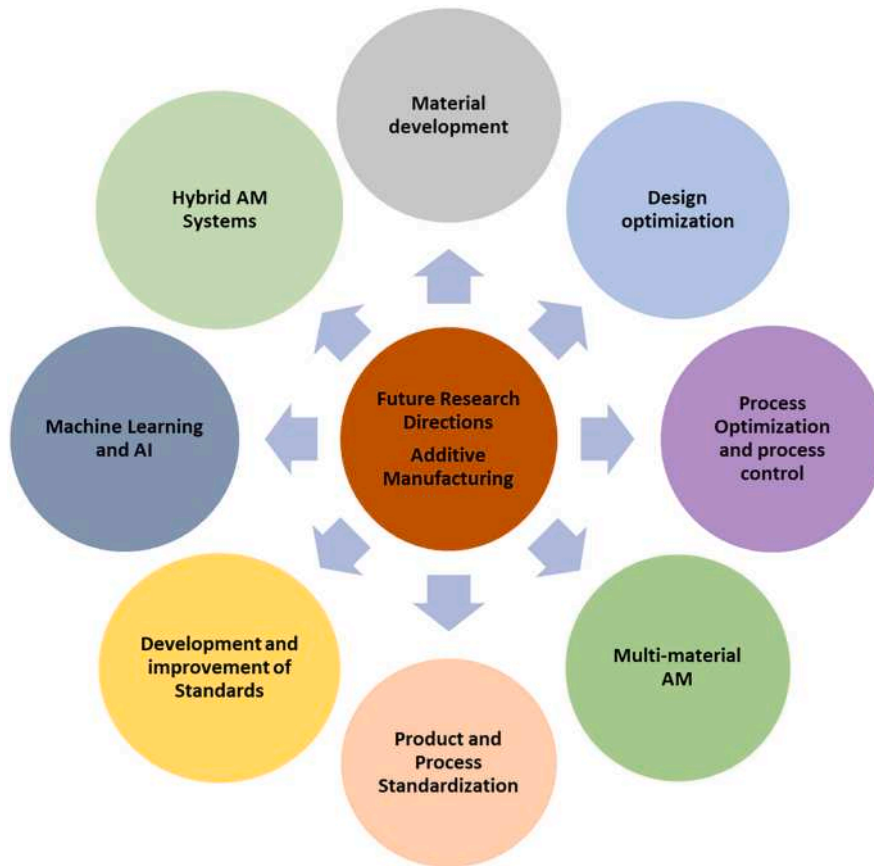


FIGURE 5.6 The future direction of research in AM. *AI*, Artificial intelligence; *AM*, additive manufacturing.

efforts are being made to develop standards for AM, including standardization of materials and processes. With the use of ML and artificial intelligence (AI) in AM, smarter AM processes will be developed in the future.

5.5 Summary

Six elements of sustainability for AM were presented here, that is, DfSAM, material, process, human factor, LC and EoL assessment, and circular economy. Each element was discussed in detail for its implications on the sustainability of AM processes. It is reasoned that AM is much more design-focused rather than process-focused as compared to the conventional manufacturing processes; therefore the sustainability of AM starts from the design phase and it is design-driven, leading to the DfSAM. Published literature advocates

that AM processes are more sustainable in terms of environmental sustainability and economic sustainability than conventional manufacturing processes.

Based on the current state of AM technologies and considering the future direction of research, it can be concluded that AM technologies are currently in the research and development phase. The adoption of AM technologies in the industry is unprecedented and increasing each year. AM may not be intended to replace conventional manufacturing; rather, it aims to complement them. However, there is no doubt that it represents the future of sustainable manufacturing.

AI disclosure

During the preparation of this work, the author(s) used Grammarly to improve the readability and language of the work. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Blockchain applications in sustainable supply chains

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6.1 Introduction

Industrial supply chains are leading contributors to man-made social and environmental damage—originating from the early days of global trade and colonialism. The emphasis on sustainable industrial supply chains is a reaction to this situation with CEOs consistently ranking it as one of their top concerns (e.g., [Kareiva et al., 2015](#)). This reaction has recently gained significant attention as stakeholder pressures from government, communities, non-governmental and civil society organizations (NGOs), and consumers continue to increase.

The environmental and social damage includes effects on climate change ([Ghadge, et al., 2020](#)), resources depletion ([Kalaitzi et al., 2018](#)), biodiversity ([Salmi et al., 2023](#)), slave labor and human trafficking ([Shilling et al., 2021](#)), neocolonialism ([Malam et al., 2024](#)), and other myriad issues. The status quo is not acceptable to the many stakeholders. There are many answers for organizations, but even the simplest solutions may or may not result in meeting an intended goal or expected consequence.

Scholarly research in environmentally and socially sustainable supply chains has seen substantial research for over three decades ([Khan et al., 2021](#)). Many issues still remain as the feasibility and barriers to addressing concerns mount as quickly as the many solutions are studied. In the end, the interdependence and complexity of environmental and social sustainability issues become even clearer as multiple stakeholders, varying institutions, inequities, and complex global supply chains predominate even in the most local and simple supply chains.

Significant research across thousands of studies appeared on evaluating supply chains to improve their environmental and social sustainability. There are multiple perspectives and boundaries associated with addressing sustainable supply chain concerns ([Sarkis, 2012](#)). We provide an overview of these dimensions in this chapter.

The role of each stakeholder—whether they are supply chain actors, consumers, governments, civil society, or communities—is dynamic and with multiple interactions.

Multistakeholder technology (especially information and communication technologies (ICT)) can support integrating sustainable supply chain principles into organizations and their supply chains. Blockchain technology—and its supporting ecosystem—can be helpful in governing and managing in these complex sustainable supply chain contexts.

The chapter focuses on one multistakeholder technology—specifically blockchain technology—a core Industry 4.0 (I4.0) technology (Bodkhe et al., 2020). We evaluate various blockchain characteristics and capabilities that may be used within the context of sustainable supply chains with some examples of use cases.

The chapter initially introduces some aspects of supply chains with the major focus on various supply chain activities and some relationships to green or environmentally sustainable supply chains. An overview of major system elements to discuss the variety of environmentally sustainable issue is presented. Two of these systems are technological and informational, which set the stage for the blockchain background. In this background, an overview of blockchain technology and its capabilities is introduced. We then explain how various blockchain capabilities can support sustainable supply chain activities considering both holistic and segmented aspects of sustainable supply chains. Specifically, upstream, organizational, and downstream supply chain segments will be considered. Practical use examples will be included in different sections and subsections. The chapter then introduces challenges and concerns with related future research and application directions. Finally, we conclude the chapter.

6.2 Sustainable supply chains and blockchain technology background

In this section, we provide an introduction to various supply chains and supply chain sustainability concepts. These concepts and relationships will be around major elemental characteristics—activities, systems, boundaries, and governance concerns—of supply chains based on general boundaries and flows analysis (Sarkis, 2012). That will be Section 6.2.1. Section 6.2.2 will dig a bit more deeply into two of these conceptual supply chain elements, technology can information. These technologies and background are mostly focused on organizational and immediate buyer and supplier technology and information management. At the end of Section 6.2.2, we begin to consider broader, multistakeholder technologies and information requirements. This then sets the stage in Section 6.2.3 for introducing blockchain technology, its capabilities, interorganizational, multitier supply chain, and multistakeholder capabilities.

6.2.1 The supply chain and sustainability concerns

Fig. 6.1 summarizes the various stages, stakeholders, activities, and flows within a supply chain. This supply chain is mostly for durable goods material flows, but will include services such as transportation, storage and distribution, utilities, and financial flows to name a few examples. We summarize some of the major elements (boundaries and constraints) in this section. Flows are also briefly described to exemplify supply chain complexity and sustainability concerns.

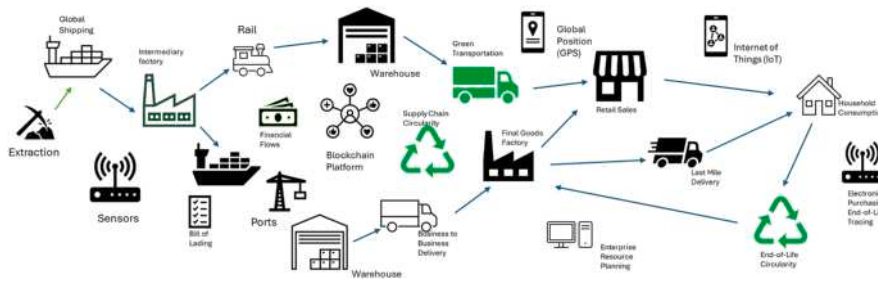


FIGURE 6.1 A simplified supply chain and its various stages, including information, technology, material, activity, and stakeholder entities throughout.

But first, let us provide a brief overview of supply chain management activities. Supply chain management activities can be segmented and described in many ways. If we take a focal organization perspective—where a given organization is the center of the supply chain—then activities can be separated into upstream activities, organizational activities, and downstream activities (Lambert & Cooper, 2000). These activities need to be managed from multiple cross-cutting processes by organizations, including customer relationship management, customer service management, demand management, order fulfillment, manufacturing flow management, procurement, product development and commercialization, and returns management (Lambert & Enz, 2017). Some of these processes, for example, procurement, are most applicable to upstream supply chain management; some are focused on focal organization management, for example, manufacturing flow management; and some processes are on downstream supply chain management, for example, order fulfillment and customer relationship management.

Upstream activities are typically viewed as supplier and vendor management activities. These activities include sourcing, purchasing, procurement, and inbound logistics and transportation activities. Each of these will have environmental concerns ranging from supplier selection and using environmental criteria, to supplier monitoring for environmental concerns, and supplier development to improve environmental issues. Green transportation and procurement with contracting, negotiation, and agreements will be central to activities in upstream supply chain management.

Organizational and operational activities would include activities and decisions related to inventory management, fabrication, and assembly for durable goods manufacturing. Inside organizations, environmental management systems, operational lean manufacturing activities to eliminate waste, and energy conservation measures each have organizational environmental implications (Sarkis & Dou, 2017).

Downstream activities include customer management and outbound logistics management. For example, practices would include marketing and sales involvement and include green marketing and package design. Product design may also require input from customers and designs for green products and evaluations. Downstream logistics may mean activities such as carbon management of distribution channels. Downstream activities closely related to environmental issues include product stewardship and returns (end-of-life) product management (Toffel, 2003).

This segmented look at the supply chain is from only one perspective, the focal organization. Yet, the supply chain, also defined as a *value chain* (Kano et al., 2020), can be more broadly considered a network of companies, stakeholders, technology, material, and information flows. Major elements to help understand and describe the supply chain include cultural, economic, informational, legal, political, proximal, organizational, technological, and temporal; these elements would be considered boundaries and constraints according to (Sarkis, 2012). Other supply chain elements may include various flows such as materials, services, finance, information, and waste flows.

Fig. 6.1, shows that globalization and global flows are core to the globalization of supply chains. Globalization means varying *cultural*, *legal*, and *political* systems, for example. Each of these systems has unique norms, values, and regulatory policies. Understanding the needs and requirements related to environmental regulations and indigenous community relationships and requirements of the environment are examples of sustainability issues affecting or being affected by supply chain activities.

For example, raw materials, starting on the left side of Fig. 6.1, are typically from extraction industries and practices. Land-based natural resources are also defined as environmental rents and are valued or recorded as such. Nonmarket valuations and performance data are needed to quantify rents across a supply chain (Hervani et al., 2022). These data are important to get a true cost of environmental resources, which is usually lacking in modern and traditional *economic* systems—and thus the need for nonmarket valuation and tools to help in that effort. Also, raw material extraction is responsible for a series of environmental burdens, including biodiversity, deforestation, carbon sink degradation, and pollution (Berthet et al., 2024). Yet, this listing of environmental burdens is not just unique to extraction stages, and they can appear anywhere across the supply chain, all the way to end-of-life postconsumer products (Toffel, 2003). Natural resource destruction may also depend on cultures (geographic regions) that may not have strict legal regulatory and political policies, for example.

Extracted raw natural resource materials are from developing nations and require global transportation to other regions of the world. These developing nations do face a *resource curse*. Countries facing the resource curse are paradoxically rich in natural resources but experience slower economic growth, have weaker democracy, and worse development outcomes (Badeeb, et al., 2017). There are multiple sustainability concerns that need to be managed in these countries.

Raw material commodities are processed as they flow through the supply chain. Processing occurs through intermediary factories and process facilities, which make basic components and elements that can be used in further industrial processing at later supply chain stages. The different factors and processes and their influence or management could be defined by their geographical (*proximal*) and *organizational* boundaries and characteristics. For example, value added (*economic* dimensions) and travel costs are included in the valuation process through these stages.

The interaction of supply chain considerations is also evident. For example, proximal characteristics influence *temporal* (timing) supply chain issues. Time-based competition will result in various environmental issues such as transportation mode selection for time-based performance. Some transportation is faster than others, and commensurate per unit environmental costs also differ—especially in terms of emissions and energy usage. For

example, maritime shipping and rail are quite efficient from an emissions and energy usage perspective. Truck and air transport, although faster (*temporal*) and more flexible, have relatively larger ecological footprints. As can be seen, these various modes of transportation can be seen throughout the supply chain; each with a differing environmental burden (Lawson, 2007).

Temporal supply chain concerns are also related to environmental sustainability concerns. For example, pollution spills caused by supply chain activities are environmental concerns that need to be managed in a short time frame. Thus monitoring and management of these supply chain environmental events need to be managed quickly and have the appropriate technology and systems to support these short-term activities. On the other scale of temporal activities are broad generational environmental implications such as climate change and biodiversity concerns. These longer term supply chain implications would need to be managed by strategic systems and decades-long planning and thinking.

Returning to transportation and production and storage activities, each appears at different stages of the supply chain from raw material to processed materials to components and final goods. Transportation and storage—integral elements of logistics or movement of materials—also require energy, resources, and generate emissions—each contributing to various environmental burdens.

We have considered and exemplified various activities and dimensions of supply chain elements, systems, boundaries, and constraints. We now turn our attention to core supply chain elements that of technological and informational systems for sustainable supply chains.

6.2.2 Technological and informational systems in sustainable supply chains

Thus far, various sustainable supply chain characteristics across seven major elements are described. Nine elements are introduced in Section 6.2.2, and two elements not explicitly mention are informational and technological elements. The discussion of these two other supply chain characteristic elements are reserved for this section. These elements are included in their own section because blockchain technology and sustainable supply chain relationships can arguable be most associated to these two elements, although economic issues are clearly prevalent as well.

Although informational concerns and technological concerns can be separated, their joint existence in the supply chain through various information and financial flows is important for operations and sustainability. Traditional information systems—such as enterprise resource planning (ERP) systems—in organizations can also support sustainable supply chain management. Table 6.1 summarizes the extensiveness of potential environmentally sustainable supply chain applications for traditional hierarchical information systems management levels (columns) and functions (rows).

These examples occur in various internal and interorganizational supply chain functions. There are strategic, tactical, and operational levels of decision-making information systems. The examples range from basic compliance concerns related to environmental concerns, to more advanced ecological design of products information management. As the information technologies get more strategic, it is likely that more functions and stakeholders will utilize them or are impacted by them. Most of these information

TABLE 6.1 Traditional information technology systems hierarchy for organizational functions and activities with environmentally sustainable supply chain examples.

Managerial decision level	Strategic level	Tactical (management) level		Operational level
Functional area	Executive Support Systems	Decision Support Systems	Management Information Systems	Transaction Processing Systems
Engineering and design	Green product markets information	Justification models for green product designs	Life cycle analysis	Environmental product and process performance information
Procurement	Strategic contractual and sustainability relationship	Supplier selection decision models with environmental factors	Reports on environmental performance of suppliers	Updating inventory of environmentally sensitive material
Manufacturing and production	Environmental technology information	Product lifecycle data to assist end-of-life disassembly planning tools	Sharing of environmental knowledge	Environmental collaboration and monitoring practices
Sales and marketing	Green consumer market development systems	Forecasting tools for green product requirements	Market-oriented sustainability programs data	Environmental purchasing intention models
Logistics	Information and communications technology in long-term data management and plans	Decision support systems for sustainable logistics such as intermodal transport, port operations	Reports on daily and weekly usage of fuel-driven vehicles	Returns data and reclaimed materials
Human resources	Environmental and safety requirements in union negotiations	Personnel selection for environmental programs	Environmental training records	Workforce environmental awareness training

Adapted from Sarkis, J., Koo, C., & Watson, R. T. (2013). Green information systems & technologies—This generation and beyond: Introduction to the special issue. *Information Systems Frontiers*, 15, 695–704 and Sarkis, J., Kouhizadeh, M., & Zhu, Q. S. (2021). Digitalization and the greening of supply chains. *Industrial Management & Data Systems*, 121(1), 65–85.

technologies are focused on intra-organizational activities and communications. Although some procurement and customer relationship information systems will be used to manage direct customer–buyer relationships. Going beyond first-tier customer or supplier relationships is difficult or nonexistent in most of them.

As technology has expanded to incorporate multiple organizations (interorganizational technology) and stakeholders (multistakeholder technology). Information and data capture, sharing, use, and manipulation can occur from multiple entities throughout the supply chain. In Fig. 6.1, it can be seen that various sensors can capture information throughout the supply chain. Example sensors would be Radio Frequency Identification (RFID) tags (Green et al., 2017). These sensors are important to capture information and share them whether with standard inventory management tools or in blockchain systems. RFID can flow with materials and products throughout the supply chain, feeding information to and from different supply chain stakeholders.

Information technology data capture can also come from dispersed sources such as smart phones, which can be possessed by consumers or by employees in factories or while transporting materials. Mobile smart phones and computer systems when linked to the Internet form some of the basic tools and technologies related to the Internet of Things (IoT). As seen later, these technologies and information systems are integral to blockchain ecosystem operations and applications.

Yet, technologies within a sustainable supply chain may not be limited to information technology. There are materials and process technologies as well. For example, materials that are biodegradable and less toxic may be used as substitutes. Having less environmentally burdensome materials is an important area of research from a materials technology perspective. Equipment technology in the supply chain may also be something that can influence supply chain performance. For example, in the agriculture supply chain having anaerobic digesters can help in valorization of agricultural waste to capture greenhouse gases (Gijzen, 2002). Process technologies can also include new processes for improving operational and supply chain management practices. Industry 4.0 technologies (other than blockchain, which will be detailed in this case) can contribute to improving organizational and supply chain practices to make them more lean with less waste generated (De Giovanni & Cariola, 2021).

The use of technologies to help decouple economic activity and growth from increased environmental burden has its own theory—ecological modernization theory (Allen & Sarkis, 2021). This acknowledgment of technology as a broad-brushed solution through a whole theoretical framework is impressive. Although technology as an only or primary cure for poor environmental performance and improved economics has come under severe criticism (Spaargaren et al., 2020), especially given the challenges associated with unintended consequences and poorly functioning technology.

To effectively manage sustainability across supply chains, information technology and technological support also need to provide resources for multiple stakeholders to help share information and help alter behavior. An overview of one such technology, blockchain technology is now overviewed. Blockchain technology has shown great promise for improving supply chain sustainability, but the technology also faces significant challenges. Applications and challenges appear later in the chapter. In this next section, blockchain characteristics are highlighted.

6.2.3 Blockchain technology

Blockchain technology has a foundation structured on distributed ledger technology (DLT). DLT securely records transactions across multiple data sites in a way that ensures transparency, security, and immutability. Its decentralized nature eliminates the need for intermediaries, making processes more efficient and reliable.

The block is a core informational object in blockchain systems. The block includes entity information. This information can include a variety of fields associated with material, information, capital, or other flows in a supply chain. There is an unalterable timestamp also associated with a block of information. Information on a block can be changed through some form of consensus mechanism, and a cryptographic hash is used to identify and link a previous block. Any new information blocks are attached in a chain to the previous block—and thus the term of blockchains. In this process, once a block is added, it cannot be retroactively altered. Unalterable data mean that the data and history are immutable. There are many structures and links that include Merkle trees and block headers and bodies. Although not in detail, this information is readily available across technical papers and documents (see [Xu et al. \[2017\]](#) for a review of some blockchain architecture characteristics and developments that are continuously evolving).

Another characteristic of DLT is replicated and decentralized databases for the blockchain. Data are stored across a network of nodes rather than a central server. This type of storage, with appropriate access keys, further supports the security and reliability of information. Where the data can only be changed or altered through various consensus mechanisms that typically require the involvement of multiple parties. See [Lashkari and Musilek \(2021\)](#) for a summary and overview of consensus mechanisms for DLT and blockchains, but note that additional approaches and techniques continue to be developed and introduced.

This description of blockchain highlights a decentralized, immutable, and relatively secure data and system. These features support data reliability and accuracy—which builds trust in the data and the system. The blocks and linkage with time stamps and other information associated with transactions information provide two additional features. The first additional feature is transparency. Decentralized information and access, as well as the history of flows, provide data transparency. The second major feature of these blocks is that the history of blocks can also help trace the transactions and flows, leading to traceability. As will be seen, transparency and traceability are critical for supply chains and their sustainability.

Two general additional blockchain features characterized by many blockchain providers (platforms) and capabilities include tokenization (for incentivization), which are related to cybocurrency characteristics. There are also automated tools such as smart contracts introduced by the Ethereum blockchain platform.

These characteristics can be supportive of sustainable supply chains from multiple perspectives. Many of these characteristics are described in the next section when blockchain applications to sustainable supply chains are discussed.

In summary, some of the key features of blockchain that together make blockchain unlike most other information technologies when you consider the “whole package” include (1) transparency and traceability, (2) security and reliability, (3) smart contract, and (4) incentivization and tokenization ([Kouhizadeh, et al., 2023](#)).

Transparency and traceability arise from shared and decentralized ledgers. Supply chain stakeholders can trace and view information through networks. A high degree of transparency and traceability can enhance fairness and access to data, increase efficiency, and reduce risks in complex systems (Saberi et al., 2019).

Security and reliability from its inherent design. Blockchain records transactions using an encrypted structure. Decentralization makes it resistant to cyber-attacks or hacks with immutable characteristics and PoS mechanisms.

Smart contracts are codified business logics, rules, and agreements of a contract. Smart contracts provide greater efficiencies through the automation of transactions and decisions.

Incentivization and tokenization are blockchain technologies that support monetizing and valuation aspects for stakeholders and processes. Blockchain can generate digital tokens and represent the corresponding value of the specific assets. Digital tokens can incentivize people and supply chain actors to adopt behaviors, provide information, validate information, or improve performance.

6.3 Blockchain applications for supporting and enhancing supply chain sustainability

In the previous sections of this chapter, various concerns and complexities associated first with standard supply chain practices are observed. These supply chain processes and activities also influence the natural environment (environmental sustainability). Adding this additional dimension results in even greater complexity to the traditional business and economic issues. Many stakeholders, types of information, and contextual elements. We have also observed that blockchain can offer various capabilities to organizations that may help mitigate the management of these complexities. We now review how blockchain's abilities to foster trust, ensure transparency and traceability, streamline operations, and incentivize people provide substantive opportunities for improving or managing sustainability in supply chains.

It is difficult to cover every potential blockchain and sustainable supply chain application, these examples provide a starting point, a foundation, for practical application and research opportunities. A structured way to cover these application examples is using an upstream, focal organizational, and downstream supply chain sustainability management structure—the examples may also cover multiple supply chain stages. A more comprehensive sustainable supply chain blockchain application listing (a listing that continues to grow) appears in Kouhizadeh and Sarkis (2018).

6.3.1 Upstream application: tracking and verifying sustainable sourcing of materials

Blockchain technology for supply chain sourcing is important because many materials can be sourced from controversial locations or through processes that are environmentally unsound. Some of these are related to laws and regulations requiring good faith efforts to make sure products or materials do not derive from or are sourced from areas of the world where conflict is arising. An example is the issue of conflict minerals traceability

requirements (Tuladhar et al., 2024). This became an issue when Apple Inc. was sued by the Congolese government of sourcing materials from conflict regions when they stated they did not. The issue here is whether Apple could prove that they did not know or could not trace their products. Thus liability and reputational risks may be reduced. Part of this traceability and accuracy issue may include incentivizing various stakeholders with providing updated and accurate information. Tokenization of information and proof can add reliability and comprehensiveness of this information.

6.3.2 Focal organization application: efficient logistics to reduce carbon emissions and environmental compliance

The first of two organizational application examples is a logistics planning and management organization goal to reduce carbon emissions through blockchain technology. Blockchain enhances logistics efficiency and reduces carbon emissions by providing a transparent, immutable ledger for tracking supply chain activities. By integrating blockchain with IoT and AI, companies can optimize freight routes, minimize empty miles, and automate load matching, reducing unnecessary fuel consumption (Gupta, et al., 2024). The digitization of logistics documents, such as bills of lading and customs forms, streamlines processes and eliminates delays, preventing emissions from idling vehicles.

For example, international maritime shipping causes substantial emissions, even from idling. Some slowdowns in maritime shipping can result from paper-based bills of lading. One study has found that shifting from paper-based bills to blockchain-based bill-of-lading can result in significant reductions. Using a traditional bill-of-lading resulted in 975.54 grams of carbon gas emissions. An Ethereum-based Proof of Stake (PoS) approach resulted in 35.17 g of carbon gas emissions (Istinić & Skrjanec, 2025). These results show about a 96% decline. Other studies have shown carbon emissions reductions at even higher ranges with averages of 98%–99% reductions (Pu & Lam, 2021). This issue is important given that many blockchain platforms have been accused of using large amounts of energy, which also mean significant amounts of carbon emissions (Shi et al., 2023).

The blockchain enables real-time data sharing among stakeholders, improving coordination and decision-making in transportation. Although there are challenges and limitations, which are discussed in the next section, the possibilities of these issues relate directly to scalability concerns and the inclusion of blockchain within a broader ecosystem of technologies.

The second example of organizational application of supply chain sustainability concerns is ensuring compliance with environmental regulations. Environmental regulatory requirements have to be met by industry and communities. The issue here is that some organizations and their supply chains may not be effectively evaluating their influence on the environment. Blockchain, through dispersed and multistakeholder technology, can capture environmental and ambient data that emerge from various locations and emissions.

For example, community and local groups may capture information through ambient monitoring. This may mean collecting information from various regions and sources that are emitted to the air or water quality that may be recorded by citizen groups. Validation can be completed by low-cost and easily accessible sensors that can be recorded through IoT and blockchain systems in “citizen science” approaches (Allena, 2020). Also, many polluting

entities in supply chains are very small and minor sources. Capturing this information from diverse groups and stakeholders for aggregate reporting can provide more accurate compliance evaluations and data for larger scale planning. This aggregation of small point-source emissions can be very valuable in addressing the significant emissions that arise from small sources (such as residential households (Liu et al., 2016) that may not necessarily be required to record, but should be managed).

An example that uses blockchain for a construction company's environmental compliance on its construction site (Zhong et al., 2022). Construction organizations need to have trustworthy environmental monitoring data so that communities and government stakeholders concerns and queries can be effectively and trustingly addressed. In this situation, smart contracts were programmed to algorithmically monitor environmental burdens and performance. The information was captured by sensors. This automation provided even greater reliability since no human intervention that may cause fraud was eliminated, providing a more trustworthy environment. The blockchain can use various Oracles or consensus algorithms, such as Kafka, Raft, and PBFT (Yang et al., 2022).

6.3.3 Downstream: end-of-life and circular supply chain application

Downstream applications can include customer relationship management and acceptance concerns with blockchain technology. For example, we have completed studies on how customers will respond to various blockchain applications and even their usage of them for sustainable supply chains (e.g., Duan, et al., 2025; Zhu, et al., 2024). Questions of trust and the utility of such systems from a downstream sustainability supply chain customer perspective were evaluated. Overall, the findings did support the application of blockchain for customer usage and utility, especially with respect to customers trusting sustainability performance in supply chains.

The focus will not be on the customer relationship and management aspect of downstream sustainability applications of blockchain in this application example. End-of-life of products and materials as part of a circular economy or circular supply chain perspective are considered.

Circular supply chains are important for supply chain sustainability to help reduce environmental resources from raw material supply chains. Supply chains that are able to reuse materials, components, and products—part of the circular economy series of practices—usually result in lessened environmental burdens (Yang et al., 2023). But the adoption of circular principles in supply chains has challenges, including, but not limited to, traceability of materials (Kumar et al., 2023), supporting reverse logistics (Sonar et al., 2024), and motivating consumers of products and materials to practice circular practices such as recycling or reuse (Helinski et al., 2024).

One area of great future opportunity for incentivizing consumers is for power battery recycling at the end-of-life of these batteries (Li, et al., 2023). Although most tokenization examples for battery recycling are conceptual, one such model includes government, manufacturer, recycler, and consumer involvement. The process begins with governments issuing tokens to manufacturers based on the recycling task. Manufacturers then purchase end-of-life power batteries from qualified recyclers using the tokens. Recyclers purchase

end-of-life power batteries from consumers of these batteries using the tokens; tokens are recorded by the consumers and can get government tax subsidies or consumers can sell tokens back to a manufacturer, who can use them again. This tokenization process requires careful tracking of ownership of actual material flow locations and tokens across multiple stakeholders in a closed-loop supply chain. It is only one example of tokenization and incentivization to be involved in a circular economy system.

Another general example (Wang et al., 2025) provides a number of points in the recovery, reverse logistics system, for remanufacturable materials in the circular supply chain. One of the initial steps is to provide incentives (pricing), maybe through bidding, in blockchain-based system using smart contracts based on retailer and recycler risk acceptance. The pricing scheme is meant to incentivize end-users to return products. Once there is agreement, various public and private keys are used in the blockchain system (that are verified) for the transaction to get completed. The product's status in the supply chain is traced, and returned product quality is then recorded and verified. This information is stored in the product chain. After this information is stored, information is transparent, and information on potential recycling strategies are recorded on the blockchain. Recycling centers will then be able to get product information, inspect the end-of-life product, and determine end-of-life processing (remanufacturability). The remanufacturer can then carry out the operations and record with verification onto the blockchain, which can then be viewed by manufacturers, distributors, or end-consumers of the product.

Both these application examples with blockchain support are either at the conceptual or demonstration level. That is, most of what is proposed has been theoretical with few, if any, broad-based and mature applications. Given the promise of these and many other sustainable supply chain applications of blockchain, the question is why adoption has not matured beyond the promise and pilot stage. Challenges do exist.

But before challenges are discussed, many other areas of application could have been did not covered, and are summarized here. Some of these sustainable supply chain applications across the supply chain are not covered include:

- Safety issues in circular and sustainable supply chains—use of blockchain can improve the manual aspects and dangers of some materials flowing in a closed-loop system (Chen et al., 2024).
- Performance measurement and management of supply chains, including social and environmental sustainability (e.g., through Industry 5.0) (Tsang, et al., 2024).
- Using blockchain for carbon trading, offsetting, and insetting across the supply chain (Zhu et al., 2025).
- Peer-to-Peer carbon trading and renewable energy sourcing through blockchains (Parhamfar, et al., 2024).
- Digital product passports for sustainable and circular supply chains in response to governmental regulations and industry practices (Zhang & Seuring, 2024).

All these applications, summarized in this section (Section 6.3), face challenges and limitations. These application challenges also represent opportunities for further research and development. Challenges are next introduced in Section 6.4, the next section. Opportunities for future research and development are discussed in Section 6.5.

6.4 Challenges and limitations to blockchain for sustainable supply chains

Blockchain technology holds significant opportunities for building sustainability in supply chains. Yet, even after more than a decade of focused research and development, many applications are limited, at best. Why?

Researchers have provided a number of reasons. But one of the first ones is a mistrust of whether blockchain itself is a sustainable technology. The ecological footprint of blockchain technology, with various aspects such as data centers, mining, and monitoring, has significant energy requirements. When integrating with other tools and technologies such as artificial intelligence and IoT, the energy requirements are even greater. Estimates have shown that cryptocurrency mining alone in 2022 surpassed the annual electricity consumption of countries such as Argentina and Australia ([Alzoubi & Mishra, 2023](#)). With this type of communication, the general public and organizations will feel that using blockchain for sustainable supply chains is hypocritical and defeats the purpose of environmentally sustainable supply chains. So why make it worse? This issue, although there are efforts to 'green blockchain', remains a major concern.

Other challenges include traditional organizational and inter-organizational concerns. The Technology-Organization-Environment (TOE) framework has been used to categorize the major challenges that have limited the application of blockchain technology for sustainable supply chain management ([Kouhizadeh, et al., 2021](#)). The list of these barriers and various reasons is quite extensive. Only major groups of barriers are summarized at this time with highlights within the major dimensions presented.

Technologically, the major barrier is that blockchain technology is still evolving ([Zhang et al., 2024](#)), which means that it is relatively immature. This evolution means that any investment or adoption of the technology will likely mean that it will be obsolete relatively quickly. Stabilization of blockchain technology is still needed. But, given new algorithms, tools, and linkages to other newer technologies, makes companies and supply chains less likely to tie themselves down to a particular technology. Immaturity also means that the knowledge and expertise to manage technologies is also immature. New developments require new insights. Managers are extremely wary of this issue. There are also concerns that blockchain technology will require additional systems, and linking these technologies to blockchain is not always an easy thing to do. The complexity has been viewed as a major barrier to its understanding by managers and supply chains ([Jimenez-Castillo et al., 2024](#)). Parts of these issues are the capability of blockchain technology to be integrated with legacy systems of the current sustainable supply chain infrastructure to gather and maintain data.

Organizational barriers include internal organizational and inter-organizational practices and limitations. Organizational knowledge and expertise (related to blockchain technologies evolving and immature characteristics) remain relatively slim. Risk-averse organizations may not wish to adopt the technology, but alternatively, on the sustainability side, they may not view sustainability as a top concern for them. Thus there are two major organizational limitations in not being able to accept the technology and the application to sustainability. It is rare that an organization will likely take these risks for a strategy that is not core to their business. Interorganizational adoption can be very resource-intensive, and there is likely a lack of trust in the technology, but in that other organizations will be able to provide the resources and data to make it effective. Sustainability information can be very sensitive;

blockchain is meant to involve multiple stakeholders. There will likely be concerns of adopting too much blockchain and transparency within and between organizations and the stakeholders (e.g., see [Zhu, et al., 2025](#)). Information privacy concerns are also a barrier due to a lack of blockchain trust—even in permissioned or private blockchains—with sustainability data. Sustainability information standardization within and between organizations will limit the information and usefulness of blockchain sharing. The same thing occurs for blockchain systems and their broader technological ecosystem, where different systems linked to the blockchain ecosystem may have different standards and metainformation requirements.

The competitive and institutional environment, external to the actual blockchain, is the third and last set of barriers we summarize in this section. One of the most important external barriers relates to uncertainty and risk. Currently, regulatory agencies have been hesitant to provide specific standards and laws to help provide a standard for blockchain; alternatively, this is also true for many sustainability standards, as circularity ([Kirchherr et al., 2017](#)). Although a definition for many sustainability issues and blockchain characteristics is provided, consensus and agreed upon, especially global standards, do not exist. The lack of standards and guidance, although some efforts are occurring ([Qi & Kim, 2024](#)), leads to risk and uncertainty across supply chains and organizations. One other major barrier is the institutional reputation of blockchain. Blockchain technology currently has a *dark-side* image. Blockchain platforms have a history and image of illegal interactions ([Sangal, et al., 2024](#)). Legitimate supply chains and organizations tend to shy away from blockchain given the black market and money laundering activity reputation of criminal enterprises who use blockchain as a vehicle for these illegal activities.

These are only some of the major barriers that exist, but the breadth and scope of barriers, from supply chain sustainability and blockchain perspectives, play a role in the slow pace of adoption. Overcoming barriers, those listed here and elsewhere, is where future opportunities for research and practice can be found.

6.5 Future outlook and opportunities

Throughout the chapter, various practices, applications, and limitations associated with blockchain technology, sustainable supply chains, and their integration are introduced. Each of these areas has an opportunity for future research and development. We highlight some promising areas in this section for future developments.

One of the most important tradeoffs is that blockchain can be good for the environment due to supporting sustainable supply chain activities, but the energy and carbon footprint can be very large. Thus one of the first future outlook considerations is greening blockchain and energy-efficient protocols. The blockchain ecosystem will include IoT and AI, and their interaction is an area of research, but greening these multistakeholder technologies will be critical. Many options exist from improving algorithms or using different supporting tools and technologies, such as Quantum computing, which may lead to a lessened environmental burden of these systems. This issue remains open, and effort is needed for greater efficiencies overall.

Carbon trading is a major aspect of blockchain for sustainability and sustainable supply chains. Tokenization of carbon credits and building a trustworthy carbon credit market can be a goal of blockchain. These issues include offsetting and insetting efforts (Zhu et al., 2025).

Blockchain technology is now an ecosystem rather than just a platform. Various tools on the blockchain platform can help address various barriers such as the scalability of blockchain operations. Blockchain ecosystem designs and developments are needed for emergent topics and applications in sustainable supply chain management such as safety in closed-loop-supply chains (Chen et al., 2024), circularity and agriculture (Sharma et al., 2025), citizen science and biodiversity management (Bengil, 2024).

From a broader research and scholarly perspective—something not discussed much due to the practical nature of this chapter—is the need for effective theorization of various blockchain technologies in sustainable supply chains. Although the literature and study of these topics has been maturing in the literature, there is still a need for more effective and improved theorizing to aid in the study of this topic (Zhu et al., 2022) and the need for additional analytical modeling developments (Bai & Sarkis, 2022). The issue of multi-stakeholder technology in a complex supply chain environment adds multiple complexities that require unique theoretical and analytical perspectives to understand and study this area.

6.6 Conclusion

Blockchain technology can revolutionize supply chains by embedding sustainability supply chains. It offers transparency, traceability, smart contracts, and tokens. These joint characteristics within a larger blockchain ecosystem empower organizations and their supply chain partners to meet environmental and social goals for multiple stakeholders.

The chapter provided background on supply chains, sustainability, and blockchain technologies. This background provided a situation where multiple applications can be viewed from an upstream, focal company, and downstream perspective. The applications range from making operations more efficient to incentivization changes in behavior to managing stakeholder concerns throughout the supply chain. The chapter only scratches the surface of what has now become thousands of articles related to this topic. Yet, paradoxically, as the knowledge and research on this topic grows, there is still a need for broad-based adoption and application of this topic. Most applications and developments remain immature and at a small scale. Advancement is still needed, and opportunities exist

To advance the field, it will require a transdisciplinary effort from across disciplines from the computer sciences to business and social sciences to environmental sciences, for progress to be made. There also needs to be multiple practitioner sectors and stakeholders in codevelopment and advancement of these applications. This means government, civil society, and industry need to work together in this advancement. The opportunities and knowledge exist, and the next steps are critical for achieving environmental and social sustainability goals.

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Harnessing big data for sustainability: opportunities, challenges, and ethical imperatives

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7.1 Introduction

In recent years, the convergence of digital technologies and sustainability imperatives has sparked a transformative wave across industries and societies. Big data analytics, characterized by its capacity to process vast and complex datasets, stands out as one of the most influential technologies of the Fourth Industrial Revolution (Industry 4.0) (Vassakis et al., 2018; Zong & Guan, 2024). Its ability to collect, store, and analyze large volumes of structured and unstructured data in real-time empowers decision-makers across the public and private sectors. This capacity makes it a powerful tool for understanding global systems and offering tailored solutions to address the multifaceted challenges of sustainable development. As environmental degradation, resource scarcity, economic inequality, and social disparities intensify, the integration of big data analytics into sustainability strategies offers a path to smarter, more adaptive, and equitable solutions.

Big data analytics is inherently interdisciplinary and cross-sectoral, making it a valuable enabler of sustainability across diverse domains. In the environmental realm, it supports applications, such as climate modeling, pollution monitoring, and biodiversity conservation. For instance, advanced sensor networks, Earth observation satellites, and Internet of Things (IoT) devices generate real-time environmental data and are analyzed using artificial intelligence (AI) and machine learning (ML), which can forecast extreme weather events, detect illegal logging, and optimize renewable energy production (Fang et al., 2014; Hussain et al., 2023; Mostafa et al., 2022; Tayyab et al., 2024). In economic systems, big data facilitates

resource efficiency, supply chain optimization, and sustainable production and consumption patterns. In social contexts, it enhances healthcare delivery, educational access, and disaster preparedness, while also providing tools for transparency, accountability, and community engagement. The real-time nature of data collection and analysis allows for predictive modeling and rapid response, enabling proactive and preventive interventions across various sectors. For example, governments can leverage big data to implement smart city initiatives and optimize urban planning, while businesses can use it to identify inefficiencies, optimize resource use, and reduce environmental footprints (Hashem et al., 2016; Matheus et al., 2020). This systemic intelligence enables not just better management but also innovation in products, services, and governance models that align with the principles of sustainability, circular economy, and climate resilience.

However, the widespread application of big data is not without challenges and contradictions. Concerns related to energy consumption, digital waste, data privacy, and bias have sparked critical discussions about the environmental, economic, and social costs of data-driven systems. The infrastructural demands of big data—ranging from high-powered servers to constant internet connectivity—can contribute to environmental degradation if not managed sustainably (Al Kez et al., 2022). At the same time, without robust regulatory frameworks and inclusive data governance, the problems of data monopolies, ethical breaches, and inequities in data access and representation can exacerbate the existing power imbalances and widen socioeconomic divides (Florio, 2023; Lukings & Habibi Lashkari, 2022). The infrastructural demands, coupled with the potential for surveillance and misuse, necessitate a critical examination of how big data technologies are designed, deployed, and governed within sustainability frameworks. These challenges and contradictions necessitate a careful examination of both the opportunities and threats posed by big data in the context of sustainable development.

This chapter explores the intersection of big data analytics and sustainability across three dimensions: environmental, economic, and social. For each dimension, the chapter highlights potential positive and negative impacts and outlines practical mitigation strategies and areas for future research. By synthesizing evidence from leading global institutions, international policy frameworks, and recent academic studies, the chapter offers a comprehensive overview of how big data analytics can be harnessed responsibly to support sustainability objectives. Ultimately, the goal is to guide policymakers, businesses, researchers, and civil society toward a more informed, ethical, and balanced approach to leveraging big data in the service of a sustainable, equitable, and resilient future.

7.2 Environmental dimension of big data analytics

7.2.1 Positive environmental impacts

Big data analytics plays a pivotal role in enhancing environmental sustainability by providing actionable insights derived from vast and diverse data sources (Fig. 7.1). By

Characteristic	Environmental Monitoring	Natural Resource Management	Waste Management	Energy Efficiency	Risk Assessment
 Data Sources	Real-time data from sensors	Weather forecasts, soil sensors	Material flow from generation to disposal	Weather forecasts, consumption data	Climate trends, hazard exposure
 Benefits	Detect and predict ecological changes	Optimize irrigation, reduce pesticide use	Improve recycling rates, support circular economy	Balance energy loads, predict consumption	Climate change adaptation planning
 Examples	Air quality monitoring, deforestation tracking	Precision agriculture, sustainable water usage	Monitoring waste lifecycle, improving recycling	Smart grids, renewable energy optimization	Analyzing climate trends, hazard exposure

FIGURE 7.1 Big data analytics for environmental sustainability.

leveraging real-time data collected through advanced sensors, satellite imagery, and remote sensing technologies, environmental monitoring systems can detect and predict changes in ecological conditions with unprecedented accuracy. For instance, air quality monitoring platforms can use big data to assess pollutant levels across urban and rural regions, allowing for prompt pollution mitigation strategies to protect public health and the environment (An et al., 2022). Similarly, forest management systems can track deforestation activities in near-real-time, enabling swift interventions and better enforcement of conservation laws (Haq et al., 2024). In the domain of natural resource management, big data facilitates precision agriculture and sustainable water usage. Farmers can utilize analytics platforms that process data from weather forecasts, soil sensors, and crop health monitors to optimize irrigation, reduce pesticide use, and increase crop yields with minimal environmental impact (Ali et al., 2025). Likewise, water utilities can detect leaks and inefficiencies in distribution networks, leading to more effective water conservation efforts (Wan et al., 2022). Furthermore, waste management systems equipped with data-driven tools can monitor the flow of materials through the waste lifecycle—from generation to disposal—improving recycling rates and supporting circular economy initiatives (Lanzalonga et al., 2024).

Another significant environmental benefit is the ability of big data analytics to improve energy efficiency and accelerate the transition to renewable energy. Smart grid technologies, powered by data analytics, enable utilities to balance energy loads, predict consumption patterns, and reduce transmission losses (Zhang et al., 2018). For example, integrating weather forecasts and real-time consumption data can help optimize the operation of solar and wind power plants, thereby enhancing the reliability and affordability of clean energy sources (Ukoba et al., 2024). Moreover, big data supports environmental risk assessments and climate change adaptation planning by analyzing long-term climate trends, hazard exposure, and vulnerability metrics at granular spatial scales (Hamed et al., 2025; Ullah, Wang et al., 2024). Overall, big data analytics allow stakeholders—including governments, corporations, and nonprofit organizations—to design and implement environmentally sustainable policies and practices. These capabilities also empower communities by making environmental information more transparent and accessible, fostering grassroots engagement and accountability in environmental governance.

7.2.2 Negative environmental impacts

Despite its potential advantages, big data analytics poses environmental risks. Among these, the substantial energy consumption associated with data centers—the backbone of the big data ecosystem—is one of the major disadvantages of big data analytics (Al Kez et al., 2022). These facilities, which store and process large datasets, require significant amounts of electricity for operation and cooling. According to estimates, global data centers account for approximately 1%–1.5% of total electricity use and contribute to significant greenhouse gas (GHG) emissions, especially when powered by nonrenewable energy sources (IEA, 2023). In addition, the rapid proliferation of data infrastructure leads to increased production of electronic waste (e-waste). Servers, hard drives, sensors, and network equipment have finite lifespans and often become obsolete within a few years, contributing to the growing global e-waste crisis (Hossain et al., 2015; Modarress Fathi et al., 2022). Much of this waste contains hazardous substances, which pose serious environmental and health risks if not disposed of properly (Robinson, 2009).

Another concern is the potential for data bias and inaccuracies in environmental modeling and forecasting. Incomplete, outdated, or poorly contextualized data can lead to flawed analyses, misinformed policy decisions, and resource allocations (Glynn et al., 2017). For example, if air quality sensors are unevenly distributed or if satellite imagery lacks resolution in certain areas, the resulting datasets may skew environmental assessments. This could perpetuate environmental injustices by underrepresenting vulnerable communities or misidentifying pollution hotspots. Moreover, the sheer scale of data operations necessitates constant hardware upgrades and software maintenance, which further strains environmental resources (Shamsi et al., 2013). The energy and materials required for the production, transportation, and disposal of this infrastructure underscore the need to consider the full lifecycle impacts of data technologies.

7.2.3 Environmental mitigation strategies and research needs

To reduce the environmental footprint of big data analytics, several mitigation strategies must be adopted across the technology lifecycle. One of the most promising approaches is the development of green data centers—facilities that are powered by renewable energy and designed for maximum energy efficiency (Ghamkhari & Mohsenian-Rad, 2013; Oró et al., 2015). Innovations, such as liquid cooling systems, energy-efficient servers, and modular architectures, can significantly reduce power usage and carbon emissions. Leading tech companies are already investing in such infrastructure, demonstrating that sustainable data operations are both feasible and economically viable. Coupled with infrastructural improvements, robust data governance frameworks are essential to ensure the integrity, transparency, and ethical use of environmental data (Sargiotis, 2024). These frameworks should mandate high data quality standards, promote open-access repositories, and support data sharing among stakeholders. Transparency in data sources and methodologies is key to building public trust and enabling cross-sector collaboration.

On the research front, there is an urgent need to develop algorithms and analytical tools that can detect and correct biases in environmental datasets. Advances in AI and ML can help identify data gaps, validate results, and ensure that decision-making processes are

inclusive and evidence-based. Furthermore, interdisciplinary research is needed to explore the co-benefits and trade-offs of digital technologies within environmental systems, considering factors, such as life-cycle emissions emissions, material intensity, and scalability. Lastly, promoting digital literacy and capacity-building at the community level can empower citizens to engage with environmental data, advocate for sustainable practices, and cocreate solutions. Equipping individuals and institutions with the skills to interpret and apply big data insights will ensure that environmental benefits are equitably distributed and socially inclusive.

7.3 Economic dimension of big data analytics

7.3.1 Positive economic impacts

From an economic standpoint, big data analytics has emerged as a transformative force across industries by enhancing productivity, operational efficiency, and innovation potential (Fig. 7.2). One of the primary advantages lies in its ability to process vast volumes of data in real-time, allowing organizations to make faster and more accurate decisions. Real-time



FIGURE 7.2 Economic transformation and sustainability through big data.

analytics plays a critical role in the proactive maintenance of industrial equipment, reducing downtime and extending asset lifespan. In addition, predictive analytics optimizes supply chains and inventory management, helping companies reduce overhead costs and respond swiftly to changing consumer demands (Wang et al., 2016). Big data also enables firms to gain deeper insights into consumer behavior, preferences, and trends, facilitating personalized marketing and improved customer engagement. By analyzing purchasing patterns and social media interactions, businesses can tailor their products and services to better meet consumer expectations, which enhances customer satisfaction and loyalty. Furthermore, data-driven decision-making strengthens strategic planning, providing firms with a competitive edge in volatile market environments (Zong & Guan, 2024). The integration of big data analytics into decision-making frameworks allows for dynamic scenario analysis, risk assessment, and resource allocation, making organizations more agile and resilient.

The economic potential of big data extends to innovation and entrepreneurship. Startups and established firms can leverage data analytics to identify unmet market needs and develop novel business models, digital platforms, and value-added services (Agostini & Nosella, 2021; Ghobakhloo et al., 2021). For instance, the sharing economy, digital marketplaces, and data-as-a-service (DaaS) models have all benefited from big data capabilities. In sectors like finance, agriculture, and healthcare, data analytics is driving the emergence of precision approaches that enhance service delivery and reduce costs. As a result, big data contributes to economic diversification and the development of knowledge-based economies. At the macroeconomic level, big data supports better economic planning and policymaking. Governments can use data to assess the impact of policy interventions, monitor inflation and employment trends, and design targeted economic programs. Real-time economic indicators derived from big data sources, such as mobile usage, satellite imagery, and online transactions, provide timely insights that complement traditional statistics. Consequently, the integration of big data into public administration can improve governance and foster inclusive economic development.

7.3.2 Negative economic impacts

Despite its substantial benefits, the economic integration of big data analytics is accompanied by several challenges and negative externalities. First and foremost, the setup and maintenance of big data infrastructure demand significant financial investment (Allioui & Mourdi, 2023). Organizations must invest in high-performance computing systems, data storage facilities, analytics software, and skilled personnel. For many small and medium-sized enterprises (SMEs), these costs are prohibitive, creating a digital divide where only well-resourced firms can reap the full benefits of big data technologies (Falahat et al., 2022). This disparity contributes to market concentration, where large corporations with vast data reserves and advanced analytics capabilities gain disproportionate advantages. These companies can refine their operations, predict market shifts, and control pricing mechanisms more effectively than their smaller counterparts. As a result, competition may be stifled, and innovation curbed, particularly in sectors where data access is a key determinant of success. Moreover, the commodification of data by dominant firms may lead to exploitative practices and reduced consumer choice.

Another significant concern is the potential displacement of workers due to automation and data-driven decision-making (Zubair, 2024). As companies adopt predictive analytics, ML algorithms, and robotic process automation (RPA), routine and analytical jobs are increasingly being performed by machines. This trend threatens job security in roles, such as data entry, administrative support, and even middle management (Van Doorn et al., 2023). Although new jobs are being created in data science and information technology, the transition requires significant reskilling and may not be accessible to all segments of the workforce. The misuse of data for economic manipulation also poses serious threats. In unregulated environments, data can be exploited to manipulate markets, engage in price discrimination, or conduct insider trading. For instance, real-time financial data could be used unethically to manipulate stock prices or gain unfair trading advantages. Such practices undermine the integrity of economic systems and erode public trust in data-driven governance.

7.3.3 Economic mitigation strategies and research needs

Addressing the economic risks associated with big data analytics requires a multifaceted approach that emphasizes inclusivity, security, and ethical governance. One of the most pressing needs is the development of cost-effective and scalable big data solutions tailored for SMEs (Falahat et al., 2022). Cloud-based analytics platforms, open-source software, and data-sharing partnerships can lower the entry barrier for smaller firms and encourage innovation across diverse sectors. Public-private partnerships can also play a crucial role in building shared data infrastructure and promoting knowledge transfer. Governments should incentivize the development of digital ecosystems that support startups and foster competitive markets (Sipakoly, 2024; Font-Cot et al., 2023). This includes investments in broadband connectivity, data literacy programs, and innovation hubs that serve as incubators for data-driven enterprises.

Cybersecurity and data protection are essential components of a resilient economic data infrastructure. Organizations must adopt robust cybersecurity measures to protect sensitive economic and financial data from breaches, theft, or tampering (Saeed et al., 2023). Regulatory agencies must also enforce compliance with data protection laws and ensure that firms adhere to standards for secure data storage, transmission, and processing. Open data initiatives represent another important strategy for democratizing access to economic data. By making anonymized and aggregated data publicly available, governments and institutions can level the playing field for all market participants (Sargiotis, 2024). Open data fosters transparency, enables independent research, and encourages innovation by allowing diverse actors to analyze and build upon shared information.

To curb monopolistic practices, regulatory frameworks should be updated to reflect the evolving nature of digital markets. Competition laws must address data concentration and ensure that dominant firms do not abuse their data assets to exclude competitors or exploit consumers (Sargiotis, 2024). Additionally, policies should promote data interoperability and portability, allowing users to transfer their data across platforms and reduce vendor lock-in. Moreover, research is needed to further understand the long-term economic implications of big data analytics, particularly in relation to labor markets, taxation, and productivity (Falahat et al., 2022). Studies should be conducted to examine the effects of data-driven

automation on different employment sectors and identify effective strategies for workforce adaptation. Economic models should also incorporate data as a factor of production, capturing its role in value creation and redistribution.

In conclusion, while big data analytics holds substantial promise for enhancing economic efficiency, innovation, and resilience, its deployment must be guided by inclusive, ethical, and forward-looking strategies. By addressing infrastructure gaps, ensuring fair competition, and safeguarding economic data, stakeholders can harness the full potential of big data in building sustainable and equitable economies.

7.4 Social Dimension of big data analytics

7.4.1 Positive social impacts

In the social realm, big data analytics holds considerable promise for improving public welfare, enhancing service delivery, and strengthening community resilience (Fig. 7.3). One of the most prominent applications of big data lies in public health systems. By aggregating and analyzing health records, mobile data, and social media activity, public health authorities can detect disease outbreaks in their early stages, monitor public health trends in real-time, and efficiently allocate medical resources. For instance, during the COVID-19



FIGURE 7.3 Pros and cons of big data in social sustainability.

pandemic, big data was instrumental in contact tracing, predicting hotspots, and optimizing vaccine distribution. Predictive models fed by big data can identify patterns of illness or vulnerability, enabling targeted interventions that are both proactive and resource-efficient. Big data also plays a critical role in disaster preparedness and emergency management. The integration of satellite imagery, weather data, social media reports, and sensor networks enables real-time monitoring of disaster risks, such as floods, heat waves, droughts, earthquakes, or wildfires (Bryant, 2022; Syed et al., 2022; Rahman et al., 2023; Ullah, Aldossary, et al., 2024). This data-driven approach allows authorities to issue timely warnings, coordinate rescue operations, and manage postdisaster recovery more effectively. During the 2015 Nepal earthquake, crowdsourced data and satellite mapping helped humanitarian organizations rapidly assess the situation and deliver aid to affected regions (Bryant, 2022).

Furthermore, big data fosters greater transparency and accountability in governance. Governments can use open data platforms and real-time feedback tools to involve citizens in decision-making processes and monitor public service performance. For example, digital platforms that track municipal services, such as waste collection, water delivery, and transportation, allow citizens to report issues and receive updates, promoting more responsive governance (Das, 2024). Similarly, transparency in budgeting, procurement, and policy implementation is enhanced through big data dashboards that provide accessible and up-to-date information to the public (Matheus et al., 2020). Moreover, data analytics can be used in education and social services to identify at-risk students, tailor learning programs, and assess the effectiveness of social interventions. Social media analytics, sentiment analysis, and digital surveys provide insights into public opinion and emerging social issues, helping policymakers better understand community needs (Verma, 2022). These capabilities contribute to more inclusive, adaptive, and efficient social systems that are crucial for sustainable development.

7.4.2 Negative social impacts

Despite these benefits, the social implications of big data are not uniformly positive. One of the most pressing concerns is data privacy. The extensive collection and analysis of personal data, ranging from health records and financial transactions to social media activity and geolocation, can result in significant breaches of individual privacy (Banerjee, 2019). When mishandled, this data can be exploited for commercial gain, surveillance, or discrimination. High-profile data scandals, such as the misuse of social media user data, have underscored the vulnerability of personal information in the digital age. Moreover, big data systems can inadvertently perpetuate or even exacerbate existing social inequalities. If data collection methods are biased or incomplete, marginalized communities may be underrepresented or misrepresented in datasets. Algorithms trained on such data can produce skewed results that reinforce stereotypes or deny access to essential services (Sreerama & Krishnamoorthy, 2022; Shahbazi et al., 2023). For instance, predictive policing algorithms that rely on biased crime data have been shown to disproportionately target minority communities, raising concerns about algorithmic justice and fairness.

There is also the issue of digital exclusion. Access to digital tools and connectivity is uneven across and within countries, often along socioeconomic, geographic, or gender lines. Communities lacking access to digital infrastructure or literacy may be excluded from data-

driven services and decision-making processes (Kaluarachchi, 2022). This digital divide not only limits the reach of big data benefits but can also deepen existing social disparities. In addition, there are ethical concerns related to consent and autonomy. Many users are unaware of how their data is collected, processed, and used, often agreeing to terms of service without understanding the implications. This lack of transparency undermines informed consent and erodes trust in data-driven institutions.

7.4.3 Social mitigation strategies and research needs

To address these challenges, a range of mitigation strategies must be implemented to safeguard social equity and ethical standards in big data applications. First and foremost, robust data privacy regulations are essential. Legislation, such as the General Data Protection Regulation (GDPR) in the European Union, provides a strong model for ensuring individuals' rights over their data, including the right to access, correct, and delete personal information (Hoofnagle et al., 2019). Similar frameworks should be developed and enforced globally to protect personal data from misuse. Moreover, ethical data governance must become a core principle in organizations that manage and utilize data. This involves establishing clear protocols for data collection, storage, sharing, and analysis that prioritize transparency, accountability, and public interest. Independent oversight bodies, data ethics committees, and regular audits can help ensure compliance and foster public trust.

Another critical area is algorithmic fairness. Developers and data scientists must actively identify and mitigate biases in datasets and models. This can be achieved through inclusive data collection practices, diverse representation in development teams, and rigorous testing of algorithms for disparate impacts. Tools, such as fairness audits, bias detection software, and explainable AI, can support these efforts. To bridge the digital divide, investments are also needed in digital infrastructure, education, and capacity-building, particularly in underserved communities. Governments and international organizations should prioritize universal access to digital services and promote digital literacy initiatives that empower individuals to engage with and benefit from big data technologies. Inclusive data governance requires the meaningful participation of diverse stakeholders, including civil society organizations, local communities, and vulnerable populations, in the data life-cycle—from collection and analysis to interpretation and application (Kaluarachchi, 2022; Marcucci et al., 2023). Participatory approaches not only improve the relevance and accuracy of data but also ensure that data-driven decisions reflect the needs and values of all segments of society.

7.5 Balancing sustainability and big data potential

While the potential of big data to advance sustainability is immense, it must be approached with a balanced and critical perspective (Fig. 7.4). As data-driven technologies become increasingly integrated into the fabric of society, it is crucial to ensure that their deployment supports long-term sustainability goals without creating new or exacerbating existing challenges (Bachmann et al., 2022). Big data, by nature, involves collecting, storing,

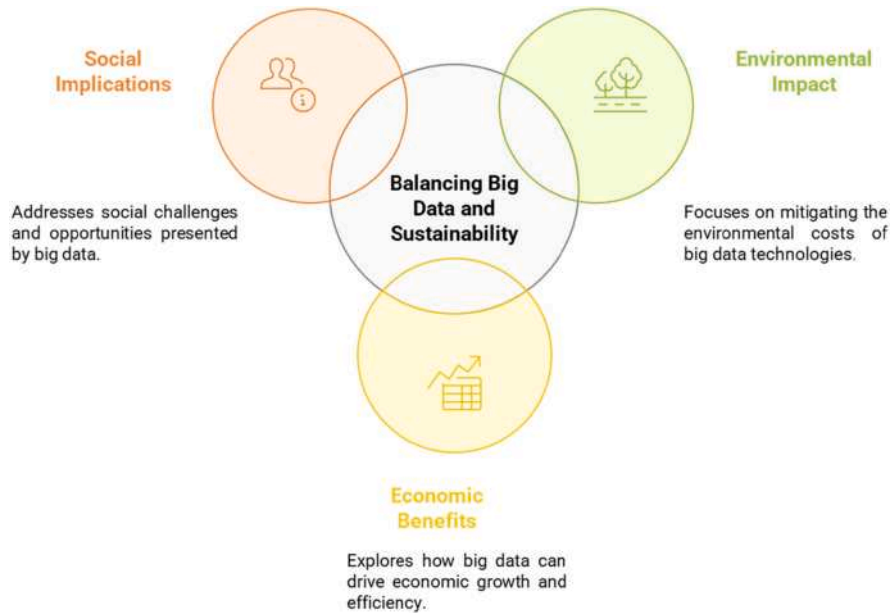


FIGURE 7.4 Navigating the intersection of big data and sustainable development.

and analyzing massive volumes of information, often in real-time. This capability offers opportunities for real-time monitoring of climate variables, predictive modeling of resource consumption, and improved decision-making in sectors, such as energy, agriculture, transportation, and public health. However, harnessing this potential requires a deliberate and holistic understanding of its environmental, economic, and social ramifications.

A systems-thinking approach is necessary to navigate the complexities of big data and sustainability. This means recognizing that interventions in one area—optimizing industrial energy use through data insights—may have unintended consequences, such as increased energy demand from data centers or potential job displacement due to automation. Sustainable development, as articulated in the United Nations Sustainable Development Goals (SDGs), calls for a harmonious balance between economic growth, environmental protection, and social inclusion (Gupta & Vegelin, 2016). Therefore any strategy that employs big data for sustainability must integrate these three pillars to avoid fragmented or counterproductive outcomes.

From an environmental standpoint, the trade-offs are particularly pronounced. The deployment of big data technologies can enable smarter ecological management, such as precision agriculture, urban traffic flow optimization, and emissions monitoring. Yet, the infrastructure supporting big data, particularly cloud computing facilities and data centers, demands significant energy and water resources, contributing to carbon emissions and potential ecological stress. Innovations, such as energy-efficient computing, green data centers powered by renewable energy, and hardware recycling programs, are essential to mitigate these effects. Further, assessing the lifecycle environmental impact of data technologies can help inform more sustainable design and operation choices.

Economically, big data can drive substantial benefits through enhanced productivity, improved resource allocation, and the creation of new business models (Schroeder, 2016). Companies that effectively leverage data insights can streamline supply chains, reduce operational costs, and develop more targeted and sustainable products and services. For instance, in the manufacturing sector, predictive maintenance based on real-time data analytics can reduce waste and prolong machinery life; however, these advantages are often unevenly distributed. Data-rich firms tend to consolidate market power, leading to monopolistic tendencies that stifle competition and innovation among smaller players. Moreover, the high costs associated with developing and maintaining big data infrastructure may exclude SMEs from fully participating in the digital economy. Addressing these economic disparities requires policies that promote open data initiatives, equitable access to analytics tools, and public-private partnerships that support digital capacity-building across all business sectors.

On the social front, big data holds promise for enhancing transparency, improving service delivery, and empowering communities (Janssen et al., 2020; Sargiotis, 2024). Governments can use data analytics to better allocate public resources, respond to disasters more effectively, and design inclusive urban planning solutions. In healthcare, data-driven models can identify disease trends and inform more personalized treatments. Nonetheless, the social implications of big data must be handled with care. The risk of privacy violations, algorithmic bias, and exclusion of marginalized groups from data-driven decision-making can deepen existing inequalities (Banerjee, 2019; Gupta & Vegelin, 2016; Sreerama & Krishnamoorthy, 2022). For example, if datasets are not representative or if algorithms are trained on biased inputs, the resulting outputs can reinforce systemic discrimination in areas, such as policing, hiring, or credit scoring. Ensuring social sustainability in big data systems involves adopting rigorous data governance frameworks that emphasize transparency, accountability, and equity.

One of the most pressing concerns across all three dimensions is the ethical use of data (Janssen et al., 2020; Sargiotis, 2024). Ethical data governance must prioritize consent, data protection, and the responsible use of insights. Clear regulations and guidelines are needed to prevent misuse, such as the exploitation of data for market manipulation or unauthorized surveillance. Ethical frameworks should also promote data democratization, ensuring that individuals and communities have agency over how their data is collected, analyzed, and utilized. Integrating ethics into the design phase of data systems, through mechanisms, such as ethical AI principles, fairness audits, and inclusive stakeholder engagement, can proactively address many of these concerns.

Collaboration among stakeholders is critical to achieving a sustainable and equitable data ecosystem. Policymakers have a central role in setting standards, funding sustainable data infrastructure, and enforcing data rights. Researchers must explore the intersection of big data and sustainability through interdisciplinary studies that consider technological, environmental, economic, and social variables. Businesses should adopt sustainability-oriented innovations and embed corporate social responsibility into their data practices. Meanwhile, civil society can advocate for transparency, challenge inequities, and contribute local knowledge that enhances data relevance and inclusivity.

To operationalize a balanced approach to big data and sustainability, a shared vision must be established—one that aligns digital innovation with the broader goals of climate

action, social justice, and inclusive economic development. This vision should be grounded in resilience, adaptability, and continuous learning, recognizing that data ecosystems are dynamic and constantly evolving. Future research and practice should aim to develop integrated frameworks that map the interplay between big data interventions and sustainability outcomes, identifying both synergies and trade-offs. By embracing a systems-thinking mindset and fostering cross-sector collaboration, the power of big data can be harnessed not just for efficiency or profit, but for the collective well-being of people and the planet.

7.6 Conclusion and future directions

Big data analytics holds tremendous promise for accelerating progress toward sustainability across environmental, economic, and social dimensions. Its ability to uncover patterns, enhance predictive capacities, and support evidence-based decision-making makes it a powerful enabler of sustainable development. From monitoring carbon emissions and optimizing resource use to improving healthcare and public services, big data has proven its versatility in addressing some of the world's most pressing challenges. However, realizing this potential requires a nuanced and balanced approach. The energy demands of data infrastructure and issues of data privacy, algorithmic bias, and unequal access to data technologies present serious risks that could undermine sustainability efforts if left unaddressed. A systems-thinking framework is essential to navigate these complexities, enabling stakeholders to anticipate trade-offs and maximize synergies across sectors. Equally important is the ethical dimension of big data use. Transparent governance, inclusive data practices, and community engagement are vital to ensuring that data-driven innovation does not reinforce existing inequalities but rather fosters equity and empowerment. Bridging the gap between technological innovation and sustainable practice will depend on inclusive collaboration between governments, researchers, businesses, and civil society. Ultimately, the future of big data in sustainability lies in our ability to align digital innovation with human-centered and ecologically responsible values. By fostering shared responsibility and adaptive strategies, big data can move from being a disruptive force to a transformative tool for building a more just, resilient, and sustainable world.

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Industry 4.0: digital technologies for sustainable outcomes

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8.1 Introduction

The fast growth in Industry 4.0 has not only revolutionized industrial processes but has also reshaped how businesses operate and interact with their environment (Bilal et al., 2024). Industries of all kinds are using Industry 4.0 technologies to empower their operations for a strong and long-term competitive advantage. A recent survey (Benjamins et al., 2020) found that 65% of organizations currently use generative AI regularly, indicating high expectations for the technology's effects on innovation and productivity in businesses. One of the reasons is the understanding of the scalability provided by information technology, which enabled the acceleration of testing of business models. In this regard, it is acknowledged that the widespread adoption of digital technology (DT) presents a disruptive chance to improve and optimize production system performance, giving those who successfully implement it a significant competitive edge. At its base, Industry 4.0 includes different DTs such as artificial intelligence (AI), the Internet of Things (IoT), blockchain, data analytics, Automation, cybersecurity, and cloud computing to improve productivity, efficiency, and decision-making. The focus of these technologies is largely linked to improving the firm's performance, but they also significantly contribute to sustainability through minimizing environmental effects, reducing waste, and optimizing resource consumption. Globally, the industrial sector is facing pressure from public and government authorities to adopt eco-friendly practices in their processes and align their objective with sustainable development goals (SDGs) using data-driven solutions.

Since sustainable development has gained widespread acceptance, a firm's capacity for innovation is no longer only centered on financial gains (Škare et al., 2024). It must simultaneously advance in the social, economic, and environmental spheres. Green supply chains and sustainable practices are significant areas of research for academics and practitioners, and they include a series of green initiative activities. Since sustainability is the primary focus of the circular supply chain and all logistics network design activities are founded on green practices, the other concepts utilized in sustainability include reuse, recycling, and a circular supply chain. The main purpose of the adoption of green and social practices by the firms is to ensure the welfare and safety of all stakeholders through the reduction of waste, greenhouse gases, and energy consumption (Agyabeng-Mensah et al., 2020). There are disruptive and innovative technologies, including IoT, big data analytics, and blockchain, which not only provide a competitive advantage but also have a positive effect in terms of sustainability (Kamble et al., 2021). The significance of DTs for the long-term viability of the industrial sector has become more apparent in the wake of the COVID-19 epidemic. According to Chatzistamoulou (2023), DT helps European industries to make the transition to sustainability, implying that using DTs allows them to change to more sustainable production paradigms. IoT-enabled smart grids and energy management systems enhance sustainability during power consumption, while, on the other hand, AI-driven automation reduces inefficiencies in production and manufacturing. Similarly, blockchain provides transparency and data analytics, which are useful for traceability and accurate prediction and support the sustainable supply chains.

Although the advantages of DTs are well acknowledged, implementation is very challenging. Digital transformation is a complex process, and its effectiveness is severely undermined by the urgent need to manage the digital skills gap. Also, digital transformation may be hindered by environmental factors, employee resistance to change, implementation costs, cybersecurity risks, and technological mismatches (Davison et al., 2023). Many employees worry that DT will take over their jobs and eventually put them out of business. As a result, employees are hesitant to engage solely with digital devices or software that puts employees at risk. So, academics and business managers need to comprehend how DT improves sustainable organizational performance and sustainable innovation capability (Daimi & Rebai, 2023). The objective of this chapter is to explore how DT can contribute to improving sustainability, what the challenges and barriers are in their adoption, and how these challenges can be addressed. Also, it will provide the strategies to use the Industry 4.0 innovations to develop a resilient and greener economy.

8.2 Digital technologies in Industry 4.0

The evolution of Industry 4.0 has changed the landscape of industries through the integration of modern DTs in supply chains, manufacturing, and service sectors. These technologies help to get the analysis of real-time data and to get intelligent decision-making through automation that can help to develop efficient, flexible, and sustainable operations (Fig. 8.1).

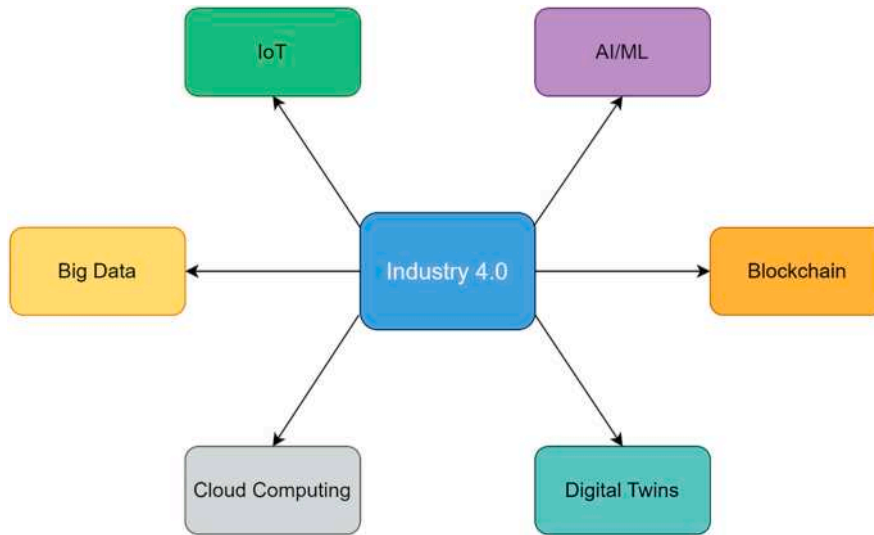


FIGURE 8.1 Industry 4.0 digital technologies framework.

8.2.1 Overview of key technologies

Industry 4.0 is controlled by several transformative DTs that combine machines, people, and systems to develop smart factories and intelligent ecosystems. The main technologies that have revolutionised the industrial landscapes include as follows:

- **IoT:** The IoT is the process of connecting physical devices and systems to a network to exchange and store data. This link enables you to take advantage of real-time, optimized usage and device monitoring.
- **Machine learning (ML) and AI:** The revolution in the field of data science in manufacturing is powered by AI and ML, which are transforming this sector through smart and efficient processes to improve efficiency and resource utilization.
- **Blockchain:** Blockchain is a digital ledger where every transaction or event is recorded and linked together in a secure, transparent, and immutable way. Blockchain is used in many sectors, but in manufacturing, it can be used to trace and track the product starting from raw materials to the final consumers, including the whole supply chain, hence promoting ethical sourcing and sustainable practices.
- **Cloud computing:** Cloud computing provides scalable, efficient, and low-priced ways to process and analyze large amounts of data. By using cloud computing, professionals and industry experts can work remotely to store, analyze, and recover data. It facilitates collaborative data access and cost-efficient solutions.
- **Digital twins:** The advent of the digital twin transformed the manufacturing industry's digital revolution. These digital models merely serve as creative and customized sandboxes that help you create the whole layout and design. They can create replicas for different physical assets and optimize the processes through simulations, which can lead to reduced waste and improved efficiency.

- **Data analytics and visualization:** This technology is useful in analyzing large amounts of data to uncover hidden patterns and trends. The data can be structured or unstructured, and this technology is useful for transforming traditional decision-making processes into data-driven.

8.2.2 Evolution from traditional to digital-driven sustainability

The transformation from traditional industry practices to digital-driven decision-making is a complete paradigm shift. In the past, the focus of the industry was to increase the output to get maximum profit without considering environmental degradation but now with the concept of Industry 4.0, firms are focused on optimizing resource consumption and reducing waste and carbon footprints to improve productivity.

- **Traditional approach:**
 - To keep the linear supply chains having minimum integration
 - Data collection and monitoring were done manually
 - High consumption of energy with high wastage of resources.
- **Digital-driven approach:**
 - Fully integrated system having real-time data collection
 - Use of resources optimally using predictive analytics
 - Using smart technology, reduction in emissions and improved energy efficiency (Fig. 8.2).

The evolution of DT and its use in industrial processes to improve sustainability is in line with the SDGs developed by the UN, particularly SDG 12, which concerns responsible consumption and production, and SDG 13, which concerns climate action.

8.3 Role of digital technologies in achieving sustainability

The existing traditional approaches for industries and businesses have changed through the adoption of DTs and by focusing on the concepts of environmental sustainability and resource optimization. These emerging DTs are playing a very critical role in the reduction of carbon footprint, wastage of resources, and consumption of energy because these industries are facing huge pressure worldwide to adopt sustainable practices. Digitalization helps with real-time monitoring, automation, and data-driven decision-

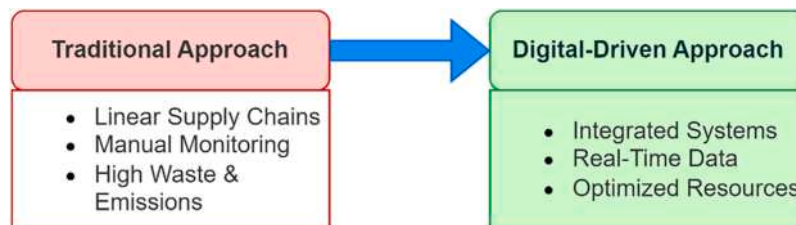


FIGURE 8.2 Digital transformation.

making to help organizations reduce resource wastage and optimize operational efficiency. These are DTs that can be integrated into the industrial processes to achieve smart production, eco-friendly management of resources, and intelligent supply chains. These innovations can collectively contribute towards the circular economy, reduction of carbon footprints, and sustainable developments to strike a balance between economic growth and environmental sustainability.

This section will explore how DT can improve the sustainability in industries. IoT helps in getting the real-time monitoring and data from environment, smart automation in industry, and efficient energy systems. This section will also discuss the role of blockchain in achieving transparency in supply chains, data analytics for the data-driven sustainability, and digital twins for impact analysis (Fig. 8.3).

8.3.1 Internet of Things and smart systems

IoT is the key contributor to industrial transformation towards sustainable processes. IoT in Sustainable Manufacturing and Industrial Automation. IoT consists of interconnected sensors, devices, and different interconnected systems, and it helps to get real-time data for monitoring, optimization, and automation. By using IoT, there is a significant improvement in energy efficiency, reduction in emissions and waste, which can contribute to a more sustainable and eco-friendly system.

8.3.1.1 Internet of Things for energy efficiency and smart grids

Energy efficiency is the core contributor to sustainable development, and IoT plays a pivotal role in the reduction of energy consumption and optimization of power management (Pandiyan et al., 2024). The use of IoT-powered smart grids and energy monitoring

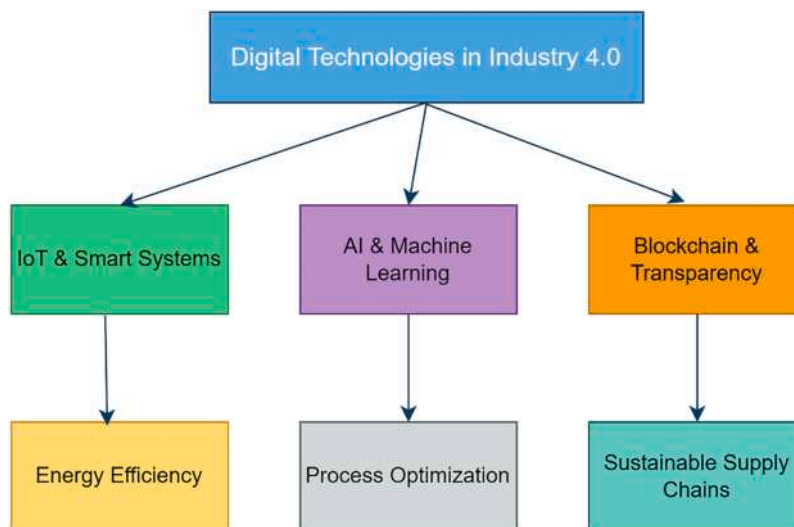


FIGURE 8.3 Digital technologies driving sustainability.

systems provides important and actionable insights to industries, which are useful to reduce the inefficiencies and to improve the sustainability. Given are some important applications of IoT for energy efficiency.

- IoT-based smart grids adjust the distribution of power dynamically and integrate different renewable sources of energy such as solar and wind to reduce the dependence on fossil fuels.
- Smart sensors are useful in tracking the consumption of energy in different facilities, which can identify the inefficiencies in the processes and help in real-time optimization.
- IoT-based automation can adjust the usage of power according to the demand and, hence, can reduce the peak loads and prevent the wastage of energy.
- ML-based algorithms can analyze the data obtained from sensors to predict the optimal patterns for energy usage and, hence, can help in reducing the operational cost.

8.3.1.2 Internet of Things in sustainable manufacturing and industrial automation

The manufacturing and industrial automation are transformed by the use of IoT to lead to sustainable production processes (Mittal et al., 2018). Industries that use IoT sensors and automation can help in reducing the waste of raw material, improve efficiency, and improve the supply chain (SC) sustainability. The core benefits of IoT for sustainable manufacturing include as follows:

- The monitoring system in industries based on IoT can detect the machine failures, which can reduce the unplanned downtime and excessive consumption of resources.
- Sensors can track the real-time usage of raw material, which can ensure the precise allocation and reduce the waste.
- IoT helps in real-time tracking of logistics, optimizes the planning of routes, and decreases the consumption of fuel as well as environmental emissions.
- Another advantage of using the smart sensors is to detect the pollutants in the air, water, and is useful to support the compliance with the regulations related to the environment (Fig. 8.4).

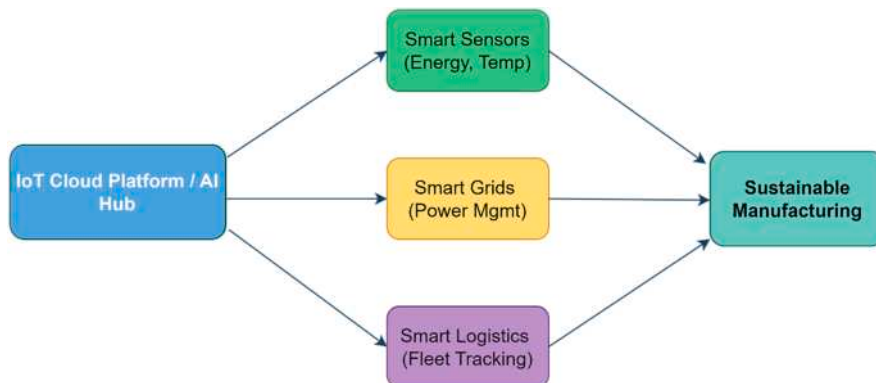


FIGURE 8.4 Internet of Things (IoT) cloud platform architecture.

8.3.2 Artificial intelligence and machine learning

In modern industries, AI and ML have played a transformative role in optimizing the industrial processes, reducing waste, and improving sustainable actions. These tools improve the capability of the organizations to analyze the large sets of data, identify the patterns, search the inefficient processes, and make data-driven decisions to improve the productivity and economic layout while reducing the environmental degradation (Anbarasu et al., 2025). ML and AI can contribute towards sustainability in various ways such as optimization of processes, predictive maintenance, efficient resource consumption, and smart decision-making. By using the insights obtained from AI, a self-regulating system can be developed that can help in the reduction of consumption of energy, reduce emissions, and increase the circular economy. This section will explore the effects of AI and ML on sustainability indicators.

8.3.2.1 Artificial intelligence for process optimization and waste reduction

The main application for the AI in sustainability is the process optimization, where AI-based systems are used to analyze the data, which can be used to increase efficiency and reduce waste (Ibnouf et al., 2025). Different sectors such as manufacturing, logistics, energy, and agriculture are becoming more and more dependent on the AI systems to promote the self-learning and self-improving systems, which can contribute to increasing the sustainability. The main contributions of AI towards sustainability include as follows:

- Energy distribution systems can be better optimized by using AI models, which can reduce the consumption of energy and can integrate renewable energy resources to improve sustainability.
- AI can improve the forecasting of inventory, routing of logistics, and procurement of materials, which can lead to a decrease in emissions and a reduction of waste.
- One of the important libraries used in AI is computer vision, which can detect the defects in manufactured products in real time and can be very helpful for the reduction of waste and inefficiencies in production.
- AI is used for the real-time adjustment of resources according to the demand pattern, which ensures the minimum wastage of resources.

8.3.2.2 Artificial intelligence-driven predictive maintenance and sustainability

For sustainable manufacturing and infrastructure management, predictive maintenance is very important. Reactive maintenance models, which were used in the past, were the main cause of unexpected failures, resource wastage, and downtime of machines, which affect the sustainability negatively. AI-based maintenance uses the algorithms that are based on ML models. These models can predict the failure of equipment before their occurrence and support the proactive approach. The main advantages of using AI-based predictive maintenance include as follows:

- Early fault detection can reduce the wear and tear.
- Use of AI ensures the operation of machines and equipment at optimal efficiency, which can prevent the extra usage of energy.

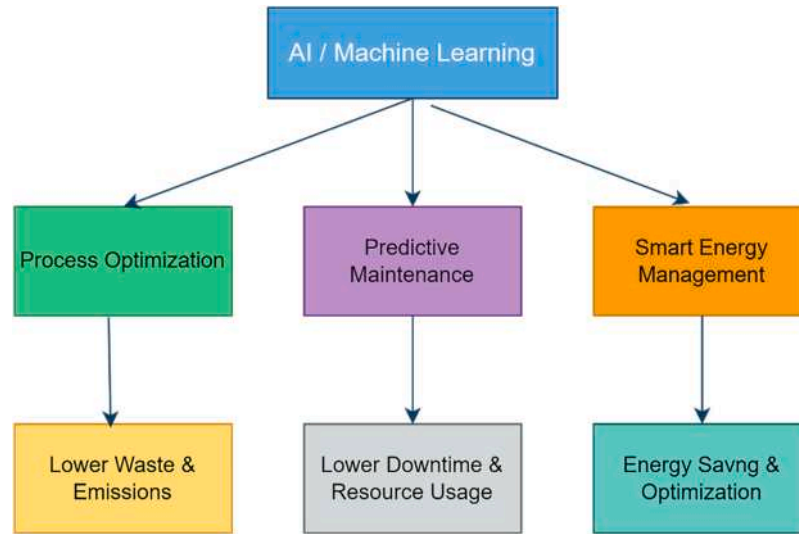


FIGURE 8.5 Artificial intelligence (AI)-enabled sustainable systems.

- AI can be used to reduce the unplanned breakdown of machines, which can further reduce the wastage of material and energy.
- Optimal schedule of maintenance can be developed by using AI, which can improve the overall efficiency of the system (Fig. 8.5).

8.3.3 Blockchain for transparency and ethical supply chains

Blockchain is regarded as a technology that will revolutionize the supply chain (SC) since it is a transparent and tamper-resistant system that will enhance the tracking and tracing system at every stage of the SC (Munir et al., 2022). Blockchain is a distributed accounting system that uses a peer-to-peer network created by computer technology to manage the expanding data. Because blockchain places a high priority on health and safety, it also aids in attaining environmental sustainability. Blockchain technology can assist in the discovery of all counterfeit goods that are detrimental to society because a fair record guarantees that all things purchased are ethically correct. It also ensures basic rights and transparency. By keeping track of the items, rework can be decreased, which lowers gas emissions and resource use. The implementation of a carbon tax is an example of a sustainable SC. Previously, measuring carbon footprints was very challenging, but blockchain technology will make it simple to track a company's footprints and help determine how much tax should be applied to them. In Northern Europe, blockchain is utilized to incentivize consumers to deposit recyclable plastic bottles or cans in exchange for monetary rewards in the form of cryptographic tokens. One example is social plastic, which aims to reduce plastic waste by turning plastic into cash. This section will further explore how blockchain helps to develop sustainable and ethical practices in SC (Fig. 8.6).

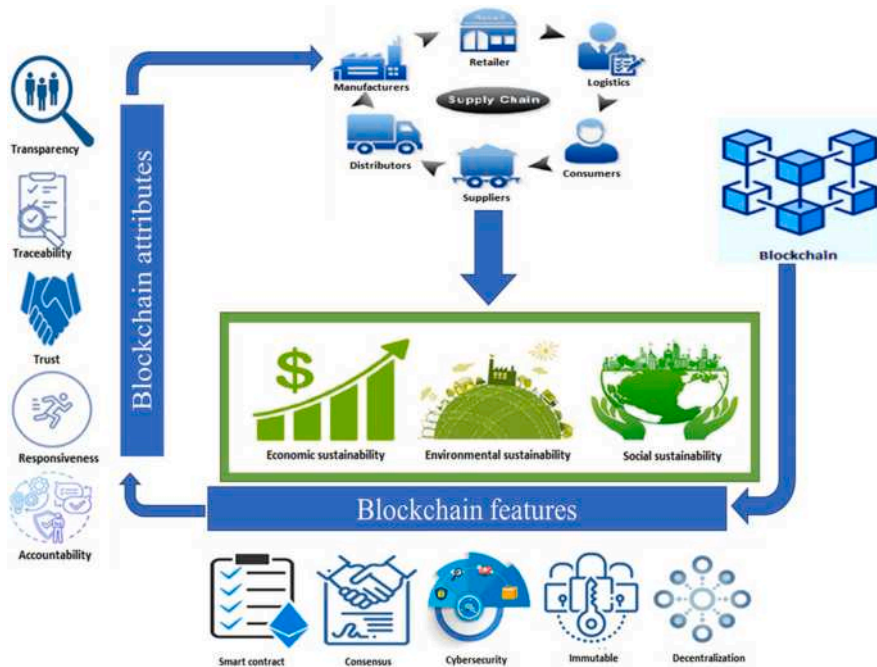


FIGURE 8.6 Blockchain features and sustainability indicators (Munir et al., 2022).

8.3.3.1 Blockchain for sustainable sourcing

If products, raw materials, and services are purchased in a way that it has very low environmental impacts, ethical labor practices prevail, and it supports fair trade, then it is called sustainable sourcing. However, it is very difficult for the firms to verify the compliance of its suppliers as a structure of SC is very complex and multitiered. The main benefit of the blockchain is that it offers transparent and verifiable records during all sourcing activities. Blockchain can support the sustainable sourcing in the following ways:

- By using the blockchain technology, a record of every transaction (raw material purchase and product movement) is permanently recorded, which can support for the prevention and manipulation of records.
- The movement of material and products can be traced by using the blockchain technology in real time. This tracing and tracking ensure the compliance of the company with ethical and environmental standards.
- The contracts based on blockchain make sure that all the suppliers are fulfilling the standards and requirements of sustainability, before any payments are made.
- One of the advantages of blockchain is that it enables tamper-proof sustainability certifications (e.g., Fair Trade and Carbon Neutral), which increases the confidence of customers in ethical sourcing. Nestlé uses the blockchain for the tracing of coffee beans, where it is originated. It leads to fair Labor practices and sustainable farming (Fig. 8.7).

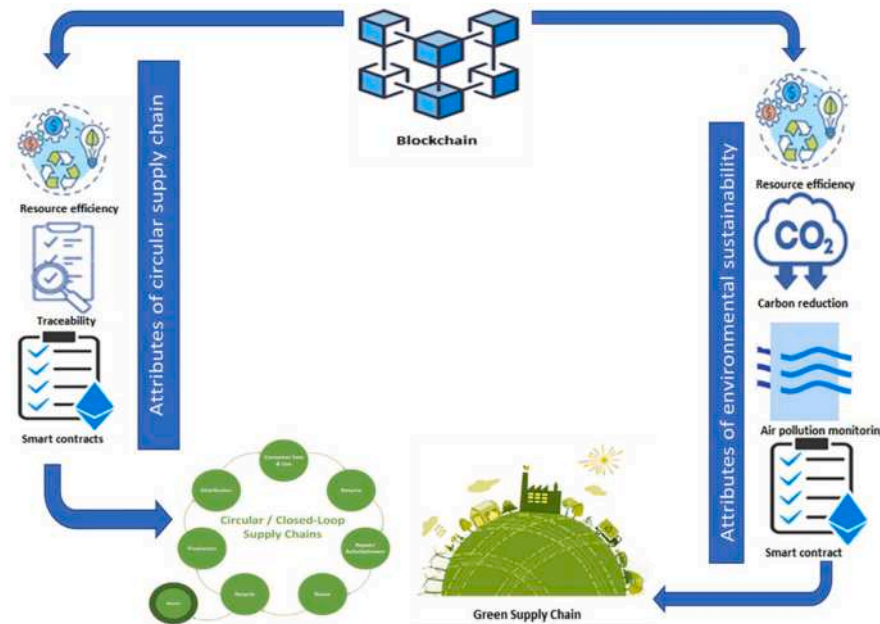


FIGURE 8.7 Blockchain features and environmental sustainability (Munir et al., 2022).

8.3.3.2 Enhancing the circular economy with blockchain

The main purpose of circular economy is to keep the use of material for a long time, that is, as long as possible. It supports the concepts of waste reduction, resource efficiency, and recycling (Apeh & Nwulu, 2025). Due to the lack of accountability and transparency, recycling efforts are wasted. Blockchain can solve this issue by tracking the flow of material, ensuring proper waste management, and ensuring efficient reuse and recycling. The role of blockchain in the circular economy can be explained as follows:

- Blockchain is an excellent ledger that can track and record all the product lifecycle starting from the extraction of raw material to its disposal. It enables better resource management.
- Firms and governments can utilize the blockchain technology for the verification of recycling efforts and can ensure that waste is properly processed.
- Blockchain can track the emissions of carbon at every stage of production, which can allow the firms to reduce the environmental degradation.
- If the government and other organizations announce the incentive programs for the consumers and organizations in the form of rewards for sustainable practices, then blockchain can be a very effective tool (Fig. 8.8).

8.3.4 Big data analytics and cloud computing

The term “big data analytics” (BDA) describes a method for extracting significant information from massive data sets. Using historical data, big data predictive analytics

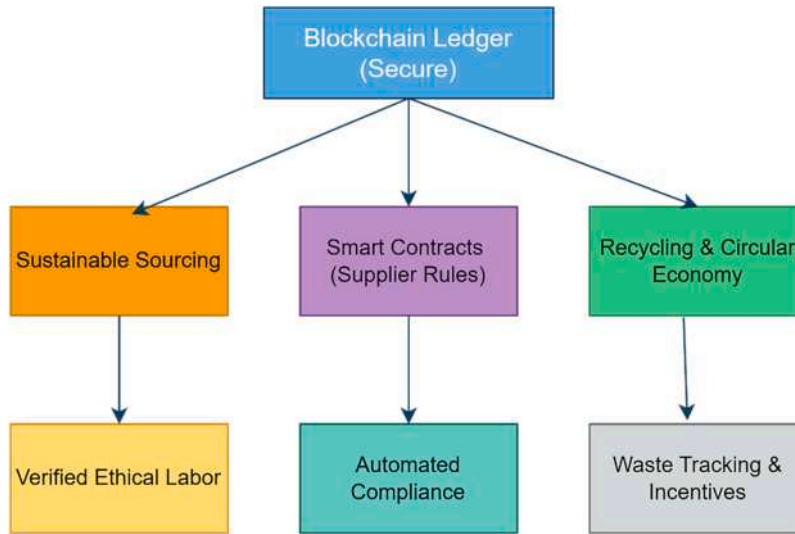


FIGURE 8.8 Blockchain for ethical and sustainable supply chains.

(BDPA) uses a variety of algorithmic techniques to anticipate future events. In today's sector, companies are fiercely competing to gain market share. Businesses must continue to earn a profit to be able to give returns to shareholders, but sustainability is more than just financial success (Munir et al., 2023). Consumers' decisions to buy are constantly influenced by ethical and environmental considerations. Environmental performance is the outcome of a company's strategic actions that limit its environmental impact. These outcomes include the organization's performance in various areas, including resource waste, air pollution, solid waste, energy conservation, and other adverse environmental effects. The financial, ethical, and social advantages in Europe are greatly strengthened by BDA (Munir et al., 2024). Predictive analytics abilities have a big influence on SC performance in terms of the triple bottom line. Equity, gender parity, child labor, hunger, and safe working conditions are among the many challenges facing developing economies. A variety of indicators seen in stock markets and financial statements can be used to gauge economic performance. Furthermore, environmental performance is measured by the Global Reporting Initiative or ISO 14001. However, the social component of sustainability has not gotten enough attention because of the complexity of the human issues involved and the challenges in achieving measurable results. BDA and cloud computing can provide cost-effective solutions, which can be useful for green manufacturing and the development of smart structures. This section will explore how these technologies can contribute to sustainable development.

8.3.4.1 Data-driven decision-making for resource optimization

Data analytics is very important and useful in making decisions based on past data to optimize the industrial processes and to reduce the consumption of resources through the identification of inefficiencies, the prediction of demand, and continuous monitoring.

Sustainable decision-making can be achieved by advanced data analytics and ML-based models, which help the organizations to reduce wastage and improve the operational efficiency.

- BDA can be used to analyze the pattern for the usage of power for the optimization of efficiency and to decrease the unnecessary consumption of energy.
- It can track the water usage and can help in the detection of leakages in industrial processes.
- Through a vast amount of data, inventory control, selection of suppliers, and logistic efficiency can be improved, and carbon footprints can be controlled.
- Through data analysis, overproduction can be controlled, and resources can be managed according to accurate demand prediction.
- Through data analysis, all the activities with high emissions can be identified, and alternative options with eco-friendly processes can be adopted. For example, Walmart uses its capacity to analyze big data for waste reduction.

8.3.4.2 Cloud-based solutions for sustainable business practices

Cloud computing provides energy-efficient computing resources, hence decreasing the requirement of infrastructure, which requires high-power consumption devices. If firms use the cloud, they can improve collaboration, reduce carbon footprints, and streamline their processes with minimum impact on the environment. Cloud computing can support the sustainability indicators in the following ways:

- It can eliminate the requirement for physical servers, hence reducing the consumption of power and electronic waste.
- Tools based on cloud computing can promote virtual teams and remote work. It can reduce emissions based on traveling and energy costs.
- Firms can avoid the unnecessary use of energy by dynamically scaling their computing power.
- They can optimize the efficiency of grid by completely analyzing and monitoring the real-time production and consumption of energy.
- Different cloud providers such as *Google Cloud*, *Microsoft Azure*, and *AWS* use the data centers, which are dependent on renewable resources. In this way, they reduce the environmental degradation (Fig. 8.9).

8.3.5 Digital twins and sustainable product lifecycle management

Digital twins can create a virtual representation of physical assets. It can enable real-time monitoring, process optimization, and predictive analytics. This technology can support the organizations through simulation and analysis and, hence, can contribute to improve the sustainability through reduction of waste, optimized consumption of energy, and increased lifespan of products. A digital twin is a dynamic digital replica of a physical system, which is continuously updated with real-time data that is collected from the sensors based on IoT, ML models, and cloud computing. Through the integration of digital twins into industrial processes, firms can improve the sustainability through better resource efficiency and

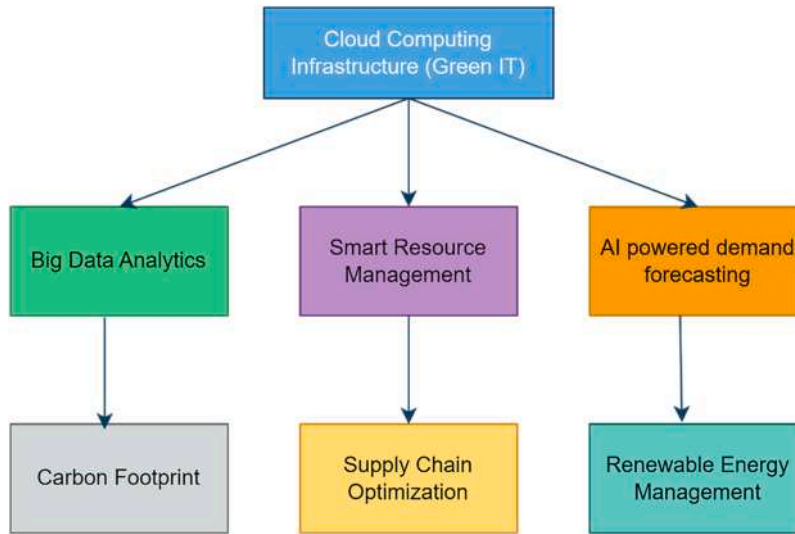


FIGURE 8.9 Big data and cloud computing for sustainable business practices.

reduce the environmental impacts. This section will discuss the different ways by which digital twins can improve sustainability.

8.3.5.1 Digital twins for environmental impact reduction

One of the power tools is digital twins, which can reduce the carbon footprints through better process optimization, early detection of failures by predicting failures, and reduction of waste (Cao et al., 2025). Industries such as manufacturing, energy, construction, and transportation use digital twins to increase efficiency and reduce emissions. Digital twins can reduce the environmental impacts in the following ways:

- Simulation of the consumption of energy patterns in factors and different residential and commercial buildings. It can support real-time adjustment to minimize the extra use of energy.
- Digital twins can stop the equipment failures and breakdowns through proper monitoring of equipment health, which can help increase the lifespans and minimize the waste of material.
- The tracking of carbon footprint can be conducted through digital twins. It can support the firms to schedule their production and adopt the green practices.
- Digital twins can improve the visibility of logistics. It can be helpful to reduce the emissions through transportation and improve the inventory management.

8.3.5.2 Applications in circular economy models

The concept of circular economy is based on the reduction of waste, resource efficiency, and the extension of the product lifecycle. Digital twins can better provide the tracking of

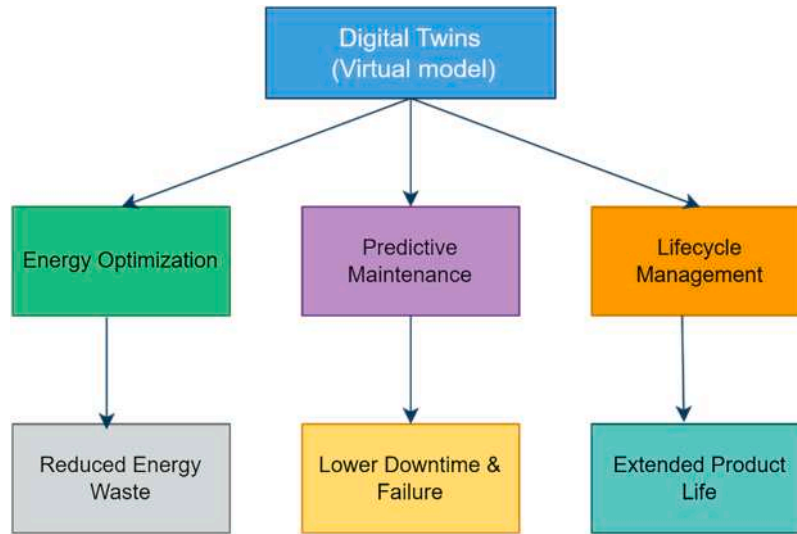


FIGURE 8.10 Digital twin-enabled sustainability model.

usage of products, provide better strategies of repair, and improve the recycling efforts. Digital twins can improve the circular economy in the following ways:

- It can continuously monitor the conditions of products. Instead of the disposal of products, it supports refurbishment, resale, and repurposing.
- Virtual simulations help the firms to test the materials before their massive production. It can then help in the reduction of waste.
- Digital twins can analyze the streams of waste and optimize the efforts of recycling, which can further improve the circular economy (Fig. 8.10).

8.4 Challenges in implementing digital technologies for sustainability

In the preceding sections, a detailed discussion was presented that , how DTs, including IoT, AI, Blockchain, Big Data, Cloud Computing, and Digital Twins, have transformed the industries into a sustainable and resilient entity, but there are significant challenges and barriers in the adoption of these technologies. These challenges can be broadly divided into financial, technical, infrastructural, and regulatory barriers. These are all obstacles that affect the successful adoption of these technologies in businesses. In this section, it will be discussed in detail how these challenges affect the implementation of these technologies to achieve SDGs.

8.4.1 High costs and return on investment concerns

One of the main problems for the adoption of DTs is the high cost of infrastructure, skilled workforce, and software and hardware facilities. If organizations must move towards

sustainability-driven transformation, they must justify and balance the return on investment (ROI). The following are the main challenges related to return on investment:

- Implementation of high-tech tools like AI, IoT, Blockchain, and Cloud Computing requires a large amount of capital to develop hardware, software, and workforce skills.
- The companies are always hesitant to make long-term investment for sustainability solutions because they cannot quantify the financial benefits of this investment.
- When DTs are integrated into the existing processes and workflows, it may lead to disrupt the whole process and can lead to the loss of productivity.
- Developing countries do not have many resources that they can use to subsidize their industries for the adoption of DTs to achieve sustainability. For example, Small and Medium Enterprises are not able to afford the systems that can be used for predictive maintenance. Although they know its long-term benefits related to operational costs and reduction in energy waste. The following are the solutions which can be adopted to control these barriers.
- The firms can reduce and control their initial costs if they shift towards Cloud and AI-as-a-Service models.
- Government, policymakers, and environmental protection agencies can introduce tax benefits to all the small and medium-sized companies to take measures for the adoption of DTs.
- Firms can incrementally integrate these technologies in different phases instead of full-scale and sudden adoption.

8.4.2 Cybersecurity risks and data privacy issues

If organizations are adopting and becoming more dependent on DTs, then it will increase the risk of data breaches and cyberattacks. These concerns of cybersecurity can discourage the firms from the adoption of DTs for sustainable solutions. The following are the challenges of data privacy and cybersecurity:

- The devices that are connected can be targeted by cyberattacks, which can cause manipulation of data and operational shutdowns.
- Blockchain is very effective for transparency; however, it is insecure for data confidentiality.
- There can be a competitive disadvantage from unauthorized access to sensitive data.
- There is privacy laws that exist globally, but many organizations are unable to comply with them.

The following are the potential solutions to lessen the negative effects of cybersecurity issues:

- Organizations can use models trained on ML to detect the real-time threat and then some security response, which is automatically generated.
- Firms can encrypt sensitive data generated through IoT and also can use private blockchains to secure all kinds of transactions.
- Threats can be minimized by adhering to all the policies according to regulatory frameworks for all the initiatives of digital sustainability.

8.4.3 Digital divide and technological barriers in developing countries

In developing countries where there exist major challenges of low-speed Internet, lack of infrastructure for computing, and scarcity of skilled labor, the digital divide is a significant concern. People do not have equal access to DTs, which creates a barrier towards sustainability efforts and increases the industrial disparities. The following are the key challenges in developing countries:

- Many developing regions do not have infrastructure for reliable Internet connectivity. They do not have access to cloud servers and computing power.
- There is a high cost for digital transformation, which is difficult to bear by the local industries.
- A significant and alarming problem is the skill gap, which is a gap in the expertise of deployment and management of DTs.
- Policymakers and different business managers have no awareness for Industry 4.0 and its potential for sustainability.

The following measures can be taken as a potential solution:

- Governments should collaborate with the tech firms to help them for expansion of digital infrastructure.
- Technology companies should work to introduce cloud computing services at a low cost so that small organizations in developing countries can adapt them.
- Subsidized training programs should be initiated in AI, IoT to bridge the skills gap.

8.4.4 Integration challenges with existing infrastructure

There are a large number of organizations that operate on incompatible legacy systems with modern technologies. It makes it very complex and expensive for their integration. The integration of these older systems with these emerging technologies requires expertise and financial resources.

- Many organizations use very old machinery, and it is very difficult for their connectivity to modern DTs.
- Companies are putting efforts to integrate data at different platforms, making it very difficult to conduct real-time analysis.
- Upgradation of companies through smart sensors and automation requires a lot of time and money (Fig. 8.11).

8.5 Future prospects and policy recommendations

The implementation of DTs to achieve sustainability has already been proven to demonstrate significant positive effects for the reduction of waste, efficient energy, and resource management but to further increase their positive outcomes, government, industries, academia and all other stakeholders should collaborate to overcome the

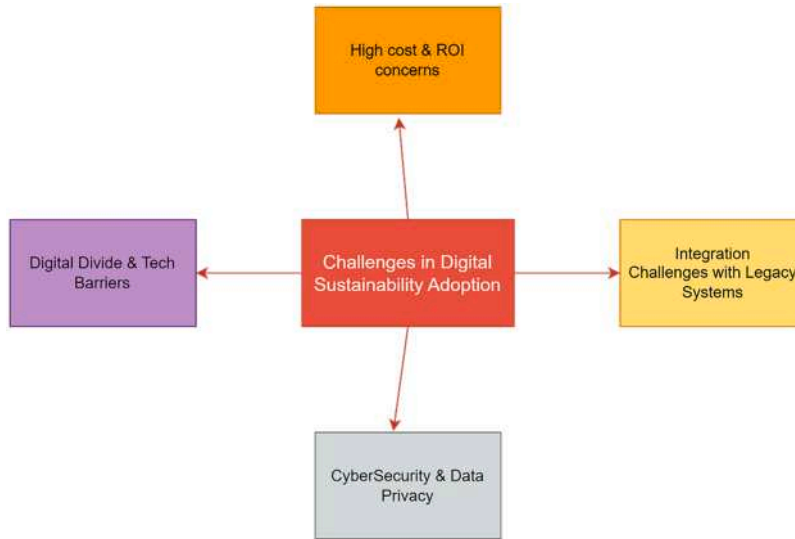


FIGURE 8.11 Challenges in implementing digital technologies for sustainability.

challenges and barriers and implement the supportive policies. In this section, it will be discussed in detail what the prospects of DTs are for sustainability efforts and what the recommended policies are.

8.5.1 Strategies for wider adoption of digital technologies

To achieve the maximum output of DTs in the sustainability domain, there is a need to develop long-term strategies with a focus on affordability, scalability, and accessibility. Organizations and government institutions should prefer the scalable solutions. Moreover, AI-based automation and high-quality Internet connectivity are required for digital transformation. Government bodies should provide tax benefits, low-interest loans, and subsidies to small and medium-level businesses so that they can be encouraged to integrate blockchain, smart grids, and AI solutions for sustainability tracking. To monitor the climate, emissions, and other sustainability indicators, the use of open-access AI and big data should be promoted. There should be customized guidelines which should be sector-specific to develop smart factories, to promote green logistics, to encourage green economy, and smart agriculture. For example, Singapore has developed a Green Plan for the year of 2030 to integrate DTs for the development of urban infrastructure and reduce the carbon footprints by 50% by the end of 2050.

8.5.2 Policy frameworks supporting green innovation

At government level, there is a need to develop and implement strong policy and regulatory frameworks to for the promotion of green innovation for long-term financial incentives, Government should impose high taxes on high level of carbon emissions and

should provide incentives to all the industries adopting blockchain, AI, and other data-driven technologies for sustainable solutions. They should develop a formal mechanism for sustainability reporting regulations to ensure that these organizations follow all the environmental regulations. Different developed countries should collaborate with the developing regions to form standardized frameworks for the adoption of blockchain in the supply chain for green innovations. There should be collaborative research between academia and industry towards sustainable digital transformation. It will not only help develop a strong regulatory framework for Industry 4.0 but also help in the reduction of carbon emissions for better compliance with global sustainability goals.

8.5.3 Role of governments, industries, and academia in driving sustainable digital transformation

There is a requirement for collaboration of all the stakeholders for the successful adoption and implementation of the digital sustainability transition. These stakeholders include the government, academia and industries. Governments can develop national-level policies, provide incentives to IoT-based smart grids, automation, and carbon tracking based on blockchain. They can invest in fast computing such as the infrastructure of 5 G, which can help in the fast processing of real-time data to promote sustainable operations. The government can help with the new research projects and startups that are focused on AI and DTs, leading towards sustainability. Industries can use predictive AI models to reduce waste, to adopt optimized logistics, and to promote the circular economy. Industries can adopt blockchain technologies to bring transparency and ethical practices to the whole supply chains. Academics can focus on AI-driven solutions for environmental modeling and sustainable solutions using digital twins. In academics, different training programs can be developed based on IoT, ML models, and blockchain. They also can add interdisciplinary subjects in their curriculum based on the knowledge of engineering, DTs, and environmental science. For example, MIT initiatives about the digital sustainability in collaboration with industries and governments for the optimized distribution of renewable sources are commendable (Fig. 8.12).

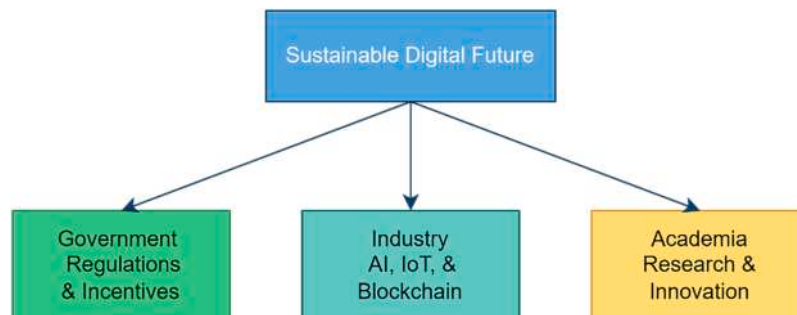


FIGURE 8.12 Collaborative framework for sustainable digital transformation.

8.6 Conclusion

Incorporation of Industry 4.0 DTs has not only brought an improvement in efficiency, transparency, and resource optimization but also redefined sustainable standards in different sectors. The way companies monitor their environmental effect, reduce waste, and implement circular economy models has been completely transformed by technologies such as AI, IoT, Blockchain, Data Analytics, Cloud Computing, and Digital Twins. This chapter, with an emphasis on its applications in intelligent production, energy management, ethical supply chains, predictive maintenance, and sustainable lifecycle management, has investigated a revolutionary role played by DT in obtaining sustainable results. These technologies have great potential, but their implementation is full of challenges such as high costs, threats of cybersecurity, digital inequality, and integration problems. To ensure their wider adoption, policy frameworks, industrial initiatives, and academic research collaborations must align with the goal of digital-driven sustainability.

The transition to a digitally supported sustainable future requires a holistic approach where technology is powered by economic feasibility, environmental necessity, and regulatory support. The Fourth Industrial Revolution (Industry 4.0) has shown how digital innovations can transform industries into more efficient, resistant, and ecologically conscious entities. However, the sustainability of digital transformation is not an automatic outcome; actually, it requires the active participation of industries, government institutes and research-oriented organizations. Using real-time IoT monitoring, AI to optimize processes, blockchain for ethical supply chains and digital twins for resource efficiency, industrial sector can achieve long-term economic growth with minimal ecological footprint. As DT continues to evolve, future research must solve challenges related to digital waste, power consumption of AI energy, and the scalability of sustainable technological solutions. Ethical considerations, inclusivity, and cross-border cooperation must also be preferred to ensure that sustainability-focused on Industry 4.0 benefits all sectors and economics.

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Digital twins, supply chains, and sustainability: an overview

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9.1 Introduction

In the face of escalating environmental challenges and increasing demands for efficient production systems in today's complex global economy, supply chains (SCs) are under increasing pressure to become more resilient, efficient, and sustainable (Ivanov & Dolgui, 2021). Digital transformation is revolutionizing traditional SC models, and one of the most promising innovations in this domain is the concept of Digital Twins (DTs). A DT is a virtual replica of a physical asset, process, or system that allows organizations to simulate, predict, and optimize performance in real time. When integrated with sustainable SC management (SSCM), DTs can enhance efficiency, reduce waste, and minimize environmental impact. The application of DT technology in production systems is a game changer for sustainability (e.g., Qi & Tao, 2018; Ragazzini et al., 2024). By integrating advanced analytics, IoT, and AI, DTs facilitate a comprehensive approach to designing and managing environmentally friendly production processes. Many uses and applications of DTs have been merging in business (e.g., Attaran and Celik, 2023; Bhandal et al., 2022).

Through the lenses of the Quadruple Bottom Line (QBL) sustainability pillars (see Fig. 9.1), this chapter gives an overview of the role of DTs in fostering sustainability within SC management, their key components, benefits, challenges, and future prospects.

9.2 Understanding sustainable supply chain management and analytics

Simply put, a SC involves all the stages, directly or indirectly, in fulfilling a customer request (Chopra, 2019). Initiated by demand, a SC spans from sourcing raw materials

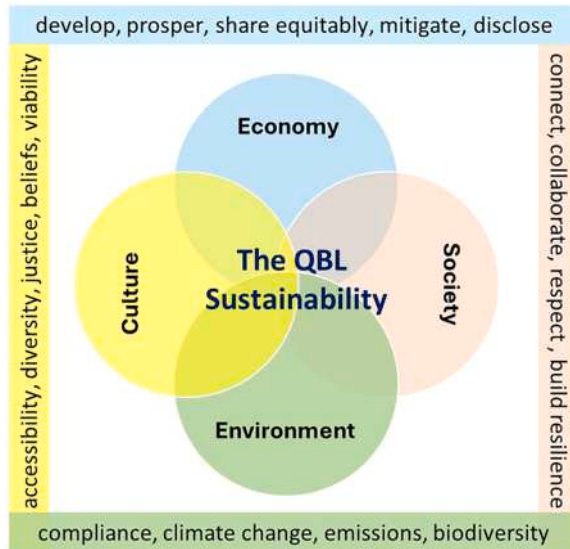


FIGURE 9.1 The QBL aspects. *QBL*, Quadruple bottom line.

through manufacturing to the final delivery of the finished product (good or service) to the consumer, including all the logistical steps of transportation, storage, and distribution across different SC members in the process.

Fig. 9.2 presents a pictorial of a typical closed-loop SC (CLSC) framework. In a conventional SC, the flow of materials is from the suppliers to the end customers in one direction. Therefore it is termed *forward* logistics or SC. However, in a CLSC, the end-of-life, end-of-use, or simply the returned products—for various reasons, such as misfit or poor quality or no longer needed—are brought back into *reverse* logistics or SC. Products may be revalorized in multiple ways, for example, by reselling, remanufacturing, or recycling. Hence, adding a reverse SC to a forward one closes and makes it more sustainable.

Typical SC members include suppliers, manufacturers, distributors, wholesalers, retailers, and consumers. Directly or indirectly, all SC members are customers of raw material suppliers. The consumer can be considered the *end customer*, who buys the product and derives value from its usage. It is crucial in SC modeling and analysis to determine for whom the problem is solved. The company for which the problem is analyzed is the “focal SC member” or “focal company.”

In Fig. 9.2, the focal SC is chosen to be the manufacturer. All the storing and moving activities related to raw and semifinished products going into the manufacturer’s plant are termed *inbound logistics*. Once the product is finalized and ready for selling, it is shipped out from the manufacturer through various marketing channels—for example, via a retailer or from the manufacturer’s outlet. The product eventually reaches consumers.

Logistics related to the finished goods is the *outbound logistics* function. Companies from which the focal company receives materials are termed *upstream* SC members. All those receiving orders from the focal company are *downstream* SC members. For example, if the

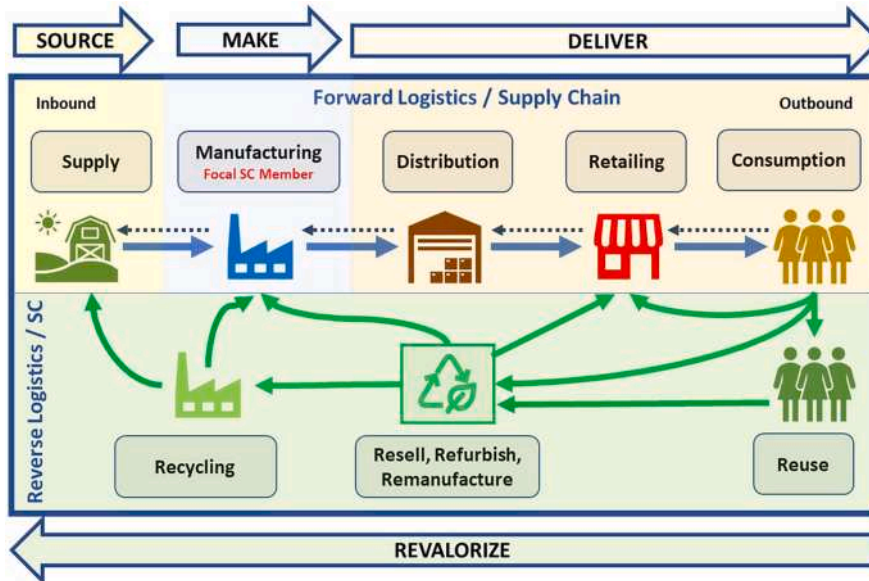


FIGURE 9.2 A closed-loop supply chain configuration (authors' own work). SC, Supply chain.

focal SC members were a retailer, the manufacturer from which it directly purchases would be a Tier-1 upstream SC member. Then, the supplier from which that manufacturer procures would be a Tier-2 upstream SC member from the retailer's relational position in the SC.

The SC Operations Reference (SCOR) Model—maintained by the Association of SC Management—helps understand the SC holistically. Fig. 9.2, using the SCOR model, identifies the SC activities within the set of suppliers as *source*, the manufacturing process as *make*, all the activities in outbound logistics as *deliver*, and the collection of products injected back into the CLSC via a reverse SC for revalorization, simply as *return*. These aggregations of the activities through the SCOR model help provide better design and utilize SC performance metrics (e.g., Ben-Daya et al., 2019; Chehbi-Gamoura et al., 2020; Maestrini et al., 2017). Ülkü and Engau (2021, p.1128) define Sustainable SC Analytics as “the set of activities and analytic tools that are big-data-driven in order to provide both optimal solutions and innovative foresight to complex SC decision-making problems with the goals of achieving cultural, economic, environmental, and social sustainability pillars.” As shown in Fig. 9.3, in a broader sense, SSCM should embrace the QBL pillars by integrating cultural, economic, environmental, and social considerations into SC operations. The goal is to maintain cultural viability, foster economic prosperity, minimize adverse environmental impacts, and enhance social responsibility.

By employing SCA, SC managers can maximize resource efficiency by reducing waste, conserving resources via smart operations, and implementing green logistics through decarbonizing their transportation, warehousing, and packaging functions by advanced shipment policies (e.g., Ülkü, 2012). Also, the QBL pillars comprehensively guide the SC sustainability in ethical sourcing by ensuring fair trade and labor practices (e.g., Bhavsar et al., 2021) and toward a circular one (cf. Ülkü et al., 2022). However, as expected, as control

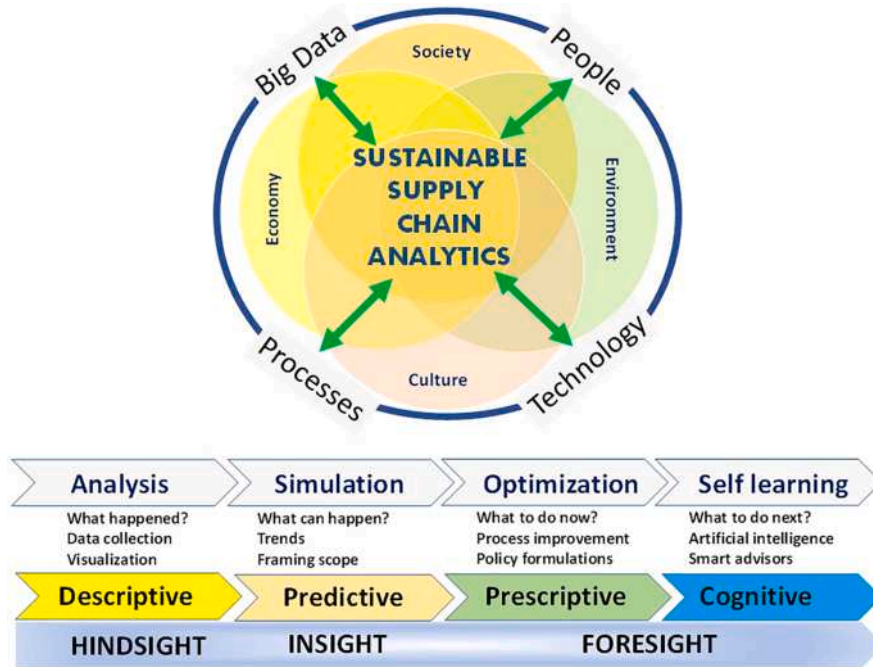


FIGURE 9.3 Sustainable supply chain analytics (authors' own work).

and performance metrics evolve for SCs, new challenges emerge. These include a lack of real-time visibility, relational complexity in managing multitier suppliers, cost constraints in implementing sustainability initiatives, and possibly, resistance to organizational change. To relieve risks in such transitions, DTs bring about new methods and opportunities. To that end, one needs to have a basic understanding of DTs and their potential use in SSCM.

9.3 Understanding digital twins

9.3.1 Definition and concept

DTs are dynamic and bidirectional digital representations of physical objects or systems based on simulation technologies. If the relationship is unidirectional, meaning the virtual entity reflects the physical entity but does not influence it, the instance will be called a digital shadow (Juarez et al., 2021). The simulation uses real-time data, artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) to model and simulate real-world behaviors to understand the present, predict the consequences of choices, and suggest a course of action (Psarommatis & May, 2023). DTs collect data from the physical world through sensors and the virtual world through databases and then impact the physical world through actuators in a constant feedback and action loop. Originally developed for product lifecycle management applications (Grieves, 2022), DTs have since expanded into

various domains, including SC management. It is used in a wide variety of applications, from supplier relationship management to the elimination of waste, logistics management, or assets optimization (Guo & Mantravadi, 2024). Thanks to real-time monitoring, DTs considerably reduce the decision-making process and provide quick feedback and metrics to decisions (Fuller et al., 2020; Grieves & Vickers, 2016). Simulations allow to test competing options before implementation, allow to anticipate failures and schedule maintenance proactively, or identify areas for energy and resources optimization and waste reduction.

9.3.2 Components of a digital twin

A DT consists of three core components: the physical entity, the virtual entity, and the communication and analytics layer, split into a realization and a metrology cycle (Jones et al., 2020). The physical entity represents a real-world object that exists independently of the DT: a manufacturing plant, a warehouse, a logistics system with several vessels, etc. It may represent a complex system or only part of it and be built around a single process or an entire value chain. In more recent applications, living beings such as livestock or humans have also been twinned. The physical entity exists in a specific environment that influences it and must also be measured and fed into the virtual entity to be an accurate representation.

The virtual entity is a copy, or a twin, of the physical entity. Twinning, or the process of creating a virtual twin, is achieved through several methods of physical metrology, for instance, sensors that inform the virtual entity of any changes in the physical world.

The communication layer is a constant cycle of measuring changes in the physical entity and recording them in the virtual entity, and computing changes in the virtual entity and realizing them through actuators in the physical entity. This double process is called a feedback loop, which applies in both directions for continuous improvement and adaptative response. Depending on the application, a wide array of technologies may be used in the communication and data integration layer, especially in real-time optimization scenarios.

In the DT of a SC, the virtual entity is “a virtual system composed of (1) a digital visualization of a physical SC and its elements (e.g., firms, flows, and products) in a computer model, (2) digital technologies providing data about the physical object (e.g., sensors, blockchain, and clouds), and (3) descriptive, predictive, and prescriptive analytics for decision-making support” (Ivanov, 2024, p. 2220).

The three components are illustrated in Fig. 9.1 in the context of a physical sustainable SC (PSSC) and its virtual counterpart, the DT sustainable SC (DTSSC).

Fig. 9.4 shows a pictorial of the three components of a DT SC: physical entity, virtual entity, and the communication between them. The focus is on a sustainable SC (SSC), an SC that embraces the four pillars of the quadruple bottom line (QBL), namely, economic prosperity, societal impact, environmental well-being, and cultural viability (e.g., Ülkü & Engau, 2021). Then, that generic SSC configuration is modeled over four fundamental functions of an SC, whereby the raw materials are purchased (source), then a product is manufactured (make), and then the final product is delivered to or picked up by the customers (deliver). However, because of better environmental and economic reasons, those products in the forward SC that are returned due to malfunction or other reasons due to customer behavior (cf., Currie et al., 2020) and those end-of-life and end-of-use products are put back into the reverse SC for recovering more value and environmental revalorization (revalorize).

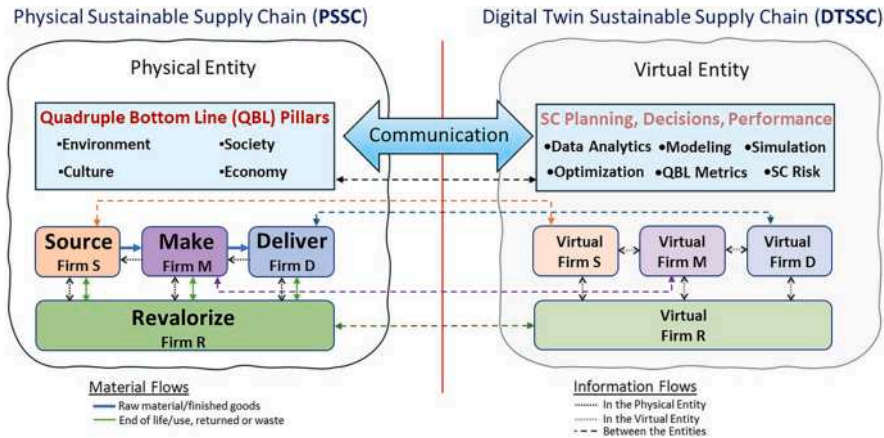


FIGURE 9.4 Example of digital twin of a sustainable supply chain, authors' own work. SC, Supply chain.

Those SC functions are labeled as Firms S, M, D, and R, respectively, for the sourcing, making, delivering, and returning and recovery, where all those firms exchange material and information. The physical entities are the individual firms and the SC as a whole. Virtual entities exist for each firm since each partner of the SC has its own goals and needs for a DT. For instance, Firm S may be interested in a simulation of the price of raw material depending on market conditions. Firm M has a negotiated price with Firm S, and the material price variations do not affect them as much, but they want to optimize their energy consumption per unit produced. Each firm's virtual and physical entities interact through a bidirectional communication layer. The value of DTs in SC comes when additional information communication flows are established between firms' physical and virtual entities.

9.3.3 Evolution of digital twins in supply chains

The concept of DTs in SC management has evolved from basic simulation models to sophisticated AI-powered platforms capable of real-time decision-making. Advances in cloud computing, big data analytics, and IoT have accelerated the adoption of DTs, making them a strategic enabler for sustainable SCs (cf. [Ülkü & Mansouri, 2024](#)).

Increasing applications of DT affirm the buy-in by various industries. For example, in the automotive industry, automakers are leveraging DTs to design energy-efficient assembly lines, monitor real-time emissions, and optimize SC logistics. For instance, a leading manufacturer used DTs to reduce material waste by 25% and energy consumption by 15% in a new production facility ([Schleich et al., 2017](#)). Wind and solar energy companies use DTs to optimize turbine placements, predict maintenance needs, and simulate weather impacts. A wind farm operator achieved a 20% increase in energy output through DT-enabled optimization. A major consumer goods company implemented DTs to monitor water usage, energy consumption, and waste generation across multiple facilities. The initiative resulted in a 30% reduction in water usage and a 40% decrease in waste ([Brous et al., 2020](#)).

The literature on DT in SCM is rich. A quick search on Elsevier's Scopus abstract database reveals that 884 articles have been published with the keywords "SC" and "digital twin" since 2011, with a notable growth year-to-year starting in 2017, as shown in Fig. 9.5

Fig. 9.6 Word link of articles with the keywords "Digital Twin" and "Supply Chain Management," based on title and abstract. Authors' own work, generated with VOSviewer 1.6.20.

Recently, DTs have gone beyond their use in the plan, make, and delivery process to focus on more strategic issues, such as resilience against the COVID-19 pandemic or geopolitical events and improving SC collaboration (Guo & Mantravadi, 2024) and coordination (Sabbaghnia et al., 2024). An example of the resilience application of DT is the application of ML to adjust inventory and cash flow in the context of physical and financial disruptions (Badakhshan & Ball, 2023). In this case, the DT is trained on cash and inventory replenishment decisions to suggest a course of action based on detected events in the physical entity. Concerning the possibilities for SC cooperation, modern DTs simulations can include several actors alongside the lifecycle of a product, for instance, the silicon photovoltaic circular economy and the CO₂ emission and power consumption needed at each step (Bartie et al., 2021). These applications have been made possible by improvements in ML and the facilitation of inter-organizational data integration through network innovations such as cloud computing and 5 G networks.

9.4 The role of digital twins in sustainable supply chain management

9.4.1 Enhancing visibility and transparency

By integrating IoT, AI, and blockchain, DTs provide end-to-end visibility, allowing firms to track environmental impacts, carbon footprints, and resource efficiency across global

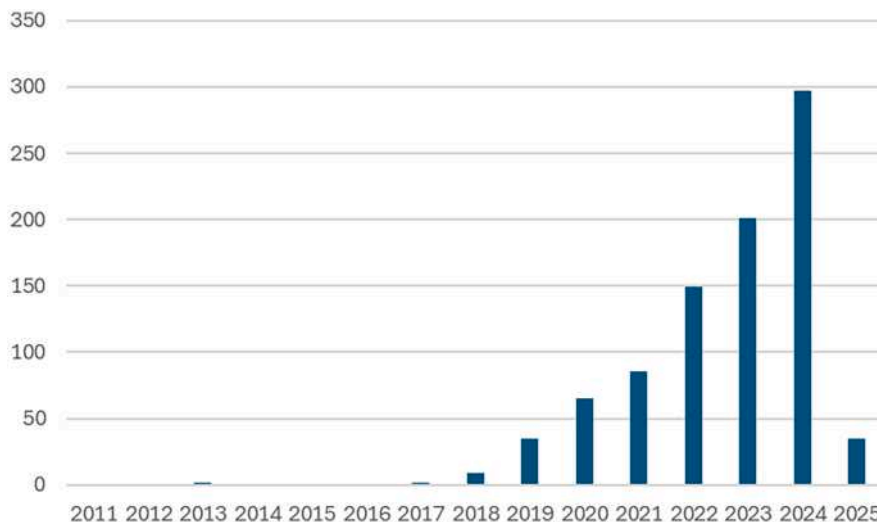


FIGURE 9.5 Scopus publications for "Digital Twin" and "Supply Chain" yearly distribution.



SCM, supply chain management.

into circular, regenerative systems (e.g., Ülkü et al., 2022).

9.4.2 Optimizing resource utilization

consumption. By integrating IoT sensors, AI, and predictive analytics, DTs allow companies

to identify inefficiencies, reduce waste, and improve asset utilization (Tao et al., 2019). For instance, in warehouse management, DTs analyze space optimization, reducing unnecessary storage costs and lowering carbon footprints. In transportation logistics, DTs optimize fleet routing by considering factors such as traffic, fuel efficiency, and emissions, ensuring more sustainable delivery models (Ivanov & Dolgui, 2021). By simulating various operational scenarios, businesses can predict demand fluctuations and adjust resource allocation accordingly, reducing overproduction and excess inventory (Batty, 2018). Additionally, real-time SC monitoring enables proactive maintenance of logistics assets, extending the lifespan of vehicles and equipment while reducing energy consumption.

As SCs become more circular and regenerative, DTs will play a pivotal role in ensuring eco-efficient and cost-effective logistics operations (c.f., Le & Fan, 2024).

9.4.3 Reducing environmental and social footprint in supply chain logistics

One of the key sustainability challenges in SCs is transportation-related emissions. DTs allow logistics companies to simulate and optimize delivery routes, reducing fuel consumption and emissions while maintaining service levels. DT technology is revolutionizing SC logistics by minimizing carbon emissions, waste generation, and negative social impacts through real-time monitoring, predictive analytics, and automation. By integrating IoT, AI, and blockchain, DTs optimize logistics operations, reducing fuel consumption and emissions by enhancing route planning, fleet management, and load optimization (Ivanov & Dolgui, 2021). For instance, Maersk uses DTs to simulate the most fuel-efficient transportation routes, reducing CO₂ footprints (Dagar et al., 2024).

In waste reduction, DTs help optimize inventory management and material usage, minimizing overproduction and excess stock, which often leads to resource wastage (Tao et al., 2019). Additionally, they support circular SC models by tracking recyclable materials and reverse logistics, ensuring that resources are repurposed rather than discarded.

From a social sustainability perspective, DTs enhance labor rights monitoring by ensuring fair working conditions through real-time compliance tracking. Blockchain-enabled DTs improve SC transparency, preventing unethical practices such as forced labor or unsafe working environments (Batty, 2018). By enabling data-driven sustainability strategies, DTs empower businesses to meet the Environmental, Social, and Governance (ESG) goals, fostering greener and more ethical SCs.

9.4.4 Enabling circular economy practices

The transition from a linear to a circular economic model will require overcoming the barriers that encourage “linear lock in,” such as cheap waste disposal fees, and implementing appropriate countermeasures to promote the transformation (Hopkinson et al., 2015). In addition, the management of reverse logistics (recall Fig. 9.2) is more complicated than forward SCs. When managing such closed-loop SCs, businesses are confronted with a high degree of uncertainty regarding the quality, quantity, and timing of product returns (cf. Ülkü & Gürler, 2018), a potential misalignment between core supply and remanufactured product demand, the diverse geographical distribution of consumers, and technology and product lifecycles. Ülkü et al. (2022, p. 217) note that they define a circular SC (CSC) as “a

sustainable and resilient SC designed to end waste by valorizing any material flows in shortened loops and slowing down consumption. Within a circular economy, which requires systems-thinking and compliance with quadruple bottom line imperatives (cultural, economic, environmental, and societal long-term well-being), a CSC creates restorative and regenerative products and processes, while cocreating with stakeholders (across multiple industries, public sectors, and consumer markets) a shared-value via the circulation of resources (raw materials, by-products, end-of-life and end-of-use products, disposed waste, process capabilities), and timely and transparent information.” This comprehensive CSC definition allows not only a holistic approach but also opens doors to new innovative ideas and research inquiries: DTs could be more pivotal in analyzing performance and supporting decision-making in a much more complex CSC environment. DTs support circular economy models by tracking product lifecycles, enabling remanufacturing, recycling, and sustainable disposal. By integrating lifecycle data, companies can design products for longevity and reuse, minimizing waste and environmental impact.

For example, under the light of the fact that many upstream suppliers and tiers make it a long SC, Yang et al., 2009 (p. 192) stated that “as SCs are extended by outsourcing and stretched by globalization, disruption risks and lack of visibility into the supplier’s status can both worsen.” Shortening the SC, if possible, has the advantage of having fewer impacts of double marginalization—additional markups imposed by the intermediary agents in the SC that increase the purchase price as seen by the consumers. The bullwhip effect—increasing variability in order sizes further up in the SC—is also more likely. By integrating IoT sensors, big data analytics, and AI, DTs provide comprehensive insights into product lifecycles, allowing businesses to extend asset longevity and promote material reuse. This technological synergy supports the transition from linear to circular value chains by enhancing efficiency and sustainability.

9.4.5 Improving supplier collaboration and compliance

DTs facilitate supplier monitoring by providing real-time insights into compliance with sustainability regulations and ethical sourcing practices. By creating real-time digital replicas of SCs, companies can enhance transparency and communication with suppliers. This enables seamless information exchange, allowing for better decision-making and faster identification of potential disruptions. For instance, it has been demonstrated that employing blockchain technology, SCs can further enhance traceability and accountability (e.g., Cui et al., 2024; Nabipour & Ülkü, 2021).

Through DTs, suppliers can be integrated into the overall system, providing them with up-to-date insights into inventory levels, production schedules, and quality control metrics. These real-time data allow for improved forecasting, inventory management, and more synchronized operations between partners, reducing lead times and mitigating risks.

Moreover, DTs facilitate compliance by ensuring that all parties adhere to established regulations and standards. By continuously monitoring the SC and capturing data at every step, businesses can track and verify that products meet required specifications and legal requirements. Any deviations from compliance can be identified and addressed immediately, reducing the risk of costly penalties or reputational damage.

9.5 Technologies enabling digital twins in sustainable supply chain management

9.5.1 Internet of things

A virtual entity's ability to reflect the physical entity's state depends on connected sensors (Jones et al., 2020). While it may be possible in local plants to rely on cabled connections, in SCs, the DT depends on the IoT, which enables sending and receiving a large volume of data (Kamble et al., 2022). Sensors monitor parameters such as energy consumption, emissions, and resource utilization, feeding critical insights into the DT. IoT devices collect and integrate real-time data from various points in the SC. Through a multilayer architecture, including several logic and communication middleware, the data are then available for complex analysis, including modeling and simulation capacities of DT (Juarez et al., 2021). The availability of applications programming interfaces (APIs) and open-source solutions, coupled with connected sensors, allows companies to save a considerable amount of time and effort to build the DT architecture and means more efforts can be dedicated to ensuring that the business needs are addressed, and the DT contributes to value creation for the SC actors (Kamble et al., 2022).

9.5.2 Artificial intelligence and machine learning

AI and ML can be used to train a DT to identify patterns, predict disruptions, and make autonomous decisions. Recent advances in ML have led to a higher quality of insights provided by ML with collected data sets of increasing complexity, including several types of unstructured data (Kamble et al., 2022). For instance, a trained DT can analyze the impact on inventory levels and cash flow of goods replenishment decisions and decide the optimal time and quantity to order (Badakhshan & Ball, 2023). ML also allows DTs to simulate the efficiency of energy recovery ventilation systems and operate them autonomously based on the simulation's results, as well as suggest optimal times for maintenance or suggest when energy system components should be changed (Bortolini et al., 2022). In agriculture SCs, ML can drive fertilization decisions, beehives and beekeepers' interaction, or the identification of potential crop diseases (Purcell & Neubauer, 2023).

9.5.3 Cloud computing and big data analytics

With a higher volume of data collected rapidly from the IoT sensors, a data management solution such as Big Data has to be implemented (Juarez et al., 2021). Big data analytics (BDA) refers to the capacity to obtain, process, and utilize insights from a large volume of data continuously and rapidly expanding. The quality of the forecasts can be greatly improved with the addition of more parameters, including environmental data such as temperature, precipitation, or real-time energy consumption by station, that would overload computing tools without BDA. Big data analytics in DT results in higher-fidelity models that consider complex interactions and offer a quicker response time. The large volume of real-time data can overload data infrastructure, however, especially if the network used was not intended to accommodate this amount of data exchange. 5 G communication greatly facilitates the implementation of DT utilizing BDA

(Jones et al., 2020). Finally, cloud computing provides the means to scale DT applications, especially if BDA is involved. DTs based on BDA are data-intensive and rely on extensive data storage and computing resources (Kamble et al., 2022). Cloud computing allows the delegation of storage and computing resources to a supplier and payment by usage, simplifying information technology management while allowing for usage peaks or an increase in use over time. This is described as scalability, where the system can adapt to real-time usage while staying efficient. Cloud computing also allows geographically actors to collaborate and facilitates the inclusion of distributed physical entities in the DT (Guo & Mantravadi, 2024).

9.5.4 Blockchain for transparency and traceability

Blockchain enhances the reliability of DT data, ensuring secure, transparent, and immutable records of SC transactions. While DTs allow for collaborative and integrated data, they usually offer limited trust and traceability (Kamble et al., 2022). Blockchains provide a solution to this by allowing tracking of the provenance of data and improving data integrity, especially for DT with numerous distributed sources of data (Hasan et al., 2020). For instance, with blockchains, users can check the log history and trace the source system of an element to improve trust in the DT's decisions and suggestions. While there are currently fewer examples of the integration of blockchains in DT than other technologies, this topic is expanding and will grow as users become sensitized to the transparency and trust issues related to data (Kamble et al., 2022).

9.5.5 Augmented reality and virtual reality

Augmented reality (AR) refers to a graphical or haptic overlay to a physical environment. It provides an additional way for the user to interact with the DT using a 3D interface. Another use case is in simulation scenarios, where virtual robots can be added through AR to simulate how they would interact with workers before the implementation (Kamble et al., 2022). It promotes collaboration between machines, workers, and virtual entities. Virtual reality (VR) refers to a digital environment typically rendered in 3D where the interface is shown to the user through headsets (Kuts et al., 2019). They are mainly used for simulations but could also be used by operators to check that the virtual entity is operating as intended in a more immersive and intuitive way.

9.6 Challenges and limitations of digital twins in sustainable supply chains

9.6.1 High implementation costs

Developing and maintaining DTs requires significant investments. The physical component requires sensors and actuators as well as a network infrastructure. The virtual entity needs to be programmed, including any ML and analytics required for the core functions of the DT. Finally, the communication and analysis layer requires architectural components

and computing resources, on premises or in the form of a cloud computing subscription. When additional technologies are integrated, the costs are even higher. A company may not have the internal skills to develop an AR interface for their DT, which means hiring external firms or investing to develop the skills in virtual human–computer interface and 3D rendering, to name a few (Kamble et al., 2022). The initial adoption costs are high, both in technology and in expertise.

9.6.2 Data security and privacy concerns

DTs involve the collection, transformation, and sharing of a large quantity of data from several sources. There are issues of privacy and security as the more data are reused and transformed, the harder it is to keep track of its source and authorized usage. Good data governance is necessary to address these issues (Jones et al., 2020). Blockchains may be part of the solution, but they are not always compatible with the existing DT architectures. Cybersecurity principles should be followed, notably network protections, firewalls, access rights management, and intellectual property management (Kamble et al., 2022). DTs are attractive targets for cyber criminals due to the amount of data and systems involved. The topic is expected to be one of the most relevant in the coming years concerning the challenges of DTs since it is still underresearched.

9.6.3 Complexity in integration

Integrating DTs with existing legacy systems and SC networks can be complex and time-consuming. At the moment, most DTs in SCM are used in the plan, make, and deliver activities (Guo & Mantravadi, 2024). Adding the source and return activities to existing DTs would extend their usefulness but at the cost of extensive technological changes. Similarly, the more source systems or physical entities are integrated, the higher the complexity, especially when several DTs with each their simulation model are expected to communicate (Juarez et al., 2021). Finally, there are issues of scalability, where the computing resources need to be adaptable if the flow of data augments or a more complex element must be simulated. Cloud computing and BDA help with the scalability problem, but they require specific skills that a company needs to develop (Kamble et al., 2022).

9.6.4 Changes in the nature of work

DTs represent a new way of making operational decisions. Workers need to trust the results of a simulation, which may need heightened transparency to trust the source and quality of data, but trust also depends on the time spent to develop the team's skills with the new system (Kamble et al., 2022). In technological changes, transparency concerning the changes and the active participation of all groups of actors are major success factors (Bordeleau & Felden, 2021). The development of a DT for SSCM likely involves groups of managers, workers, and technical personnel of several companies. How these groups interact and how they are allowed to participate will influence their acceptance of the DT. Some groups may also oppose the new practices despite being involved in the development, and this resistance must be anticipated by active leadership. The social aspect of the DT

system means that the participation of varied individuals is not only expected but desirable (Bordeleau, & de Santa-Eulalia, & Mosconi, 2021). Enterprises are part of a network of business partners where decisions are decentralized but based on shared data, which means each unit may make decisions based on a larger dataset. Trust between partners is essential, and resistance from a few of the actors can derail the project.

9.7 Digital twins and sustainable supply chains: emerging research topics

9.7.1 Advancements in computing technologies

Constant improvements in AI and simulation methodologies promise advancements to the decision-making capacity and autonomy of DTs in increasingly complex systems, but improvements in this area are concentrated in a small group of commercial solution vendors (Kamble et al., 2022). There is room for the development of more open-source solutions. Future research and development should focus on developing the skills necessary for creating and maintaining DTs, as well as integrating AI and ML advances into existing systems to maintain their relevance. To reduce dependency on vendors, developers may offer transparency regarding the development method and make the source code available to the public, especially for applications that are still limited, such as blockchain integration (Hasan et al., 2020). Finally, as technology advances, the combination of several DTs in an integrated DT system should emerge as a popular topic in the coming years (Juarez et al., 2021).

9.7.2 Expansion of 5 G connectivity

The rollout of 5 G will improve real-time data transmission, enhancing the accuracy and efficiency of DTs in SC management (Jones et al., 2020). 5 G is used in both the physical-to-virtual and the virtual-to-physical directions. DTs largely depend on wireless communication networks, especially in distributed SCs. With increased applications of DTs outside of single-site applications, more cases of 5G-connected DTs will be studied.

The expansion of 5 G connectivity will significantly enhance the capabilities of DTs in SC sustainability by enabling faster, more reliable data transfer and real-time communication across various networked devices. With ultralow latency and high data throughput, 5 G will facilitate real-time monitoring of SC activities, allowing for better decision-making and enhanced operational efficiency. This will improve resource allocation, reduce waste, and optimize energy use, contributing to sustainability goals (Tao et al., 2019).

Future research will focus on the integration of 5 G networks with IoT and AI to enhance DTs' abilities to simulate and manage complex SC networks. Additionally, 5G-enabled DTs will enable more efficient transportation management and predictive maintenance, reducing emissions and energy consumption (Kritzinger et al., 2018). Research will also examine the role of 5 G in smart logistics for improving last-mile delivery and recycling processes (Ivanov & Dolgui, 2021).

9.7.3 Greater adoption of circular economy models

DTs will play a crucial role in promoting sustainability by facilitating product lifecycle management and closed-loop SCs. These technologies enable real-time tracking of a product's lifecycle, from design and production to end-of-life. By providing insights into usage, wear, and environmental impact, DTs allow companies to optimize the product's performance, extend its lifespan, and plan for recycling or remanufacturing (Tao et al., 2019). In closed-loop SCs, DTs ensure that resources are continually reused, reducing waste and supporting a circular economy. This helps businesses reduce their environmental footprint while enhancing operational efficiency.

9.7.4 Employing digital twins and sustainable development goals for sustainable city logistics

Future research on DTs, sustainable city logistics, and the sustainable development goals (SDGs) will focus on leveraging DT technology to optimize urban logistics systems while addressing the environmental, social, and economic challenges that cities face. As cities strive to meet SDGs, particularly in areas like responsible consumption and production (Goal 12) and climate action (Goal 13), DTs can offer a unique solution for modeling and simulating urban logistics systems to improve traffic management, public transportation, and last-mile delivery operations (Tao et al., 2019).

Research will delve into developing intelligent transportation systems through DTs, which integrate real-time data to optimize routing, reduce carbon emissions, and promote the use of green logistics strategies (Kritzinger et al., 2018). A critical aspect of future studies will be creating sustainability metrics specific to city logistics, evaluating energy consumption, waste reduction, and air quality, in line with SDGs (Ivanov & Dolgui, 2021). Additionally, AI and ML will be explored to enhance decision-making for sustainable mobility solutions (e.g., Abouelrous et al., 2023; Zhan, Li, & Qi, 2020), driving circular economy principles in urban logistics (Wu & Lee, 2021). The impact of smart city technologies like DTs on social inclusion and equitable access to services (Goal 10) will also be examined (Batty, 2018).

Ultimately, future research will focus on integrating DTs into urban planning and sustainable transport networks, aiming to make cities more resilient, sustainable, and efficient.

9.7.5 Integrating sustainability metrics with digital twin supply chains

Future research on sustainability metrics and DT SCs will focus on integrating advanced technologies and frameworks to better track, measure, and improve the sustainability of SCs. As DTs enable real-time monitoring and simulation of SC activities, there is a growing need for research on sustainable performance metrics to assess environmental, social, and economic impacts comprehensively. Key areas of exploration will include developing integrated sustainability models that combine product lifecycle analysis, resource optimization, and waste reduction (Tao et al., 2019). Additionally, incorporating circular economy principles into DTs will be essential for closed-loop SCs, ensuring the efficient reuse and recycling of materials (Kritzinger et al., 2018).

A major focus will be on creating real-time sustainability dashboards within DT systems, allowing companies to monitor carbon footprints, energy consumption, and social responsibility in real time. Research will also explore how to leverage AI and ML to improve sustainability decision-making within DT ecosystems. Furthermore, the standardization of sustainability metrics across industries will be critical for enhancing comparability and transparency. DTs could especially prove useful in SC risk management (c.f., Yun & Ülkü, 2023) and humanitarian SCs (Ülkü et al., 2024). Finally, addressing data privacy and security concerns related to DT technology in sustainability applications will be an important avenue of research (Ivanov & Dolgui, 2021).

9.8 Final remarks

In the face of escalating environmental challenges that probe SC resilience and increasing demands for efficient production systems, industries are pivoting toward sustainable practices to reduce resource consumption and environmental, social, and cultural footprints. Central to this transition is DT technology—a sophisticated, dynamic, and evolving solution that integrates physical and virtual systems to enable real-time monitoring, simulation, and optimization of processes. The use of DTs is poised to deliver upon its many promises in many industries. They empower manufacturers to design, simulate, and validate production systems with unparalleled precision and flexibility, ensuring alignment with sustainability goals.

Having moved from idea to reality much faster in recent years, DTs are transforming the landscape of SSCM by enhancing efficiency, reducing waste, and promoting ethical practices. While challenges exist, continuous technological advancements and strategic implementation efforts will drive their adoption in the coming years. As organizations strive for sustainability, DTs will emerge as a critical tool in achieving resilient, transparent, and eco-friendly SCs. Despite challenges, the ongoing evolution of this technology promises a future where industries can balance productivity with environmental responsibility.

Furthermore, as industries progress toward more sustainable practices, the role of DTs will become even more pronounced. DTs will combine with more technologies, such as AR and AI, for better connections, insights, and analytics. Future advancements in AI, IoT, and decentralized technologies will drive the integration of DTs across diverse sectors, ensuring that they remain a cornerstone of sustainable development. The ongoing focus on interoperability, scalability, and enhanced predictive capabilities will empower stakeholders to achieve new heights in sustainable production. With their ability to align industrial activities with environmental imperatives, DTs stand poised to redefine the landscape of modern manufacturing and service systems, SCs, and beyond.

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Sustainable manufacturing practices in the digital era

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10.1 Introduction

The corporate world is constantly changing. Organizations regularly develop new products and service concepts to meet the opportunities and expectations of their consumers, improve performance, and consolidate their brands in the market. To achieve their organizational goals, companies must seek methods that balance responsibility, transparency, and accountability, principles that guide corporate governance (CG) (Dandapani & Shahrokhi, 2022).

CG is a set of policies and procedures by which the organization is led, directed, and controlled. It defines functions, structure, and the role of the Board of Directors (Campbell, 2007). The role of the Board of Directors must be significant in the connection between the governance structure and the financial performance of organizations, which is the main element of interest for stakeholders (Naciti, 2019).

A company's governance must be established considering social, environmental, and ethical dimensions. Together with governance, these elements were ESG (environmental, social, and governance), factors representing an investment in innovation in companies' businesses, attracting and cultivating talent, and the search for new organizational strategies (Castellano et al., 2024; Kai et al., 2024). Research into CG has advanced significantly, and recently, there has been significant progress in academic research into the association between CG mechanisms and sustainable development goals (Yang et al., 2024). For Steiner et al. (2025), many key governance mechanisms are associated with the sustainability of organizations, and management actions must be conducted by the principles of legality, morality, and efficiency (Steiner et al., 2023).

A great ally of CG in organizations is the culture of digital transformation (DT). When permeated by the company, with initiatives that seek technological development and the

constant improvement of the services and products developed, great advantages can be obtained, with applications in technologies and strategies that improve the coordination of the company's supply chain (Nasiri et al., 2020). Developing and applying technologies allows companies to strive for better performance, achieve sustainable and resilient results (Frank et al., 2019; Tardio et al., 2023), and support social performance (Lerman et al., 2024). The incorporation of technology as an organizational culture in Operations and Supply Chain Management (OSCM) must take place in line with company objectives and strategies, following the principles of governance mechanisms.

Companies' involvement with technology influences supply chain governance (Biondo et al., 2024; Yang & Han, 2023), contributing to the emergence of new business models (Bodrožić & Adler, 2018). DT has a fundamental role in defining and improving green operations in OSCM literature (Franco et al., 2024). When incorporated into organizations' CG practices, Digital Corporate Governance (DCG) is a management process that ensures that company procedures are carried out using digital technologies.

The sustainable development of companies' DCG actions must be carried out by considering aspects involving natural resources, especially issues related to environmental pollution, global warming, and the balance of the environment. For Yildiz Çankaya and Sezen (2019), these elements form the basis of green supply chain management (GSCM).

GSCM was created to incorporate environmental thinking into the product life cycle within supply chain management (Srivastava, 2007). The principle of this management is for companies to identify the source of environmental problems in their supply chain, properly understand their origin, and seek solutions that can guarantee the effectiveness of the solution to the problem identified. Implementing green practices in the supply chain can reduce companies' costs, encourage recycling, reuse, and remanufacturing of materials and increase the flexibility of ecological product design (Khan et al., 2018). Green practices improve environmental sustainability and reduce the cost of production (Khan et al., 2017).

Sustainable production and organizational performance are directly linked, with green production significantly improving companies' ESG performance (Wei et al., 2024), especially when associated with CG. Implementing and improving GSCM has been a goal for companies to gain a better reputation in the market and seek financial credit lines for companies with green certification. Obtaining the "green factory" designation has motivated companies to adjust their production and operations to achieve better environmental performance (Wei et al., 2023). The integration network between companies practicing green practices has become an important aspect of the supply chain. According to Ullah et al. (2024), integrating companies with green customers and green suppliers can increase companies' green innovation performance.

From the perspective of conducting green practice under CG and technology use in organizations, this chapter explores the impact of integrating DCG with GSCM operational aspects on operational, workers, financial, and innovation performance indicators. A quantitative survey using confirmatory factor analysis, correlation matrix, and slope graphs was employed to analyze the relationships and explore the multi-faceted effects of integrating DCG and GSCM.

10.2 Key concepts and their importance for sustainable manufacturing practices in the digital era

The progress of organizational practices is geared toward the advent of sustainable development. Although many organizations, particularly small and medium-sized ones, remain indifferent to implementing digitalization tools and methods in their businesses (Shah et al., 2020), industries are under pressure from stakeholders to adopt transparent communication about environmental and social impacts in their operations (Sartal et al., 2014). In this context, companies have sought improvements in their supply chain, such as adopting green and CG practices associated with digital strategy. While green practices can bring positive results, directly impacting the environment and companies' production costs (Khan et al., 2017), DCG impacts organizations' environmental governance, directly interfering in the processes dealing with environmental damage and resource waste (Li et al., 2024).

GSCM practices have proven to be fundamental to company performance, prioritizing sustainable development in their supply chain, and companies should be encouraged to adopt these practices (Kosasih et al., 2023). Its benefits extend from innovation in the company's products and processes to reducing operating costs and innovating products and processes, mainly improving the corporate image. Consumers and business partners better regard companies that invest in green practices (Khan et al., 2022; Nambung & Jang, 2017). This gives them better market growth opportunities, mainly by increasing customer loyalty.

Governance plays an important role in companies, determining objectives and ensuring their fulfillment with transparency and accountability (Hale, 2008; Samaratunge & Alam, 2021). Defining the processes and methods by which the company's management will be conducted is essential for good governance. Without this, it will not be possible to assess whether the results obtained align with what was planned and the procedures to be adopted for adjustments in the supply chain.

A presentation of the definitions of the topics covered in this chapter may be interesting for a better understanding. Three operations will be analyzed for green practices: green manufacturing, green purchasing, and green packaging. Each of the topics in this chapter, as well as the concept of DCG, will be presented in the following sections.

10.2.1 Green manufacturing

Green manufacturing is defined as producing products with economic reach, aiming to minimize environmental impacts, and assuming the social responsibility of employees and consumers throughout the product's life cycle (Zhang & Haapala, 2015). Green manufacturing aims to promote companies' sustainable practices by using renewable technologies in their supply chain to minimize dependence on natural resources and environmental impacts through recycling processes and the reuse of waste materials (Ahn et al., 2013). For Wang and Zhang (2013), green manufacturing is the only way to provide for the sustainable development of industry, with reducing energy consumption being the sector's biggest challenge. A degree of investment in green manufacturing will benefit the company involved in the green investment (Ma et al., 2018).

The main indicators for evaluating green manufacturing are the environmental impact of developing or improving products and whether these developments have a long lifespan (Lerman et al., 2022). The processes adopted by the companies are also relevant, especially if they are developed using recyclable raw materials, with less resource consumption and a low environmental impact.

10.2.2 Green purchasing

Purchases of inputs are the starting point for the flow of materials in an organization (Preuss, 2002) and reflect the promotion of green activities carried out by companies. Eltayeb et al. (2011) point out that green purchasing controls suppliers' environmental performance, being a powerful agent of change to improve the impact of the company's operations on the natural environment (Zailani et al., 2012). According to Foo et al. (2019), green procurement capabilities have significant positive effects on green procurement practices, a situation that has yet to be observed, for example, for companies' innovation capabilities. These capabilities are related to companies' integration, financing, and intraorganizational green management.

The legal basis must be considered when assessing green purchasing. Companies must analyze whether they make purchases based on the environmental specifications established by product design and whether product labeling follows standards to minimize environmental impact (Lerman et al., 2022). It is also important to evaluate companies' purchasing processes, identifying whether they are carried out with environmentally certified partners and materials that do not damage the environment (Foo et al., 2019).

10.2.3 Green packaging

Using packaging that is suitable for the environment, in a nature-friendly solution (Zhang & Zhao, 2012), through the composition of biodegradable products that do not cause pollution in the product's life cycle stages. Green packaging directly contributes to the environment, demonstrating the organization's green purchasing practices and improving the company's overall performance (Pinto, 2023). According to Salandri et al. (2022), companies have sought to adopt green practices to improve their operational performance. When agility plays a moderating role, using eco-materials or green packaging impacts company operations (Lerman et al., 2022).

Companies should use as few materials as possible in green packaging, which should always be reusable and environmentally friendly. Companies should also encourage the promotion of recycling and packaging reuse programs.

10.2.4 Digital corporate governance

DCG deals with using technological systems within the management of organizations and integrating digital solutions into company processes and methods. According to Li et al. (2024), DCG has a significant impact on the environmental governance of companies by detecting environmental damage and waste of resources in advance, enabling the public dissemination of information that makes it possible to reach the actions taken by companies, and providing the public with channels for participation in actions, establishing active contact with the consumer public. According to Margherita et al. (2024), new digital

technologies can be combined with the green transition, creating great opportunities for sustainable development and enabling companies to embark on a digital and green manufacturing journey.

Companies must define strategies that facilitate and standardize understanding among their teams, shareholders, partners, and clients. The best way to standardize processes is through applied technology, in which the processes are already presented, making it easier to obtain performance indicators. Companies' digital strategy significantly influences their sustainable business, financial performance, and governance practices, showing that these topics should be studied together (Siswanti et al., 2024).

The DCG process must consider whether companies carry out risk management in their decision-making, and must consider in its planning that shareholder rights and profitability must be sustainable over time. A governance program must be mature, with anticorruption, extortion, and bribery targets and antilabor actions, promoting fiscal transparency in processes and activities (Castellano et al., 2024). Alignment with the digital process must ensure that everything possible in the supply chain has been digitized and that large amounts of data have been collected from different sources. That information has been properly exchanged in the supply chain with digitization. A strong communication network between the different sectors of the supply chain must be sought, and the interface with customers must also be improved through digitalization.

10.3 Conceptual model and hypothesis development

A conceptual model was drawn up for the research carried out in this chapter. In this model, the DCG acts as a moderating agent to identify the inclusion of green operations (green manufacturing, green purchasing, and green packaging) in company performance (operational, employee, financial, and innovation). The conceptual model is shown in Fig. 10.1.

The model presents three hypotheses to identify whether DCG moderates the results of green practices on organizational performance. The academic literature has already explained the effects of green practices on the performance of organizations, such as Erbasi and Akandere (2020), who concluded that adopting green practices significantly predicts the tasks assigned to workers, contributing to their performance. DT strategies associated with base and front-end technologies influence the company to achieve high levels of GSCM performance (Lerman et al., 2022). For Fok et al. (2022), the more a company's employees are aware of green practices, the more likely they are to have a positive sustainability performance. Green practices are important for organizations, being the main environmental drivers of companies' financial performance (Miroshnychenko et al., 2017). A correct and balanced adoption of green practices can benefit companies economically (D'Angelo et al., 2023).

Organizations' use of DCG also brings positive results for company performance. The benefits include easy accessibility, reduced operating costs, and obtaining performance results in real-time (Febriyanti et al., 2023). Some DCG practices have shown satisfactory results, such as the E-Governance system presented by Manoharan et al. (2023), in which the cities that adopt it show good indicators in the areas of privacy and security, usability, content, services, and citizen and social engagement.

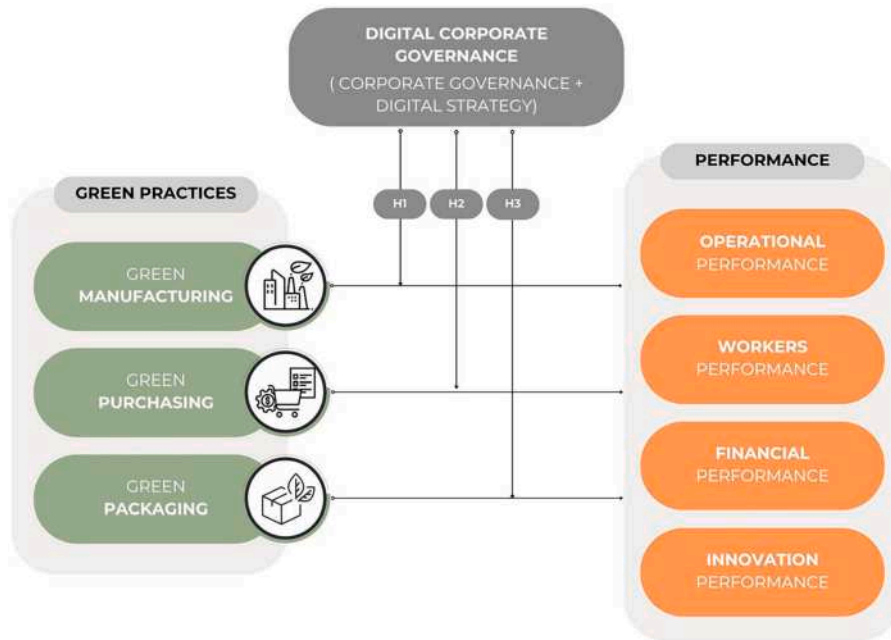


FIGURE 10.1 Conceptual model. This figure shows the research model.

As can be seen, applied individually, green practices and DCG provide positive results for the companies that adopt them. In the research presented in this chapter, the research aims to assess whether integrating CG policies with green practices can bring better results for organizations. We therefore hypothesize that

- H1.** *The moderating effect of Digital Corporate Governance on green manufacturing affects performance.*
- H2.** *The moderating effect of Digital Corporate Governance on green purchasing affects performance.*
- H3.** *The moderating effect of Digital Corporate Governance on green packaging affects performance.*

10.4 Methodology

A cross-industry survey targeting experts in sustainable and DT practices in OSCM was conducted. To minimize selection bias and enhance randomization, it was avoided preselecting respondent profiles, though self-selection bias was addressed by distributing the survey via a customized association channel. Emails were sent weekly between September 2023 and January 2024, resulting in 371 valid responses.

Fig. 10.2 shows the research methodology, which includes confirmatory factor analysis and the integration of constructs, the correlation matrix between the constructs, and the analysis of the slope graphs.

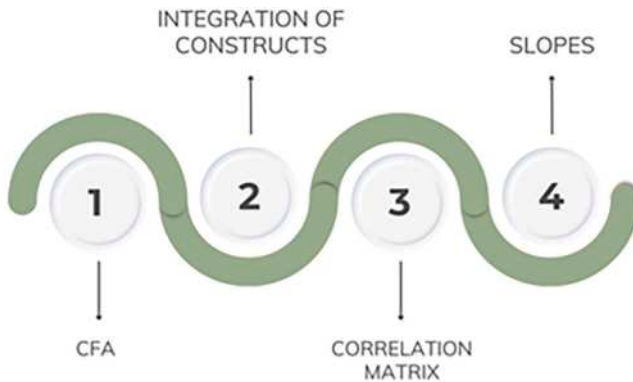


FIGURE 10.2 Methodology. This figure shows the research methodology steps.

The proposed econometric model was based on the academic literature's green practices, digital strategy, CG, and Performance constructs. Moreover, the proposed econometric model included eight constructs: one construct of [GREEN_MANUFACTURING], one construct of [GREEN_PURCHASING], and one construct of [GREEN_PACKAGING], based on [Lerman et al. \(2022\)](#); one multiconstruct of [DIGITAL_CORPORATE_GOVERNANCE] divided into [DIGITAL_STRATEGIES], and [CORPORATE_GOVERNANCE] based on [Nasiri et al. \(2020\)](#) and [Fafaliou et al. \(2022\)](#) and [Sancha et al. \(2023\)](#), respectively; one construct of [OPERATIONAL PERFORMANCE], one construct of [WORKERS PERFORMANCE], one construct of [FINANCIAL PERFORMANCE], and one construct of [INNOVATION PERFORMANCE] based on [Devaraj et al. \(2007\)](#), [Buffington et al. \(2017\)](#), [Narasimhan and Kim \(2002\)](#), and [Kang et al. \(2022\)](#), respectively. These constructs aim to explain the interaction between the variables, showing the consistency of data grouping and the proposed hypotheses. The results obtained in the statistical analysis validated the constructs according to the literature ([Hair et al., 2018](#)). All constructs' measures are reported in [Appendix A](#).

Before conducting the regression analysis, it was verified that four key assumptions—normality, linearity, homoscedasticity, and multicollinearity—were met, following the recommendations of [Hair et al. \(2018\)](#). Skewness and kurtosis values for normality were reviewed, which confirmed that the data were normally distributed in the individual constructs. When integrated, the thresholds are augmented as expected in moderating relationships ([Hair et al., 2018](#)). Linearity was assessed by plotting partial regression graphs for each independent variable. To check for homoscedasticity, scatterplots of standardized residuals against predicted values were visually inspected. Finally, we calculated the variables' Variance Inflation Factor (VIF) to ensure low standard errors and stable regression estimates. All VIF values were below the recommended threshold of 10, indicating no issues with multicollinearity, even when moderating effects were included.

Since the outcomes presented had several negative correlations, it also was added the analysis of slope graphs as the last methodological step to check if organizations with mature approaches in DCG and green operations still negatively influenced performance metrics.

10.5 Results

To test the main hypotheses, digital strategy and CG constructs were initially integrated into DCG, and after, the moderating effect of DCG in each green operation was calculated to test the association with performance metrics, as shown in [Table 10.1](#). The outcomes suggest our three main hypotheses are all supported, even though innovation performance has no significant correlation, and there is negative correlations for operational, workers, and financial performance.

Because all correlations for operational, workers, and financial performance presented negative associations, the slope graphs were created to check the potential negative effect of DCG and green operations integration. [Fig. 10.3](#) highlights all nine slopes, evidencing the negative association between those practices' operational, workers, and financial performance when integrated. It is possible to perceive this pattern since all low-development moderators' lines are above medium and high-development lines. Then, it is possible to conclude that the outcomes are not positive when organizations try to develop and integrate DCG and green operations simultaneously. To check the individual relationships, [Appendix B](#) was elaborated, which presents the single effects from all measured constructs, evidencing the positive associations with all performance metrics. Next, the chapter discusses the dark side of performance when dealing with multiple strategies simultaneously.

10.6 The dark side of multiple strategies

Companies seek out different strategies to achieve their objectives through the guidance of their Board of Directors. However, sometimes strategies can clash, causing methods to conflict and lose impact in the pursuit of organizational objectives. In a business relationship, this incremental and evolutionary process in which the results of the objectives can vary, generating a rupture, can be treated as the dark side of the organizational objective ([Basu et al., 2023](#)). When treated together, green practices and DCG have improved company performance without definitively differentiating themselves from companies that do not employ these practices. Thus, it can be interpreted that, individually, green practices, CG, and digital strategy positively impact organizational performance ([Appendix B](#)). However, when combined, performance is no longer differentiated, indicating that companies can perceive this combination as a barrier with too many actions to carry out and observe. Internal and external barriers can hurt operational, environmental, and social indicators and, eventually, affect companies' capacity for innovation ([Aniceski et al., 2024](#)). In general, the results indicate that integrating green practices with DCG does not improve the innovation capacity of manufacturing firms, and it shows negative results for operational, workers, and financial performance.

Positive performance results involving green practices are associated with a moderating effect of agility ([Salandri et al., 2022](#)). Green practices are growing in the GSCM in association with agile and lean practices ([Udokporo et al., 2020](#); [Waqas et al., 2022](#)) or even associated with resilience ([Alipour et al., 2022](#); [Khanzadi et al., 2024](#)), demonstrating that they are volatile and flexible actions, factors that can be compromised if the company adopts governance policies and technologies for this area of activity.

TABLE 10.1 Statistical outcomes.

Variables		1	2	3	4	5	6	7	8	9
1	Green manufacturing	–								
2	Green purchasing	.534** (<i>P</i> =.000)	–							
3	Green packaging	.545** (<i>P</i> =.000)	.447** (<i>P</i> =.000)	–						
4	Digital strategy	.194** (<i>P</i> =.000)	.331** (<i>P</i> =.000)	.128* (<i>P</i> =.014)	–					
5	Corporate governance	.303** (<i>P</i> =.000)	.432** (<i>P</i> =.000)	.286** (<i>P</i> =.000)	.289** (<i>P</i> =.000)	–				
6	Operational performance	.468** (<i>P</i> =.000)	.395** (<i>P</i> =.000)	.471** (<i>P</i> =.000)	.234** (<i>P</i> =.000)	.317** (<i>P</i> =.000)	–			
7	Workers performance	.243** (<i>P</i> =.000)	.295** (<i>P</i> =.000)	.216** (<i>P</i> =.000)	.308** (<i>P</i> =.000)	.427** (<i>P</i> =.000)	.569** (<i>P</i> =.000)	–		
8	Financial performance	.207** (<i>P</i> =.000)	.216** (<i>P</i> =.000)	.264** (<i>P</i> =.000)	.272** (<i>P</i> =.000)	.360** (<i>P</i> =.000)	.471** (<i>P</i> =.000)	.495** (<i>P</i> =.000)	–	
9	Innovation performance	.549** (<i>P</i> =.000)	.293** (<i>P</i> =.000)	.433** (<i>P</i> =.000)	.183** (<i>P</i> =.000)	.241** (<i>P</i> =.000)	.463** (<i>P</i> =.000)	.307** (<i>P</i> =.000)	.487** (<i>P</i> =.000)	–
Skewness		–.720	–.699	–.525	–1.282	–1.615	–1.176	–1.795	–1.471	–.851
Kurtosis		–.742	–.160	–.988	1.680	2.780	.945	3.774	1.527	–.407

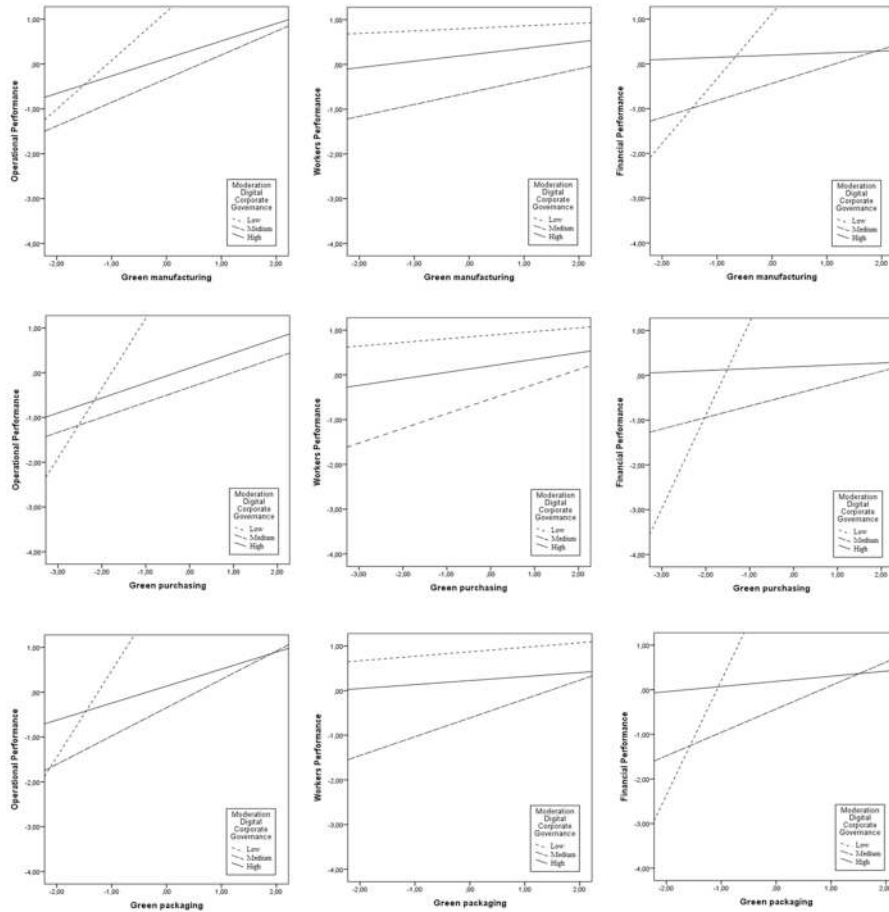


FIGURE 10.3 Slope graphs. Slope graphs to interpret negative outcomes.

In practical terms for company managers, the research conducted in this chapter indicates a dark side to focusing jointly on CG strategies, digital strategies, and green practices, which can negatively influence organizations' performance. Companies should focus their actions on the practices that are important to them, focusing on attitudes that allow them to search for what the market offers as input and is looking for as a product.

The adoption of a commitment to sustainable development must be treated as a strategic objective and something very positive for companies, as it means cost reduction, decent jobs with talent retention, care for safety and health at work, and continuous training which increases the quality and productivity of companies (Wilson, 2018). To achieve a sustainable production initiative, Shah et al. (2020) indicate that companies must focus on adopting some practical approaches and strategies, such as

1. Reduction of negative environmental impact: Companies must seek sustainable manufacturing concepts from the 6Rs: reduce, reuse, recycle, recover, redesign, and

- remanufacture. Adopting these practices will make production more sustainable, protect the environment, and add economic and social value to production (Rashid et al., 2019).
2. Reduction in energy consumption: The industry's energy demand is growing, mainly due to technological advances and the increase in Industry 4.0 base technologies, which support and improve industrial performance (Benitez et al., 2019). Therefore companies must invest in renewable energy resources and seek energy efficiency strategies in their operations.
 3. Reduction in the use of nonrecyclable or toxic materials: To protect the environment and promote the reduction of material disposal costs, the raw materials used throughout the production of the final product must be recyclable or of nontoxic origin.

10.7 Practical recommendations and conclusions

This chapter aimed to explore the integration of the DCG with the GSCM's operational green practices on company performance indicators. Through quantitative research using confirmatory factor analysis, correlation matrix, and slope graphs conducted to assess the companies and the market's profiles, it was able to understand that the green practices and DCG do not influence performance, which can be considered a negative side effect of organizations' application of multiple actions in favor of better green performance results. In this way, it is understood that companies can focus on adopting green or DCG practices to promote sustainable growth in emerging markets.

Several practical recommendations can be employed:

1. It is understood that the company should select partners with the same goal of sustainable outreach, making it easier to acquire renewable materials, such as green packaging and other products that enable implementing a product life cycle that adheres to the circular economy.
2. Invest in training your teams, promoting internal marketing to establish an organizational culture focused on green practices, and encouraging stakeholders to present new ideas and solutions that align with the company's strategic objectives.
3. Managers should invest in new technology systems to increase the company's production capacity and reduce losses by using simple solutions that enable better performance. Investment in technology is also a practical recommendation for promoting sustainable growth, under which governance strategies can be more easily implemented and monitored, assessing and achieving objectives, and accountability with improved processes. The adoption of DCG makes it easier to integrate ESG practices, catalyzing the growth of companies' revenues and increasing their attractiveness to investors, factors that lead to improved organizational performance.

Implementing green and ESG practices in companies results from internal policies established by the Board of Directors and should be promoted and permeated among teams and business partners. The challenges of implementing new cultures are great, and it takes time to produce satisfactory results. Still, it is up to company leaders to persist in achieving lasting sustainable growth. This chapter concludes that integrating several

approaches, including corporate initiatives, digital strategies, and green operations, may hamper organizational performance, and academics and managers should cautiously avoid an overoptimistic view of DT and sustainability integration.

Appendix A: Constructs measures

(DIGITAL STRATEGY) (Retrieved from [Nasiri et al., 2020](#)). Likert scale: from 1—strongly disagree to 7—strongly agree. RMSEA=0.044; CFI=0.997; TLI=0.993; AVE=0.622; Cronbach's alpha=0.881; CR=0.890. Factor loadings are shown in parentheses.

- a. Digitalize everything possible (0.661).
- b. Collect large amounts of data from different sources with digitization (0.850).
- c. Create a stronger communication network with digitization (0.822).
- d. Exchange information with digitization (0.923).
- e. Improve the interface with consumers with digitization (0.648).

(CORPORATE GOVERNANCE) (Adapted from [Fafaliou et al., 2022](#); [Sancha et al., 2023](#)). Likert scale: from 1—strongly disagree to 7—strongly agree. RMSEA=0.061; CFI=0.993; TLI=0.979; AVE=0.475; Cronbach's alpha=0.762; CR=0.781. Factor loadings are shown in parentheses.

- a. Our leaders conduct risk management for decision-making (0.749).
- b. Our leaders seek for fiscal transparency in processes and activities (0.644).
- c. Our leaders implement a mature action plan in its governance to address anticorruption, extortion, bribery, money laundering, and antilabor practices (0.774).
- d. Our leaders consider shareholder rights to be sustainable over time and profitable (0.569).

(GREEN MANUFACTURING) (Retrieved from [Lerman et al., 2022](#)). Likert scale: from 1—strongly disagree to 7—strongly agree. RMSEA=0.015; CFI=0.999; TLI=0.999; AVE=0.638; Cronbach's alpha=0.891; CR=0.897. Factor loadings are shown in parentheses.

- a. Our company assesses the environmental impact of developing/improving products (0.714).
- b. Our company develops products with recyclable raw materials (0.770).
- c. Our company develops products with lower consumption of resources (0.883).
- d. Our company develops products with a low environmental impact (0.890).
- e. Our company develops products with a high lifespan (0.716).

(GREEN PURCHASING) (Retrieved from [Lerman et al., 2022](#)). Likert scale: from 1—strongly disagree to 7—strongly agree. RMSEA=0.055; CFI=0.996; TLI=0.989; AVE=0.608; Cronbach's alpha=0.892; CR=0.885. Factor loadings are shown in parentheses.

- a. Our company makes purchases based on environmental specifications established by product design (0.753).
- b. Our purchasing process is done with partners with ISO 14001 certification (0.691).
- c. Our purchasing process follows procedures that minimize environmental impact (0.863).
- d. Our purchasing process follows product labeling standards to minimize environmental impact (0.853).
- e. Our company seeks to purchase materials that do not harm the environment (0.721).

(GREEN PACKAGING) (Retrieved from [Lerman et al., 2022](#)). Likert scale: from

1—strongly disagree to 7—strongly agree. RMSEA=0.078; CFI=0.995; TLI=0.984; AVE=0.680; Cronbach's alpha=0.908; CR=0.912. Factor loadings are shown in parentheses.

- a. Our company's packaging is reusable (0.920).
 - b. Our company's packaging uses the minimum possible materials (0.894).
 - c. Our company uses environmentally friendly materials in its packaging (0.952).
 - d. Our company encourages the use of reusable packaging (0.683).
 - e. Our company promotes packaging recycling and reuse programs (0.615).
- (OPERATIONAL PERFORMANCE)** (Retrieved from [Devaraj et al., 2007](#)). Likert scale: from 1—strongly disagree to 7—strongly agree. RMSEA=0.033; CFI=0.998; TLI=0.994; AVE=0.473; Cronbach's alpha=0.828; CR=0.814. Factor loadings are shown in parentheses.
- a. Our company has improved productivity over the last 2 years (0.522).
 - b. Our company has improved order lead time over the last 2 years (0.601).
 - c. Our company has improved inventory levels over the last 2 years (0.780).
 - d. Our company has improved quality (reduced scrap or rework) over the last 2 years (0.809).
 - e. Our company has improved overall equipment effectiveness over the last 2 years (0.682).
- (WORKERS' PERFORMANCE)** (Retrieved from [Buffington et al., 2017](#)). Likert scale: from 1—strongly disagree to 7—strongly agree. RMSEA=0.065; CFI=0.997; TLI=0.992; AVE=0.784; Cronbach's alpha=0.947; CR=0.948. Factor loadings are shown in parentheses.
- a. We improved employee productivity over the last 2 years (0.838).
 - b. We improved employee autonomy over the last 2 years (0.909).
 - c. We improved employee collaboration over the last 2 years (0.976).
 - d. We improved employee flexibility over the last 2 years (0.828).
 - e. We improved the quality of employee work over the last 2 years (0.868).
- (FINANCIAL PERFORMANCE)** (Retrieved from [Narasimhan and Kim, 2002](#)). Likert scale: from 1—strongly disagree to 7—strongly agree. RMSEA=0.073; CFI=0.998; TLI=0.989; AVE=0.728; Cronbach's alpha=0.914; CR=0.914. Factor loadings are shown in parentheses.
- a. The sales increased over the last 2 years (0.857).
 - b. The return on investment (ROI) increased over the last 2 years (0.913).
 - c. Profitability increased over the last 2 years (0.918).
 - d. Market share increased over the last 2 years (0.731).
- (INNOVATION PERFORMANCE)** (Retrieved from [Kang et al., 2022](#)). Likert scale: from 1—strongly disagree to 7—strongly agree. RMSEA=0.062; CFI=0.999; TLI=0.992; AVE=0.693; Cronbach's alpha=0.907; CR=0.899. Factor loadings are shown in parentheses.
- a. The sales increased over the last 2 years (0.857).
 - b. The ROI increased over the last 2 years (0.913).
 - c. Profitability increased over the last 2 years (0.918).
 - d. Market share increased over the last 2 years (0.731).

Appendix B

Correlation matrix for individual constructs
[Table 10.2](#)

TABLE 10.2 Individual constructs.

Variables	1	2	3	4	5	6	7	8	9
1 Green manufacturing	-								
2 Green purchasing	.534** (P=.000)	-							
3 Green packaging	.545** (P=.000)	.447** (P=.000)	-						
4 Digital strategy	.194** (P=.000)	.331** (P=.000)	.128* (P=.014)	-					
5 Corporate governance	.303** (P=.000)	.432** (P=.000)	.286** (P=.000)	.289** (P=.000)	-				
6 Operational performance	.468** (P=.000)	.395** (P=.000)	.471** (P=.000)	.234** (P=.000)	.317** (P=.000)	-			
7 Workers performance	.243** (P=.000)	.295** (P=.000)	.216** (P=.000)	.308** (P=.000)	.427** (P=.000)	.569** (P=.000)	-		
8 Financial performance	.207** (P=.000)	.216** (P=.000)	.264** (P=.000)	.272** (P=.000)	.360** (P=.000)	.471** (P=.000)	.495** (P=.000)	-	
9 Innovation performance	.549** (P=.000)	.293** (P=.000)	.433** (P=.000)	.183** (P=.000)	.241** (P=.000)	.463** (P=.000)	.307** (P=.000)	.487** (P=.000)	-
Skewness	-.720	-.699	-.525	-1.282	-1.615	-1.176	-1.795	-1.471	-.851
Kurtosis	-.742	-.160	-.988	1.680	2.780	.945	3.774	1.527	-.407

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Engineering and managing prescriptive maintenance

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11.1 Introduction

Prescriptive maintenance (PsM), as a new revolutionised maintenance concept, has gained a lot of interest in the last couple of years. In general, prescriptions mean recommended, time-dependent actions to improve the future, for example, reducing the load on equipment to function longer. [Ansari et al. \(2019\)](#) defined PsM as a concept that answers the question “How can we control the occurrence of a specific event?” (How should it happen?) by providing actionable recommendations for decision-making and improving and/or optimising forthcoming maintenance processes. [Padovano et al. \(2021\)](#) have defined PsM as a concept that is able not only to predict the future health status of the system but also to recommend autonomously timed decisions regarding specific maintenance tasks (inspection, repair, and replacement) or action plans. This definition tries to make the difference between predictive maintenance (PdM) and PsM. PdM, according to ISO 14224:2016 ([International Organisation for Standardisation, 2016](#)), is defined as maintenance based on the prediction of the future condition of an

Item estimated or calculated from a defined set of historic data and known future operational

parameters. In this sense, PsM can be defined as maintenance based on the prediction of the future condition of an item estimated or calculated from defined prescriptions, historical data, and known future operational parameters.

In [Fig. 11.1](#), the relationships between PsM, condition-based maintenance (CbM), and PdM are illustrated. PsM utilises the CbM to diagnose the current condition status and define what shall be done to prescribe the condition until a preferred maintenance visit is possible. Moreover, it utilises the PdM to predict future conditions and remaining useful time, considering the operating parameters and prescription actions.

To operationalise such a definition, an architecture is usually required, which could be based on data-driven, model-based, or hybrid analytics ([Ansari et al., 2019](#)). [Lepeniotti et al. \(2020\)](#)

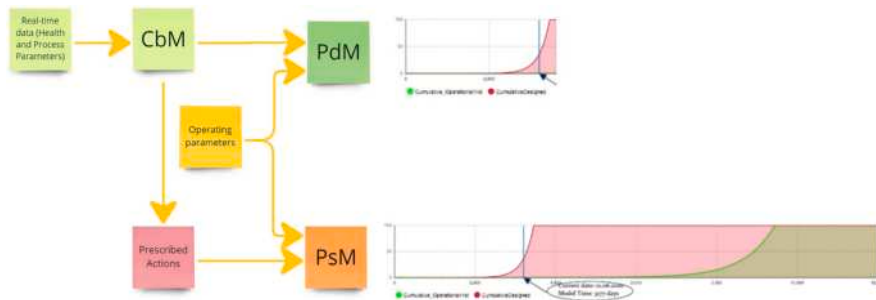


FIGURE 11.1 From condition-based into prescriptive maintenance.

proposed a data-driven architecture named PriMa, which combines four main elements: data management, predictive data analytics toolbox, recommender and decision-support dashboard, and semantic-based learning and reasoning. PriMa architecture was demonstrated on on three-axis machine for milling, turning, and honing, with the aim to prescribe when the cutting tool shall be replaced without sudden failures that might damage the machine and manufactured product. The cutting tools are wearing over time, and therefore, the wear-out calculation is performed by simulation-based digital shadow. Joshi (2020) has demonstrated a PsM program for a topside crude oil pump, where redundancy allowed prescription in terms of load allocation and distribution. Another PsM architecture is proposed by Padovano et al. (2021) and further developed by Elbasheer et al. (2022) for the shop floor. This architecture added a scenario analysis and testing module to test several maintenance and production schedule alternatives. The shop floor status is determined by real-time sensor data condensed in an input history for the real shop floor (digital mirror), and the future output is forecasted through a simulation model.

The definition and architecture of PsM highlight three main requirements: (1) the equipment shall be ready to offer the defined prescriptions (e.g., reduce load), (2) the analytical model shall be capable of predicting future conditions under the prescribed condition, (3) the maintenance program shall be connected to the production and operations planning unit to define the optimal prescription level. It becomes clear that prescriptive models shall be developed, the physical assets or systems shall be engineered to be PsM-ready equipment, and the PsM program shall be managed properly. Therefore, this chapter tries to answer the following questions:

- How shall PsM-ready equipment be engineered?
- How shall the PsM model be developed?
- How shall the PsM program be managed?
- What are the potential benefits of PsM?

In the following section, the potential benefit of PsM will be illustrated from an industrial point of view. Later, an industrial work process and methods to engineer PsM-ready equipment will be described, followed by a model-based approach to build a PsM model. Finally, a general industrial management framework for PsM management is explained.

11.2 Potential benefits of prescriptive maintenance

Prescriptive maintenance is still not well defined, and its benefits compared to condition-based maintenance (CbM) and PdM are not well clarified. The most well-known difference between CbM, PdM, and PsM is that CbM is about “what happened or what is happening,” whereas PdM is about “What and when will happen,” and PsM is about “How and when should happen.” Let’s clarify that using a generic potential–functional failure curve (P–F curve), shown in Fig. 11.2.

The P–F curve represents the deterioration in the equipment condition over time. Let’s assume that a CBM program diagnosed a degraded fault (potential failure point, P) happening in specific equipment at the moment (equipment of interest), and then the PdM program predicted that the functional failure point (F) would happen in one week. However, the next possible scheduled maintenance visit is in 2 weeks and you desire your equipment to make it until the next scheduled maintenance campaign visit. In other words, the target is to prevent the functional failure from happening within one week or tolerate the degrading fault for a period of two weeks.

It means you need to do some prescriptions to extend the life of the equipment by 1 week more, for example, stop the equipment of interest and use redundant equipment, or reduce the loading on the equipment of interest. The new predicted failure point under the planned prescriptions is called the prescribed failure point (F_{ext}). Thus, the main benefit of prescribing the useful lifetime is to avoid production losses due to equipment unavailability while avoiding extra maintenance visits. Offering a longer time to plan for the maintenance visit is definitely another benefit.

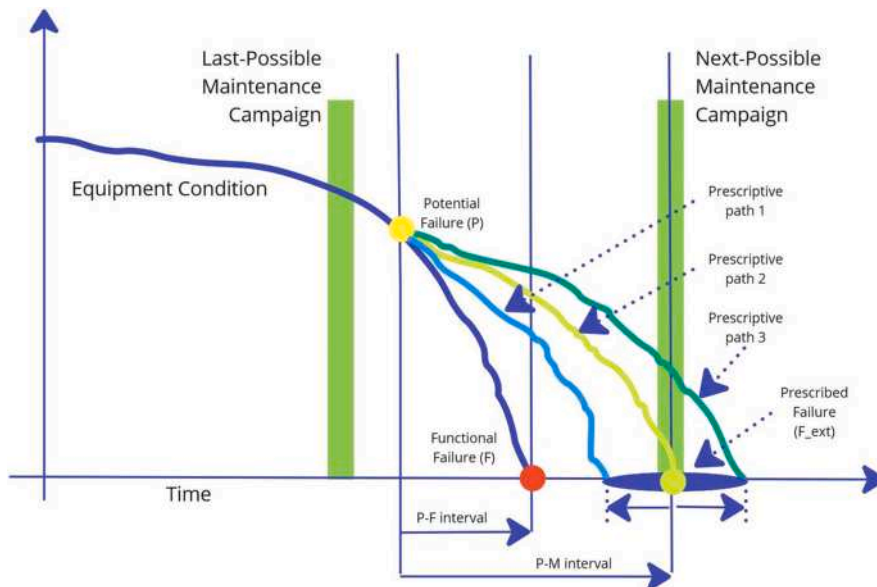


FIGURE 11.2 Asset deterioration curve and prescriptive maintenance concept.

PsM is significantly important for industrial applications where accessibility is limited or maintenance visits are very costly. For example, offshore wind turbines have prescheduled maintenance campaigns on an annual basis; particularly, summer months are the preferred season due to accessibility and low production rate (Fox et al., 2022). Another application is the unmanned oil and gas installations, where scheduled maintenance campaigns (every 3, 6, or 12 months) are predefined and preferably no extra maintenance visit between the scheduled maintenance campaigns is expected. Definitely, in offshore wind turbines and unmanned oil and gas installations, some equipment might fail, and corrective maintenance visits are required. In this context, PsM offers a resilience approach to tolerate the condition deterioration until a preferable maintenance visit is possible. Sun et al. (2022) highlighted that “reliability-based and risk-based approaches focus on preventive maintenance to avoid component failures and are applicable before unexpected disruptions occur.” However, the resilience approach focuses on systems’ recovery when failures are unavoidable. The recommended prescriptions in the perspective maintenance program shall target to enhance the capacity of the asset to absorb, adapt, and restore the asset from disruption conditions within an optimal cost. Absorbing capacity refers to the ability to handle the potential failure and mitigate the consequences. Adapting capacity refers to the ability to handle a certain amount of lost performance without external maintenance activities. Restoring capacity refers to the ability to gain new healthy conditions through external maintenance activities. Thus, the main principle in PsM is adapting the resilience and survivability approach.

11.3 Engineering prescriptive maintenance-ready equipment

Building a maintenance management program requires a systematic approach to ensure its fitness for the purpose and effectiveness. Specially, for complex industrial systems that are characterised by a high degree of interrelations, diverse components, nonlinear behaviours, and emergent properties that often make them challenging to understand, predict, and manage. This systematic approach is named as project execution model (PEM), which serves as a roadmap that outlines the stages, decision gates (DG), and activities involved in executing a project from start to finish, guiding the team through the project life cycle, defining key milestones, processes, and deliverables. For most of the project, the stages and decision gates are common; however, the activities in each stage and the checklist for each decision gate are different.

For instance, most maintenance management program projects have the following stages: (1) business identification, (2) business planning, (3) concept planning, (4) system definition or front-end engineering design (FEED), and (5) detailed engineering stage, named execution, procurement, and construction (EPC). These five stages mainly convert a business need into a physical product or service. In Fig. 11.3, the project stages and decision gates are illustrated.

Decision gates serve as checkpoints to evaluate the project’s progress, ensuring that the project aligns with its objectives and meets predefined criteria, and determine whether it should proceed to the next phase or stage.

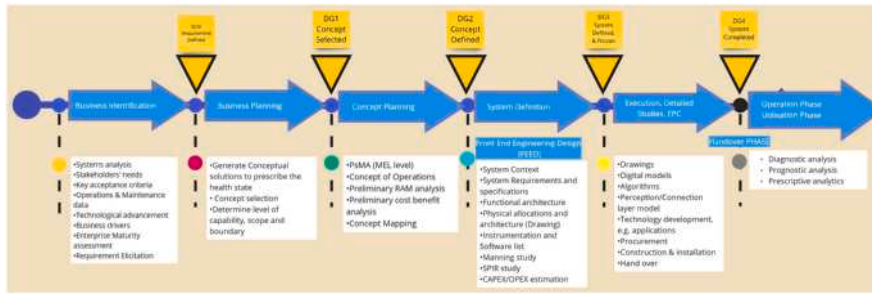


FIGURE 11.3 Project execution model for prescriptive maintenance program.

The project starts with stage 1, where systems analysis is performed to define the preferred maintenance campaigns, stakeholder requirements, and acceptance criteria. At the end of stage 1, a decision gate meeting is organised to determine if a business opportunity has been identified or not. If the business opportunity is approved, the conceptual solutions to prevent, prescribe, or correct the equipment conditions shall be explored and evaluated. At the end of stage 2 (business planning), a decision gate meeting is organised to approve the selected conceptual solution and the defined project scope, that is, which equipment will be engineered to be PsM-ready equipment. In stage 3 (concept planning), the selected conceptual solution shall be defined and planned. To define the PsM, the equipment failure modes shall be defined and with prescribed actions that would cover that failure mode and enable lifetime toleration. Moreover, the PsM architecture shall be developed at this stage to define how it is going to work. Furthermore, three checks shall be performed. First, a preliminary reliability analysis (or RAM—reliability, availability, maintainability) is needed to define how the prescription mechanism impacts the equipment availability and associated production performance.

Second, the life cycle costing and lifetime benefit analysis are needed to define the economic feasibility. Third, the concept mapping analysis, for example, the innovation big picture matrix (Fox, 2013), is needed to identify the specifications that might lead to negative impacts in the short, medium, and long terms. At the end of stage 3, a decision gate meeting is organised to approve the technical architecture and specifications that will be engineered in stage 4 (system definition) and built in stage 5 (engineering, procurement, and construction).

11.3.1 Prescriptive maintenance analysis

It becomes clear from the PEM of the PsM, three elements are required: (1) define the potential prescriptive actions and determine their coverage and confidence, (2) define and build the PsM model, and (3) define and build the architecture of the entire PsM program. To define the potential prescriptive actions and determine their coverage and confidence, the PsM analysis (PsMA) method is recommended. Similar to scheduled maintenance, where failure modes, effects, and criticality analysis (FMECA) is used and failure mode and symptoms analysis (FMSA) is used for condition-based maintenance, PsMA can be used for PsM. In Fig. 11.4, a preliminary PsMA worksheet is presented, which consists of 10 columns.

Technical Hierarchy	Function	Failure Mode	Failure effect (Impacts & Consequences)	Failure Criticality (Probability & Consequences)	Failure Mechanism	Prescriptive Action (type and level)	Prescription Coverage	Prescriptive Analytic technique	Prescription Confidence
Pump 1	Pumping water	Breakdown	Production stops	Critical	Fatigue wear	Reduce loads	2	Model-based	Medium
...									
Equipment N									

FIGURE 11.4 Template of prescriptive maintenance analysis worksheet.

The first column, the technical hierarchy, is about the physical system or equipment that is under investigation or analysis. For each piece of equipment, nine aspects shall be defined as follows: (1) its function, (2) potential failure modes which might be several modes (breakdown, burned, leakage, etc), (3) failure effect, (4) failure criticality, (5) failure mechanism (a process that leads to failure), (6) prescriptive action such as load reduction, (7) prescriptive coverage to determine how many failure modes can be covered by the recommended prescriptive action(s), (8) prescriptive analytic technique that generates insights about the equipment health status under the implemented prescriptive action, (9) prescriptive confidence to determine how accurate and how far the implemented prescriptive action can let the equipment survive before a maintenance work is done.

For example, a cooling system in the wind farm substation consists of several water pumps. The water pump has fatigue wear as a dominant failure mode, which can be prescribed by reducing the load, that is, the flow rate. The engineer believes that reducing the load will total coverage of the failure mode and therefore the prescription coverage is set as 2 (0 is not covered, 1 is partially covered, 2 is totally covered). A model-based prescriptive analytics is determined to predict the prescribed failure point. Due to the complexity of modelling the fatigue wear for water pumps, the accuracy of the prediction is set to be medium, as shown in Fig. 11.4.

11.3.2 Evaluating prescriptive maintenance models

To determine the confidence of the prescriptive action and analytical model, two criteria shall be evaluated: (1) prescription accuracy and precision and (2) prescriptive horizon. Prescription accuracy and precision assess how well the prescribed actions align with the expected results (successful outcomes) and how well the prescriptive model's predictions match actual observations or results. The prescriptive horizon refers to the time frame or period over which the prescriptive actions are recommended or implemented. In Fig. 11.5, a simple evaluation matrix is shown, where both criteria are considered to assign a confidence level to the selected prescriptive action and associated analytical model.

11.4 Developing a prescriptive maintenance model

Developing a PsM model involves creating a system that goes beyond PdM (forecasting when failure would occur based on data) to prescribing specific actions (forecasting when failure

Prescriptive Horizon	Prescription Precision		
	Low (1)	Medium (2.5)	High (5)
Low(1)	1	2.5	5
Medium(2)	2	5	10
High(3)	3	7.5	15

FIGURE 11.5 Evaluation matrix for prescriptive maintenance model.

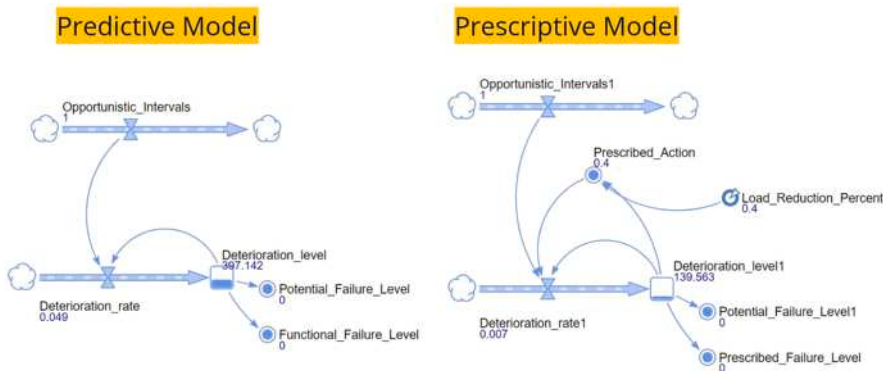


FIGURE 11.6 Deterioration and maintenance models.

would occur under the prescription conditions). This means that gathering and analysing data from various sources, including sensors, historical maintenance records, equipment performance metrics, and contextual data, is a core element in any PsM. Then, developers move beyond prediction to prescribe specific actions or maintenance interventions, which involves integrating the predictions with business rules, constraints, and optimisation algorithms to recommend the best course of action. Afterwards, the PsM model shall be integrated into the operational framework, such as existing maintenance management systems, IoT devices, or control systems. There are several types of prescriptive analytics approaches: (1) model-based analytics, which involves simulation and what-if analysis, (2) data-driven analytics, which involves techniques like reinforcement learning (RL), neural networks, and ensemble methods, (3) decision optimisation involves employing mathematical models and algorithms such as linear programming, integer programming, nonlinear programming, and others.

To understand how a prescriptive model can be built, let's take a simple case. The studied case is about on pump that has a known deterioration curve over time. Moreover, it has an annual scheduled maintenance campaign (2 weeks), which shall be considered an opportunistic maintenance interval as long as the prescriptive action will allow the pump to survive until the next scheduled maintenance campaign. To show the effect of PsM over PdM, two models are built, as shown in Fig. 11.6. The PdM model, Fig. 11.6 left, predicts the

pump deterioration curve, potential failure point (at 70% of deterioration), and the functional failure point. On the right side of Fig. 11.6, the PsM model predicts the pump deterioration curve under a full loading regime until the potential failure point is detected and then it predicts the pump deterioration curve under a reduced loading regime (60% reduction). The PsM model can prescribe the load once the potential failure point is reached and impact the determination rate (Deterioration rate 1) and level (Deterioration level 1). To build a PsM model, the system dynamics approach is used using AnyLogic software. In Table 11.1 the PsM model is described.

11.4.1 Description of the predictive and prescriptive maintenance models

To illustrate how the PsM model works, let's run the model and assume that we are able to reduce the load by 40% once the potential failure point is detected. Fig. 11.7 illustrates that the prescribed failure point (blue peak) is still located before the next maintenance campaign interval. This means a 40% load reduction will not be helpful to let the pump survive until the next maintenance campaign interval and more load reduction is required to handle the pump deterioration. Let's run the model with a 60% load reduction and see the results. Fig. 11.8 illustrates that the prescribed failure point (blue peak) is located after the next maintenance campaign interval. That means the prescribed load reduction of 60% is helpful to let the pump survive until the next maintenance campaign interval.

Model-based PsM can be more complex and requires agent-based simulation. Another type of PsM model is the optimization type. Cho et al. (2022) used a set of predictions of the components with detections obtained from the predictive system as input to the decision-making model. RL algorithms are also capable of learning, exploring, discovering system dynamics, and optimizing given objectives, particularly when underlying dynamics are unknown (hard to model using a model-based approach). Yuan (2023) suggested a prescriptive power allocation module utilizing deep RL, aiming to distribute the load among various batteries solely relying on raw sensor data. This approach extends the operational lifespan of multi-battery systems by proactively managing their workload.

11.5 Managing prescriptive maintenance

Even though the PsM model, built in the previous section, is a simple model, it illustrates the entire picture of the PsM program and highlights what should be managed over time. To put the prescriptive maintenance program in use, the management framework by NORSOK Z-008 (NORSOK, 2017) is recommended, as shown in Fig. 11.9. To adapt the PsM program into the maintenance management loop, four aspects shall be considered: (1) goals and requirements for the PsM program shall be clearly stated, (2) the concept of PsM shall be modeled and integrated into the generic maintenance program (which covers scheduled and corrective maintenance), (3) predictive and prescriptive analytics shall be performed and determine what shall be prescribed, to what extend and for how long, and (4) RL mechanism where potential failure point, functional failure point, prescribed failure point, loading profile and monitored deterioration profile shall be all reported. One of the most common

TABLE 11.1 Description of the predictive and prescriptive maintenance models.

Element	Function	Formula	Comment
Opportunistic intervals	Feeds the scheduled maintenance intervals into the deterioration rate	=1-pulseTrain(8640,336,8976,70000)	PulseTrain function generates first event after 8649 operating hours, then the maintenance event lasts for 2 weeks (336 h) and it is repeated every 8976 h during the 70,000 h. Opportunistic Intervals same as Opportunistic Intervals1
Deterioration level	Accumulates the deterioration rate over time	Deterioration level at time t = Initial Deterioration level+ Deterioration rate	Initial value is 0.1
Deterioration rate	Estimate the deterioration rate every time unit (in this study, time unit is an hour)	=Deterioration coefficient *Deterioration level* Opportunistic Intervals	Deterioration coefficient is 0.0001225, Multiplying deterioration level as deterioration increases over time, Opportunistic intervals stops deterioration under the maintenance intervals
Potential failure level	Detects potential failure at 70% of deterioration	rint(Deterioration level) == 70? time(): 0	rint() returns an integer number, Potential Failure Level same as Potential Failure Level 1
Functional failure level	Determines functional failure at 100% of deterioration	rint(Deterioration level) == 100? time(): 0	
Prescribed action	Reduces the load Once the potential failure point is detected	rint(Deterioration level1) >= 70? Load Reduction Percent: 1	
Load reduction percent	Determines the level of load reduction	0.4	0.4 means 60 % load reduction
Prescribed failure level	Determines functional failure at 100% of deterioration	rint(Deterioration level1) == 100? time(): 0	

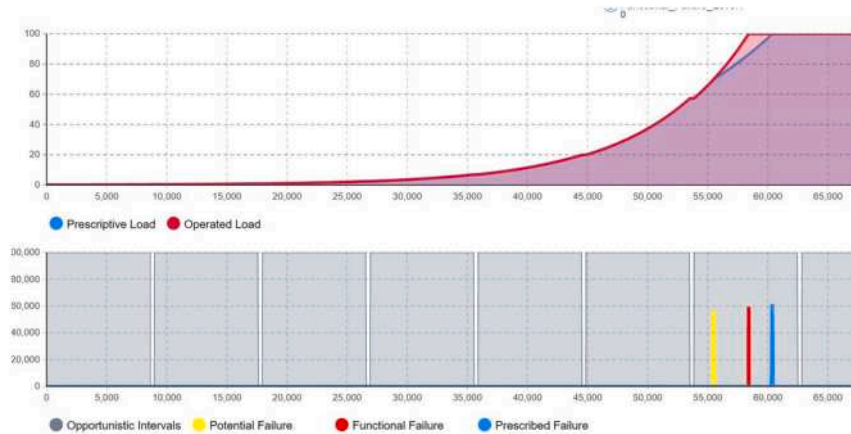


FIGURE 11.7 Deterioration curve under normal loading and prescribed loading (40% load reduction) conditions.

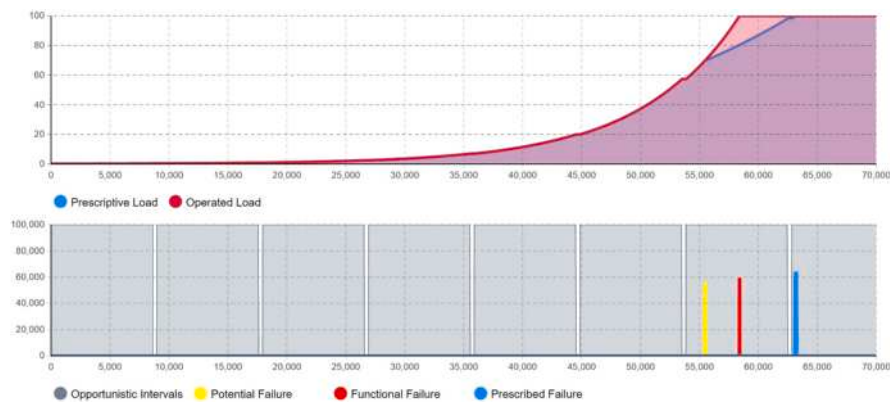


FIGURE 11.8 Deterioration curve under normal loading and prescribed loading (60% load reduction) conditions.

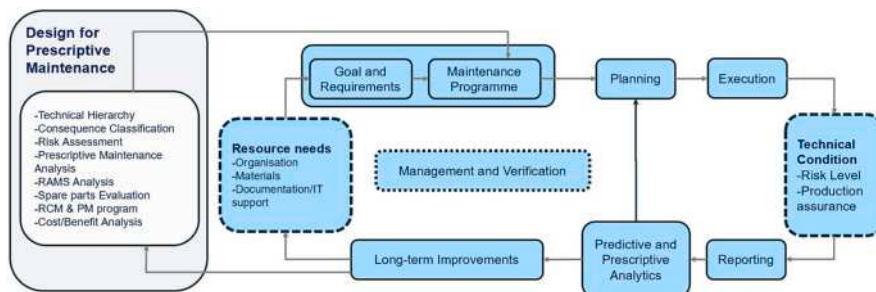


FIGURE 11.9 Maintenance management loop with a prescriptive maintenance programme.

frameworks to manage the collection and exchange of reliability and maintenance data for equipment is the one recommended by ISO 14224 ([International Organization for Standardization. Petroleum, 2016](#)).

11.6 Conclusions

The chapter defines and explains PsM and when it can provide benefits. Thinking and designing PsM shall take place in the project phase to ensure it fits the purpose and satisfies the user's needs. Methods like PsMA are helpful for engineers to define the technical specifications for their PsM models and programs and may inspire new engineering methods to support the implementation of PsM. Definitely, it shall be tested further and revised. Very rare agent-based simulation and RL models are implemented to support PsM applications.

PsM encourages a new paradigm of system and equipment design, where a long-term control or surviving mechanism system is attached. "System survivability" typically refers to the ability of a system to continue functioning or operating despite challenges, disruptions, or adverse conditions. A system that is considered survivable is designed or capable of withstanding various threats, failures, or disruptions and still maintain its essential functions or core capabilities. This could include resilience to physical damage, cybersecurity threats, or other risks that might otherwise compromise its operation.

Conflict of interest

The authors declare no conflict of interest.

Abbreviations

CbM	condition-based maintenance
PdM	predictive maintenance
PsM	prescriptive maintenance

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Predictive maintenance and intelligent asset management in Industry 4.0

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12.1 Introduction

“Maintenance is the combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function” (EN 13306:2001 Maintenance terminology). The standard EN 13306:2001 defines the item as any part, component, device, subsystem, functional unit, equipment, or system that can be considered individually.

Maintenance planning encompasses all activities involved in developing a structured and regularly scheduled work program to ensure optimal equipment performance and prevent significant failures. This process includes selecting the most effective maintenance strategies, as well as planning and scheduling tasks efficiently.

Conversely, maintenance control and supervision focus on monitoring key aspects to guarantee proper execution of maintenance management within an industrial setting. This involves gathering field data to assess asset reliability, overseeing work progress and reporting, managing inventory, and controlling costs.

Maintenance plays a crucial role in the overall success of a manufacturing company, as it directly influences both productivity and product quality. Due to the multifaceted nature of maintenance management, which encompasses the integration of various organizational functions and operational processes, its implementation presents inherent complexities and necessitates a highly systematic and rigorous approach. Finally, it is widely recognized that maintenance costs represent a significant portion of the overall production budget. Studies indicate that a substantial share of these costs is often incurred unnecessarily. Additionally, maintenance-related consequence costs can be considerable, arising from factors such as

equipment downtime or inadequate maintenance practices. Poor maintenance strategies may also lead to increased capital being tied up within the supply chain, further impacting operational efficiency. In summary, the substantial direct and indirect economic impact of maintenance emphasizes the potential for improvement and reinforces its strategic significance. In summary, effective maintenance management integrates multiple organizational functions, making its implementation inherently complex and requiring a systematic approach. Beyond cost considerations, a well-structured maintenance strategy is essential for asset reliability, operational efficiency, and long-term productivity, ultimately enhancing competitiveness in an increasingly demanding industrial landscape.

12.2 Theoretical framework

12.2.1 Evolution of maintenance strategies

12.2.1.1 *From reactive to predictive maintenance*

Asset maintenance encompasses all activities focused on monitoring, restoring, improving, or preventing the loss of an asset's functionality, whether partially or completely (Manzini et al., 2010). A maintenance strategy outlines the guidelines that govern the execution of these maintenance tasks. This strategy defines the types of maintenance actions to be carried out, the timing of those actions, the prioritization of different components or subsystems, the management of spare parts, and the involvement of the technical maintenance team (Velmurugan & Dhingra, 2015). Maintenance strategies can be divided into four main categories, as illustrated in Fig. 12.1:

- *Corrective maintenance.* This strategy, also referred to as reactive or failure-based maintenance, involves addressing issues after they occur, often in response to emergencies caused by equipment failure or breakdown. Such activities are unplanned (Swanson, 2001). This approach is only appropriate for assets or systems where their failure would not significantly impact the business. Otherwise, it can lead to high maintenance costs, as the focus is on repairing or replacing damaged assets, which is typically more expensive than preventive measures that enhance the asset's performance. Additionally, this strategy can incur further costs due to service disruptions, including penalties for downtime, production delays, and other related expenses (Gallimore & Penlesky, 1988).
- *Preventive maintenance.* To mitigate the consequences of reactive maintenance, a preventive maintenance strategy can be implemented. Also referred to as time-based maintenance, this approach aims to prevent or minimize asset failures (Shafiee, 2015). This strategy relies on the expertise of the plant, infrastructure, or asset manager, who schedules various maintenance activities at different intervals over time. The goal is to avoid service interruptions, or, when unavoidable, to minimize their impact by planning them in advance (Bashiri et al., 2011). Preventive maintenance includes *scheduled maintenance* and *opportunistic maintenance* strategies (Pinciroli et al., 2023). Scheduled maintenance aims to prevent the asset from losing functionality by performing maintenance actions at scheduled intervals, which can be either irregular or periodic. Typically, statistical data from the assets, such as failure times and maintenance

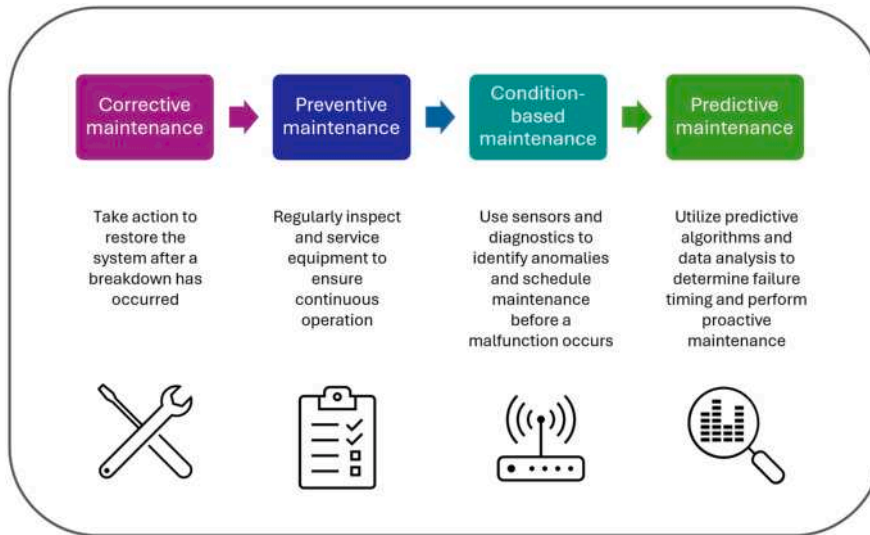


FIGURE 12.1 Comparison of maintenance strategies: corrective, preventive, condition-based, and predictive. Each strategy varies in approach, from fixing failures after they occur to using data and analytics to predict and prevent breakdowns before they happen. Source: Adapted from Sutharssan, T., Stoyanov, S., Bailey, C., & Yin, C. (2015). *Prognostic and health management for engineering systems: A review of the data-driven approach and algorithms*. The Journal of Engineering, 2015(7), 215–222. <https://doi.org/10.1049/joe.2014.0303>.

durations, are used to develop the maintenance plan (Manzini et al., 2010). Scheduled maintenance is ideal for high-risk systems where failure could lead to severe safety risks, significant production losses, or where careful planning can yield economic benefits, such as when spare parts are not readily available and need to be ordered in advance. Opportunistic maintenance focuses on conducting maintenance on multiple asset elements or subsystems simultaneously. For example, it combines maintenance activities for components with similar failure rates and operating conditions, or it takes advantage of a planned shutdown or an unexpected breakdown to service several components at once (Shafiee & Sørensen, 2019). This strategy is particularly well-suited for systems with similar components or those that undergo extended, planned shutdowns, such as nuclear power plants during refueling (Pinciroli et al., 2023). It is also beneficial for systems requiring costly equipment rentals, like cranes or ships, for maintenance activities.

- *Condition-based maintenance (CBM)*. It involves scheduling maintenance activities based on signs of asset degradation or deviations from its normal performance (Nikolaev et al., 2019). Also referred to as diagnosis-based maintenance, this strategy relies on detecting anomalies through advanced technologies like the Internet of Things (IoT) and Cloud Computing, which are used to monitor the asset's condition. This strategy can be further improved by incorporating artificial intelligence (AI) algorithms to diagnose issues and gather detailed status data (Mabkhot et al., 2018).
- *Predictive maintenance*. It has emerged as a highly researched and critical area within the Industry 4.0 paradigm, leveraging advanced technologies to optimize equipment reliability and operational efficiency (Zenisek et al., 2019). As an extension of CBM, it

takes monitoring data further by using it for prognostics (Hu et al., 2022), meaning it estimates the time of failure, enabling maintenance activities to be planned in advance. This approach requires the development of both monitoring systems and prognostic tools. The varying and uncertain conditions in which components operate can significantly affect degradation and failure mechanisms, necessitating the proper handling of data with multiple sources of uncertainty. Predictive maintenance is ideal for systems that benefit from the same advantages as CBM but also gain from advanced planning, such as when spare parts are not readily available and must be ordered ahead of time. Various techniques can be employed to combine all available information to enhance the accuracy of maintenance predictions (Animah & Shafiee, 2018; Fang et al., 2017). These techniques can be either data-driven or model-driven. The data-driven approach relies on Big Data techniques, requiring a substantial volume of data on the asset's condition, which can be gathered through proper sensor deployment. Based on this data, analysis algorithms are developed to identify trends in the asset's behavior (Liu et al., 2018).

12.3 What is Industry 4.0

Industry 4.0 refers to the digital transformation of value creation and delivery processes across three levels: micro (equipment), meso (intraorganizational), and macro (value network). It encompasses a highly interconnected network of intelligent materials, components, machinery, central factories, suppliers, distribution channels, and even end customers (Ghobakhloo et al., 2021). In particular, recent advancements in Information Technology (IT) have made it possible to monitor equipment and establish direct communication between machines within a cyber-physical system (CPS) (Ustundag & Cevikcan, 2017).

The concept of Industry 4.0 was first introduced in 2011 with the aim of advancing the German economy (Roblek et al., 2016; Vogel-Heuser & Hess, 2016). The timeline of industrial revolutions can be summarized as follows: the first industrial revolution emerged in the late 18th century, characterized by mechanical production facilities powered by water and steam. The second industrial revolution began at the start of the 20th century, marked by mass production driven by electrical energy. The third industrial revolution arose in the 1970s, distinguished by automated production systems enabled by electronics and internet technologies. Currently, the fourth industrial revolution, referred to as Industry 4.0, is underway. It is defined by the integration of CPS into production, leveraging heterogeneous data and knowledge integration. The primary objectives of CPS are to meet the agile and dynamic demands of production processes while enhancing the overall effectiveness and efficiency of the industrial sector.

12.3.1 Concept and principles

Industry 4.0 represents a paradigm shift in manufacturing and industrial processes, characterized by the seamless integration of digital technologies into every aspect of production. At its core, Industry 4.0 leverages connectivity, advanced analytics, and automation to create smart factories capable of real-time decision-making and adaptive

operations. This revolution is guided by a set of key principles that define how technologies such as the IoT, AI, and CPS transform traditional manufacturing into a more flexible, efficient, and customer-focused ecosystem.

The following are the foundational concepts and principles that form the framework of Industry 4.0, driving innovation and value creation in modern industries.

1. **Interoperability:** Interoperability can be defined as the ability of two or more systems, programs, or products to exchange and interpret each other's data effectively (Chen et al., 2024). Interoperability is a critical achievement in enterprise modeling, driven by the integration of information and manufacturing systems (Panetto & Molina, 2008). Machines, devices, sensors, and humans can connect and communicate via the IoT and other digital technologies.
2. **Information transparency:** Information transparency in Industry 4.0 is achieved by collecting and analyzing data from physical systems to create a virtual environment that supports informed decision-making (Ghadimi et al., 2019). Various agents in the supply chain can send and receive information in real time through predefined information exchange protocols. This structured message-passing framework enhances the transparency of operations, enabling seamless communication and data sharing among all involved entities. By ensuring that accurate and timely information flows across the supply chain, Industry 4.0 fosters better coordination and decision-making at all levels. The creation of a virtual environment by collecting and analyzing data from physical systems to facilitate informed decision-making.
3. **Technical assistance:** Systems provide support to human operators through automated decision-making and task execution, enhancing efficiency and safety. Technical assistance involves tools and systems designed to help understand and manage events, such as detailed visualizations that enable humans to address issues quickly and efficiently (Javed et al., 2021).
4. **Decentralized decision-making:** Decentralized decision-making focuses on enabling automated processes that operate independently, reducing the need for human involvement and shifting the role of the operator to that of a supervisor (Javed et al., 2021). CPSs can make autonomous decisions and perform tasks independently, reducing reliance on centralized control.
5. **Horizontal and vertical integration:** Engineering, production, marketing, suppliers, and supply chain operations must all work together to establish a collaborative environment for system integration, guided by the flow of information and aligned with the degrees of automation involved (Saucedo-Martínez et al., 2018). Horizontal integration refers to the integration between companies, serving as the basis for close, high-level collaboration among multiple organizations. It leverages information systems to enhance the product life cycle, fostering an interconnected ecosystem within the same value creation network. Vertical integration represents a networked manufacturing system and involves intra-company integration. It forms the foundation for information exchange and collaboration across various levels of an enterprise's hierarchy, including corporate planning, production scheduling, and management.
6. **Virtualization:** Virtualization enables the separation of physical computing or manufacturing resources from their usage, allowing workloads to be seamlessly transferred to

another resource during execution (Borangiu et al., 2019). The creation of virtual replicas of physical processes, often referred to as “digital twins,” is used to monitor, simulate, and optimize operations.

7. Service orientation: Process integration introduces a service-oriented approach, where all entities within the production system are interconnected, supporting the development of a product-service system (Kamble et al., 2018). The resulting flexibility and agility from this service orientation enable organizations to adapt rapidly to market changes. This approach also fosters collaboration among various stakeholders, allowing them to work together to cocreate value for consumers.

12.3.2 Technological pillars of Industry 4.0

Industry 4.0 paradigm consists of nine technological pillars (Cristians & Methven, 2017; Jones et al., 2019; Pierdicca et al., 2017; Vaidya et al., 2018) that are as follows:

- Industrial Internet of Things (IIoT)
- Big Data and Analytics
- Horizontal and Vertical System Integration
- Simulation
- Cloud Computing
- Augmented Reality
- Autonomous Robots
- Additive Manufacturing
- Cybersecurity.

These nine technologies serve as the foundation for advancing new interconnection technologies. While each can be applied independently, their simultaneous implementation reveals the full potential of Industry 4.0, enabling state-of-the-art technological solutions driven by data collection and intelligent manufacturing processes (Hofmann & Rüsch, 2017).

The foundational technologies of Industry 4.0 encompass the IIoT, Big Data and Analytics, Horizontal and Vertical System Integration, Simulation, Cloud Computing, Augmented Reality, Autonomous Robots, Additive Manufacturing, and Cybersecurity. Collectively, these nine technological pillars enable the transformation of traditional factories into “intelligent” or “smart” factories, characterized by full integration, automation, and optimized production processes (Zolotová et al., 2020).

These technologies facilitate enhanced efficiency and foster innovative interactions among suppliers, manufacturers, customers, and between humans and manufacturing systems (Vaidya et al., 2018). The IIoT extends the IoT concept (Atzori et al., 2010; Gubbi et al., 2013) to the industrial sector, enabling machine-to-machine communication without human intervention (Xu et al., 2014). Through the interconnection of physical objects equipped with sensors and standardized internet protocols, IIoT establishes networks encompassing all components of the supply chain. IoT is recognized as a core technology underlying CPSs (Lee et al., 2015; Monostori et al., 2016; Nunes et al., 2015), which integrate computation, communication, and control systems (cyberspace) with natural and human-made systems (physical space) (Monostori et al., 2016). CPSs merge the virtual and physical worlds, effectively dissolving the boundaries between them (Saldivar et al., 2015). In a smart

factory, complex and diverse systems are integrated to achieve high performance and reliable operations (Morgan & O'Donnell, 2015). Data generated by CPSs, combined with customer-management systems, serve as the foundation for Big Data analysis (Vaidya et al., 2018), enabling real-time decision-making supported by powerful computational capabilities and high-bandwidth data transmission.

Big Data comprises four dimensions: data Volume, data Variety, the Velocity of data generation and analysis, and the Value derived from data (Witkowski, 2017). The synergy of Big Data, Cloud Computing, and CPSs forms industrial networks, driving the establishment of smart factories (Erboz, 2017). The proliferation of IoT sensors has further advanced Big Data Analytics and Machine Learning tools, which find applications in trend analysis, process monitoring, quality prediction and control, fault diagnosis and classification, online soft sensing, and process control (Ge et al., 2017).

Horizontal and Vertical System Integration ensures connectivity across the entire supply chain, achieving seamless coordination among all actors within dynamic systems (Peres et al., 2018; Stock & Seliger, 2016). Simulation, as a digital tool, supports production system design and facilitates effective maintenance. It plays a role in value networks and real-time optimization of intelligent system data (Chong et al., 2018).

Cloud Computing (Hassan, 2011; Zolotová et al., 2020) enables the on-demand sharing of processing resources and devices. It allows information sharing across systems, from individual production lines to entire plants (Marilungo et al., 2017), and supports off-site analysis (Tao et al., 2018), enhancing the scalability and flexibility of intelligent manufacturing systems (Chen et al., 2018).

Augmented Reality enhances human-machine interaction by overlaying digital data onto the real world, creating a coherent blend (Figueiredo et al., 2014). It provides real-time information for tasks such as maintenance and logistics through smart devices, including wearable Augmented Reality tools and head-mounted displays (Chong et al., 2018; Nee et al., 2012; Ong et al., 2008).

Autonomous Robots are increasingly self-sufficient, cooperative, and versatile, capable of interacting with each other or assisting operators (cobots) in performing tasks (Djuric et al., 2016; Sadik & Urban, 2017). Additive Manufacturing involves converting digital designs, such as 3D CAD models, into physical objects via 3D printing (Chong et al., 2018), making it ideal for producing small batches of customized products (Chua et al., 2010).

Lastly, Cybersecurity protects shared information and CPSs from cyber threats, ensuring the security and reliability of smart manufacturing environments (Wells et al., 2014).

12.3.3 The integration of artificial intelligence with Industry 4.0 technology

In the contemporary information-driven era, data have emerged as the most critical asset for companies aiming to achieve a competitive advantage in their industry (Harding et al., 2006; Taranto-Vera et al., 2021). Companies strive to leverage available data to enable data-driven decision-making and achieve a competitive advantage. Within the framework of Industry 4.0, the notion of “smart manufacturing” has arisen (Kusiak, 2017), where the integration of Big Data, the IoT, CPS, and AI is harnessed to establish environments in which intelligent machines interact seamlessly, facilitating the automation of production lines and enabling the monitoring, detection, processing, and analysis of data and information to

prevent equipment failures (Pinciroli et al., 2022). AI and Machine Learning technologies, supported by the extensive data collected through modern digital advancements, have become fundamental components of the CPSs driving Industry 4.0. While AI is frequently equated with Machine Learning, it is a broader discipline encompassing various aspects of intelligence, such as perception, sensing, reasoning, and knowledge representation, alongside its Machine Learning capabilities (Jan et al., 2023). The integration of AI-related technologies has significantly transformed industrial operations, offering advancements in maintenance, control, process monitoring, production optimization, service management, and simplification of operational changes (Alenizi et al., 2023). In Industry 4.0, AI enables smart system management across multiple branches through continuous monitoring, issuing alerts for potential issues, and leveraging virtual tools for remote oversight. Unlike traditional systems that react only after errors caused failures, AI-powered monitoring systems perform real-time analyses to identify and address issues proactively, reducing operational costs. Furthermore, AI facilitates scenario simulations for parameter optimization, improving overall system performance. By identifying patterns and predicting future trends, AI enhances system management, minimizes costs, and optimizes the utilization of human and material resources.

12.4 Technology for maintenance and sustainability

12.4.1 Internet of Things and smart sensors

The introduction of Industry 4.0 technologies has transformed factories into “intelligent” and smart environments (Zolotová et al., 2020). As highlighted in the previous section, these technologies are commonly categorized into nine key pillars by various researchers, several of which play a pivotal role in maintenance processes. Notably, the IIoT and Cloud Computing are consistently emphasized in numerous studies, underscoring their foundational importance to Industry 4.0 (Zolotová et al., 2020).

The IIoT enables the interconnection of physical devices via the internet, facilitating the exchange of both global and local data (Alqahtani et al., 2019; Karkalos et al., 2019; Olaf & Hanser, 2019). CPSs, driven by IIoT, serve as technological enablers for effective organizational collaboration. CPSs support the achievement of shared objectives by enabling seamless communication among various stakeholders through multiple sensory input/output devices (Dinardo et al., 2018; Roy et al., 2016). These systems significantly influence industrial services in manufacturing, particularly in enhancing the efficiency and quality of maintenance operations. This is primarily due to CPSs’ capabilities in predicting and initiating service activities as well as enabling remote diagnostics. Additionally, CPSs collect extensive real-time data on machine conditions, which serves as a foundation for Big Data analysis (Peres et al., 2018), an invaluable tool for planning maintenance activities. For instance, wireless data transmission and diagnostic algorithms, coupled with portable vibration sensors, monitor the condition of bearings and gears (Ooijevaar et al., 2019). Similarly, a Prognostics and Health Management (PHM) methodology, leveraging advanced sensor systems to monitor the health of industrial robots and optimize future maintenance

strategies, can be effectively implemented (Qiao & Weiss, 2019). Furthermore, a sensor-based maintenance policy has been developed to facilitate preplanned maintenance activities, effectively reducing overall costs (Xia et al., 2019). Finally, CPSs leverage advancements in sensing and information technologies to provide robust support for PHM decision-making, enabling predictions of machine deterioration (Xia & Xi, 2019).

12.4.2 Big Data and Cloud Computing

The advantages of Industrial Big Data analytics in maintenance include enhanced predictive capabilities, the attainment of near-zero downtime, optimized asset performance, and data-driven decision-making. The use of Big Data has been applied to design efficient and sustainable robust layouts for industries, where maintenance evaluation emerges as a key aspect for planning (Kumar et al., 2018). Maintenance decision-making plays a highly relevant role in management (Ansari et al., 2018; Sénéchal, 2018), facilitating the development of optimal strategies (Kumar et al., 2019; Simon et al., 2018). The primary objective of Big Data analysis is to support real-time decision-making, which is typically achieved through analytical, data-driven algorithms (Subramaniyan et al., 2018). Some paradigms for cost-effective and reliable monitoring systems have been identified, particularly when data from various sources are integrated (Mourtzis & Vlachou, 2018). Among these, an adaptive scheduling multicriteria algorithm considers real-time data from production line elements, such as machines or human operators, and provides maintenance guidelines. Fuzzy interpretation of machine states has been proposed to derive dynamic characteristic values related to “machine health.” Additionally, technological gaps between the demands of Industry 4.0 applications and existing Big Data technologies used for predictive maintenance have been analyzed, resulting in a data processing framework designed to address identified weaknesses (Sahal et al., 2020).

Cloud technology can be seen as complementary to IoT, Big Data, and Simulation, given its dual functionality as both a storage solution and a Cloud Computing platform. A cloud system plays a crucial role not only in storing information collected from CPSs (Fernández-Caramés et al., 2018; Mourtzis & Vlachou, 2018; Wan et al., 2017) but also in enabling on-demand computing. Beyond data storage, Cloud Computing facilitates the sharing of processing resources and other devices on demand. This approach allows users and enterprises to process their data by accessing a shared pool of configurable computing resources, including networks, servers, storage, applications, and services (Zolotová et al., 2020).

12.4.3 Artificial intelligence and machine learning

Industrial systems generate vast amounts of data that capture information about processes, events, and alarms occurring across production lines. When these data are processed and analyzed, it reveals valuable insights into manufacturing processes and system dynamics. By leveraging data-driven analytic methods, it becomes possible to derive actionable insights that support strategic decision-making. This, in turn, offers numerous benefits, such as reducing maintenance costs, minimizing machine faults, decreasing repair downtimes, optimizing spare parts inventory, extending the lifespan of spare parts, enhancing production efficiency, improving operator safety, validating repairs, and ultimately boosting overall profitability (Biswal & Sabareesh, 2015; Peres et al., 2018; Sezer et al., 2018).

Recently, novel maintenance strategies leveraging AI techniques have been developed to enhance maintenance management and optimization (Monostori, 2014). Notably, deep reinforcement learning, which integrates reinforcement learning with deep learning, has been applied to tackle complex and large-scale maintenance decision-making problems.

The design of a Machine Learning system for a predictive maintenance application typically involves the following steps: historical data selection step; data preprocessing step; model selection, model training, and model validation step; and model maintenance step (Carvalho et al., 2019). In particular, the historical data selection phase focuses on determining how data is collected and stored, ensuring that the most valuable data are identified for designing the Machine Learning model. In predictive maintenance, this phase is also referred to as the data acquisition step, with the goal of obtaining data relevant to system health. The data preprocessing phase involves preparing and transforming the data to ensure that it can be effectively utilized by the ML model. This includes tasks such as data transformation (e.g., normalization), data cleaning (e.g., handling missing values and removing outliers), and data reduction (e.g., dimensionality and numerosity reduction). As will be shown in Section 5, the preprocessing phase plays a critical role in organizing and analyzing the collected data for enhanced understanding and meaningful interpretation.

12.4.4 Edge computing

Edge computing is a distributed computing technology designed to bring applications closer to their data sources, such as IoT devices and local edge servers (Cao et al., 2020; Khan et al., 2019; Satyanarayanan, 2017). Edge computing plays a pivotal role in the digital transformation of smart factories, offering a groundbreaking approach to industrial maintenance. By processing data directly at or near the machines, this technology ensures real-time anomaly detection, minimizing latency compared to traditional cloud-based models. This capability is essential for implementing predictive maintenance strategies, preventing critical failures, and maximizing equipment uptime. Additionally, local processing significantly reduces network traffic, enhancing both efficiency and the security of sensitive data management. Unlike Cloud Computing, edge computing provides several key advantages: it reduces network strain by decentralizing data processing to the network's edge, enhances user privacy by processing and storing data locally at the edge, and optimizes costs and resource utilization associated with cloud operations (Shi et al., 2016; Yu et al., 2023). Edge computing facilitates real-time fault detection by enabling data processing directly at the source, such as sensors attached to industrial machinery (Bala et al., 2024). This approach significantly reduces latency compared to centralized cloud processing, allowing for quicker anomaly identification and minimizing the risk of operational disruptions.

12.4.5 Sustainability in maintenance

Sustainable manufacturing requires integrating sustainability-related aspects into maintenance management to ensure high asset performance, equipment availability, and product quality while minimizing resource and energy consumption (Garetti & Taisch, 2012; Takata et al., 2004).

The sustainable management of maintenance processes should aim to minimize environmental impact, ensure stakeholder safety, and achieve efficient resource and energy management

(Jasiulewicz-Kaczmarek & Drozyner, 2011). This can be facilitated by integrating lean and green practices into maintenance management (Jasiulewicz-Kaczmarek, 2014). Maintenance strategies must be selected based on both conventional and sustainability criteria due to the strong connection between maintenance and sustainability issues (Nezami & Yildirim, 2013). Operationally, maintenance actions should prioritize equipment whose availability and productivity variations significantly affect throughput and value generation for sustainable manufacturing (Durán & Durán, 2019). In particular, maintenance can contribute to developing sustainable practices, as demonstrated in the foundry industry (Saniuk et al., 2015).

Integrating sustainable development into maintenance processes allows the maintenance function to focus on extending asset lifespan and ensuring high technical efficiency with optimal resource use (Jasiulewicz-Kaczmarek, 2012). Furthermore, maintenance influences sustainability both directly, through the execution of its processes, and indirectly, by affecting assets and equipment, and consequently, the manufactured product (Franciosi et al., 2020). As a result, the efficiency or inefficiency of maintenance has a significant impact on an organization's sustainability objectives.

Maintenance-related environmental impacts are significant and must be incorporated into maintenance strategies. Poorly defined maintenance practices for manufacturing assets result in hazardous emissions, production waste from system malfunctions, inefficient energy use, ineffective resource consumption, and wasted stored materials (Liyanaage & Badurdeen, 2010). Maintenance systems are closely connected to environmental issues and can be modeled as complex systems using system dynamics techniques (Kazemi, 2013). Improper maintenance operations also cause additional transportation, leading to higher energy consumption, emissions, and increased packaging requirements, along with potential spills during transportation. Furthermore, production downtime due to maintenance delays results in wasted energy for heating, cooling, and lighting (Raouf, 2009). Maintenance activities also directly impact the environment in various ways.

Despite the emphasis on achieving sustainability-oriented maintenance management, the primary impact of maintenance processes remains centered on the economic dimension of production systems. Environmental impacts are typically limited to emissions, spare parts, and oils associated with maintenance execution, while social impacts are confined to factors such as operator training and job satisfaction.

Finally, workers and stakeholders play a central role in the industrial environment, where the primary social impact of maintenance relates to health and safety. Poor maintenance practices lead to unsafe and unhealthy working conditions, accidents, and hazardous situations (Jasiulewicz-Kaczmarek & Drozyner, 2013).

12.5 Predictive maintenance in Industry 4.0

Machines, processes, control systems, and other assets are widely employed across various engineering and industrial applications. However, without an effective maintenance program, these subsystems inevitably degrade and fail over time.

As extensively illustrated in Section 12.2.1.1, maintenance strategies can be categorized into three levels (Bousdekis et al., 2015; Guc & Chen, 2022). Reactive maintenance refers to

unplanned tasks that need to be performed urgently to restore track availability, even without a planned period of control or access. Preventive maintenance focuses on conducting regular inspections and updates, but it often leads to the premature disposal of components, wasting their useful life. In contrast, predictive maintenance involves determining whether maintenance is needed for a system based on its current condition (Garg & Deshmukh, 2006). In particular, predictive maintenance aims to determine the optimal timing and specific components for maintenance, maximizing system utilization while minimizing unnecessary waste of remaining operational life. By identifying the ideal operational condition before failure occurs, predictive maintenance enables users to determine the exact part of a complex system that needs attention. This approach reduces downtime, optimizes spare parts management, and extends the overall lifespan of equipment.

In the context of Industry 4.0, predictive maintenance has significantly advanced, leveraging enabling technologies to utilize real-time detection and predictive algorithms for monitoring and anticipating the condition of physical systems (Bousdekis et al., 2019; Zonta et al., 2020).

Data gathered from multiple sensors in Industry 4.0 environments offer new possibilities for developing solutions to predict an asset's remaining useful life (RUL) (Yan et al., 2017).

Indeed, a key requirement for successfully implementing effective predictive maintenance is having sufficient data from all aspects of the manufacturing process (Kiangala & Wang, 2018). This approach can reduce maintenance costs and downtime while enhancing productivity and quality (Zonta et al., 2020).

Predictive maintenance can be divided into two different categories: Statistical Predictive Maintenance and Condition-Based Predictive Maintenance (Theissler et al., 2021).

Statistical Predictive Maintenance relies on data that is not directly tied to the specific condition of an individual vehicle. Instead, it uses historical maintenance records or data collected from a fleet of vehicles or an entire population (Theissler et al., 2021). Statistical approaches serve as the cornerstone of data-driven prognostic methods, utilizing statistical and learning techniques that largely originate from the principles of pattern recognition (Peng et al., 2010). Condition-Based Predictive Maintenance involves assessing the system's health in real time by monitoring live data to guide maintenance decisions (Carnero, 2006). CBM focuses on intervening only when specific conditions derived from sensor measurements are no longer met, ensuring that maintenance is performed solely when necessary (Li, Peng, et al., 2020).

12.5.1 Condition-based predictive maintenance and artificial intelligence

Predictive maintenance systems leverage CPSs from Industry 4.0 technologies, the IoT, and Big Data analytics to create self-aware and self-sustaining machines (Lee et al., 2014). AI plays a critical role in analyzing large volumes of data from predictive maintenance sensors, facilitating fault detection and diagnostics to prevent production interruptions (Tao et al., 2018). Advances in Big Data analytics have elevated the strategic significance of data-driven manufacturing (Ji & Wang, 2017). As a result, self-learning manufacturing systems are evolving to make proactive, informed maintenance decisions, adapting to emergencies, and predicting and preventing errors and failures. These systems utilize both historical and real-time data collected from predictive maintenance sensors and follow a comprehensive

process, including data acquisition and preprocessing, feature engineering (such as feature extraction and selection), and model training and prediction (Zhang et al., 2019).

The maintenance system has evolved into a fail-safe approach focused on ensuring equipment safety by detecting defects and estimating RUL. This is achieved through the systematic application of advancements in AI and IT-based testing methodologies (Zhang et al., 2019). The integration of AI into maintenance processes not only reduces maintenance costs but also prolongs the RUL of equipment (Qiao & Lu, 2015).

The implementation of a CBM policy involves three essential steps (Lee et al., 2004; Veldman et al., 2011):

1. Data collection: Relevant data are gathered either offline or online through various methods, such as process control systems, vibration measurements, oil sampling, and others.
2. Data analysis: The collected data are cleaned and analyzed to ensure accuracy and usability for further processing.
3. Decision-making: Using the results of the data analysis, informed decisions are made to recommend effective and efficient maintenance policies.

CBM is based on predicting the degradation of equipment. These predictions can be achieved through Machine Learning analysis of known machine characteristics and the assessment of process parameters (Acernese et al., 2021).

Machine Learning techniques are valuable tools for leveraging data to develop predictive maintenance models and reduce failure-related costs. Various studies have utilized different Machine Learning approaches, including classification methods, filtering and prediction techniques, and regression models (Jardine et al., 2006). Various researchers have successfully implemented principal methods in prognostic processes, such as Bayesian models, fuzzy logic, Monte Carlo simulation, neural networks, Kalman filters, Markov models, and Support Vector Machines (Quatrini et al., 2020). Notably, a model specifically designed for fault detection and diagnostics in dynamic stochastic systems has been proposed to enhance maintenance effectiveness (Berka & Macek, 2011), further reinforcing the critical role of advanced mathematical tools in predictive maintenance.

12.5.2 Data-driven Prognostics and Health Management and artificial intelligence

PHM is an advanced, integrated technology that utilizes knowledge, information, and data related to system performance, control, operation, and maintenance (Jouin et al., 2016; Zio, 2016). Its key functions include (1) detecting the onset of anomalies, (2) identifying and diagnosing existing failures, and (3) forecasting the system's future health state, and estimating its RUL to provide dynamic support for maintenance decision-making (Compare et al., 2020; Xia et al., 2018).

Traditionally, PHM implementation involves processes such as data acquisition, anomaly detection, diagnostics, prognostics, and maintenance decision-making. PHM should be incorporated from the initial stages of engineering system conceptualization, design, and development to ensure its seamless integration into the overall system framework, with the goal of meeting the operational requirements (Al-Mohamad et al., 2020; Li, Verhagen, et al., 2020).

Diagnostic and prognostic tasks in complex systems or plants are challenging due to the wide range of equipment failures, associated process responses, and the extensive number of process variables monitored, often in the thousands in modern process plants, resulting in information overload (Zio, 2023). Therefore it is crucial to develop automated methods for PHM of industrial equipment to effectively support human operators.

The typical workflows of a PHM system can be conceptually illustrated, as shown in Fig. 12.2, with three key tasks: fault diagnostics, prognostics, and CBM. The first task focuses on diagnosing and identifying the root causes of system failures. These identified root causes provide valuable insights into prognostic models and offer feedback for improving system design. The second task uses processed data and existing system models or failure mode analyses as inputs, leveraging a library of prognosis algorithms to dynamically update degradation models and predict system failure times. The third task utilizes prognosis results, such as the RUL distribution, to evaluate the costs and benefits of various maintenance actions and determine the optimal timing and method for preventive maintenance to minimize operating costs and risks. All three tasks are designed to operate dynamically and in real time.

In addition to these primary tasks, there are other essential components depicted in Fig. 12.2, which are often prepared offline and require only periodic updates during system operation. For instance, signal processing and feature extraction involve preprocessing

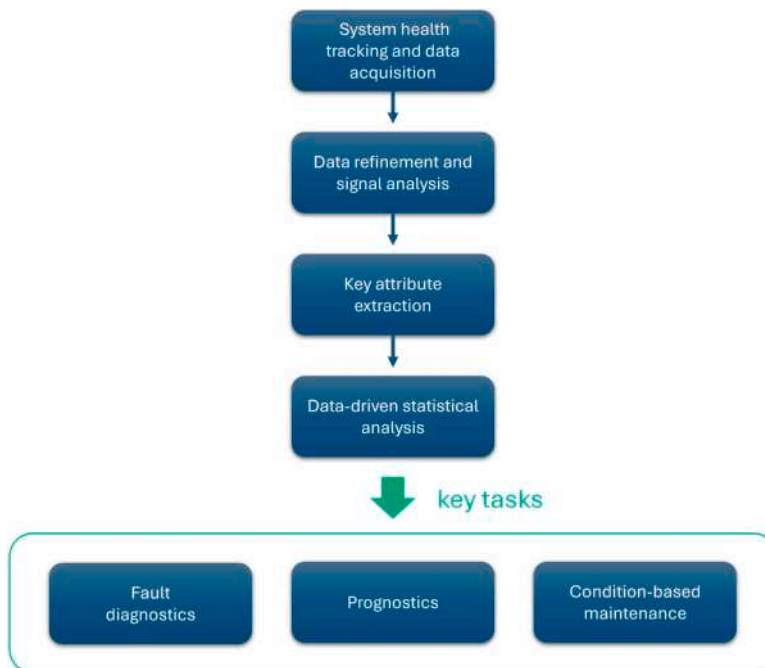


FIGURE 12.2 Typical workflows of a Prognostics and Health Management system. Source: Adapted from Sutharssan, T., Stoyanov, S., Bailey, C., & Yin, C. (2015). *Prognostic and health management for engineering systems: A review of the data-driven approach and algorithms*. The Journal of Engineering, 2015(7), 215–222. <https://doi.org/10.1049/joe.2014.0303>.

signals using methods derived from engineering knowledge, expert experience, or statistical analysis of historical data. This step aims to remove noise, reduce data complexity, and transform the data into suitable formats for further analysis. Similarly, diagnosis and prognosis algorithms can be developed offline to address the unique characteristics of signals and system properties. When new sensor signals are received, appropriate algorithms can be selected to compute RUL distributions, determine maintenance actions, or identify the root causes of irregularities.

Traditionally, data-driven techniques in PHM have primarily relied on statistical methods. However, advancements in sensor technology and signal processing, driven by the digital transformation of Industry 4.0, have led to the growing adoption of AI techniques (Sutharssan et al., 2015). AI refers to a machine's ability to exhibit human-like intelligence, particularly in responding to inputs from its environment. In recent years, AI has acquired significant attention across various applications, especially in scenarios where massive volumes of data are generated at high speeds. In such cases, conventional statistical methods often become inadequate for analysis. Within the domain of predictive maintenance and PHM, numerous AI algorithms have been proposed to predict the health status of engineering systems. As aforementioned, a critical aspect of these efforts is the estimation of RUL at the system, subsystem, or component level, which forms the foundation of the entire prognostic process.

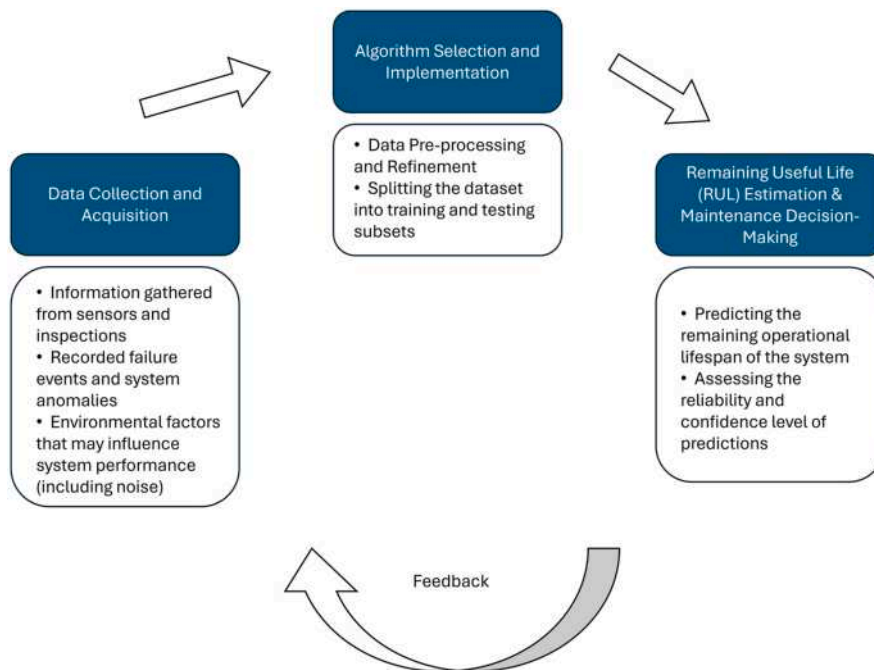


FIGURE 12.3 A sequential process illustrating the application of artificial intelligence in Prognostics and Health Management. Source: Adapted from Ochella, S., Shafiee, M., & Dinmohammadi, F. (2022). *Artificial intelligence in prognostics and health management of engineering systems*. Engineering Applications of Artificial Intelligence, 108. <https://doi.org/10.1016/j.engappai.2021.104552>.

PHM, enhanced by AI technology, further advances knowledge-based failure diagnosis and data-driven failure prediction. Following the rule-based expert system, knowledge-based failure diagnosis effectively addresses the accuracy limitations of static time series prediction (Langella, 2007; Nan et al., 2008). Additionally, data-driven failure prediction enables the development of self-learning models, such as autoregressive moving average models, artificial neural networks, and Kalman filters, to analyze potential correlations in product failures. This approach facilitates the integration of equipment fault diagnosis data, reduces maintenance costs, and enhances the efficiency of maintenance operators by organizing and reusing historical product failure information (Wang et al., 2021). Fig. 12.3 illustrates a flow process for the use of AI in PHM, detailing the stages from data acquisition to maintenance decision-making through predictive modeling.

12.6 Intelligent asset management in Industry 4.0

Asset management (AM) encompasses the comprehensive oversight of a group of assets throughout their full technical life cycle, ensuring optimal performance, adherence to predefined service and security standards, and the achievement of a satisfactory return on investment (Schneider et al., 2006).

The term “asset management” has been widely adopted since the International Organization for Standardization (ISO) established its definition in ISO 55000 (ISO, 2014). It is defined as a comprehensive approach aimed at generating value from asset systems. While AM shares the traditional goal of maintenance engineering, enhancing system reliability, it extends beyond improving safety and cost efficiency to delivering broader performance benefits for organizations and their stakeholders (Amadi-Echendu et al., 2010; Petchrompo & Parlikad, 2019). Within this integrated framework, decisions regarding asset selection and enhancement are guided by multiple performance metrics, ensuring that the utility of the system reliability is maximized.

Effective AM is a crucial responsibility in today's highly competitive industrial landscape (Dehghani & Vahidi, 2022; Mirhosseini & Keynia, 2021).

Implementing effective AM strategies allows companies to boost revenue while promoting a sustainable economy (Ariza Rocha et al., 2020; De Faria et al., 2015). The performance of numerous industries is often assessed using the Maintenance Cost to Value of Replacement Asset ratio (Panjumba & Chatthaworn, 2021; Weber & Thomas, 2005). Generally, maintaining this ratio within the 2%–3% range signifies efficient AM. However, achieving and sustaining these levels requires the integration of technology-driven AM systems (Yu et al., 2020).

Intelligent AM in predictive maintenance is driven by an integrated ecosystem of advanced technologies that enable real-time monitoring, data-driven decision-making, and optimized maintenance strategies. The IoT plays a fundamental role in this transformation by leveraging intelligent sensors to continuously collect and transmit data on critical asset parameters, such as temperature, vibration, pressure, and energy consumption, facilitating seamless communication between physical assets and digital infrastructure (Su et al., 2024). Indeed, modern online monitoring systems provide an optimal solution for

managing critical, high-value assets. These technologies prioritize key equipment within the system, facilitating proactive maintenance approaches and AM by predicting potential major failures in advance (Elsisi et al., 2022; Judd et al., 2005; Kunicki et al., 2020). An intelligent sensor network facilitates optimal process control, condition monitoring, and AM (Raj, 2019). Big Data and Data Analytics further enhance this process by enabling the storage, processing, and analysis of vast amounts of structured and unstructured operational data, allowing for the identification of degradation patterns, anomaly detection, and the optimization of maintenance schedules through predictive insights (Kusiak, 2018; Lee et al., 2014). AI and Machine Learning methodologies provide the computational framework for developing predictive models capable of assessing equipment degradation, estimating RUL, and autonomously recommending corrective actions, significantly improving operational efficiency and reducing unexpected failures (Wuest et al., 2016).

To ensure rapid data processing and response times, edge computing is employed to perform computations directly on IoT devices or gateways, thereby reducing latency, minimizing reliance on cloud infrastructure, and optimizing bandwidth utilization (Bonomi et al., 2012; Shi et al., 2016). Complementary to edge computing, Cloud Computing and IIoT platforms provide the scalability needed to manage distributed data sources, execute advanced analytics, and enable remote access to real-time asset performance dashboards, facilitating proactive decision-making across multiple industrial environments (Buyya et al., 2009). Computer Vision and Image Processing are also leveraged to conduct automated inspections of assets by detecting anomalies, wear, or defects through AI-powered analysis of images and video feeds, further minimizing manual inspection efforts in hazardous or inaccessible environments (Krizhevsky et al., 2012; Redmon et al., 2016).

A key innovation in predictive maintenance is the adoption of Digital Twin Technology, which creates high-fidelity virtual replicas of physical assets to simulate performance under various conditions, predict potential failures, and optimize maintenance strategies in real time through continuous synchronization with operational data (Fuller et al., 2020). By integrating blockchain technology, organizations can ensure secure, tamper-proof records of asset performance, maintenance activities, and supply chain transactions, while advanced cybersecurity measures safeguard industrial control systems from cyber threats and unauthorized intrusions (Teoh et al., 2023; Truong et al., 2023). Additionally, the deployment of 5 G and advanced connectivity enables ultrareliable low-latency communication to support high-density IoT ecosystems, allowing for seamless data transmission, remote diagnostics, and real-time AM, which are critical for modern industrial environments (Cheng et al., 2018).

To fully leverage the potential of these interconnected technologies, Decision Support Systems (DSS) play a critical role by integrating predictive models, sensor data, and AI-driven recommendations into a unified framework for operational decision-making. These systems enhance the efficiency of maintenance planning by providing structured, data-driven insights that assist engineers and decision-makers in optimizing maintenance schedules, prioritizing asset interventions, and allocating resources effectively. By combining historical data, real-time monitoring, and AI-powered predictions, DSS ensures that maintenance decisions are proactive rather than reactive, reducing downtime, minimizing operational costs, and improving overall asset reliability (Bumblauskas et al., 2017; Gottinger & Weimann, 1992). Together, these technologies form an integrated framework

that enables intelligent AM, reducing downtime, improving operational efficiency, and extending the lifespan of critical infrastructure in industries such as manufacturing, energy, and transportation.

12.7 Challenges and limitations

Despite the significant advancements in intelligent AM and predictive maintenance, several challenges and limitations hinder its full-scale implementation across industries. One of the primary concerns is data quality and availability. Predictive maintenance relies heavily on high-quality, continuous, and accurate data from IoT sensors, but many industrial environments still lack standardized data collection protocols, leading to inconsistencies and incomplete datasets. Additionally, data integration challenges arise due to the heterogeneity of industrial assets, which often operate on different communication protocols and legacy systems, making seamless interoperability difficult.

Another critical issue is the complexity of AI and Machine Learning models used for predictive analytics. While these models are highly effective in detecting anomalies and forecasting failures, they require extensive training with large volumes of labeled historical data, which is often unavailable or unreliable in many industries. Moreover, the interpretability of AI-driven decisions remains a concern, as many Machine Learning models function as “black boxes,” making it difficult for maintenance teams to understand and trust the predictions and recommendations provided by these systems.

Computational and infrastructure limitations further constrain the adoption of predictive maintenance. Implementing edge computing and cloud-based analytics requires significant investments in IT infrastructure, including high-performance computing resources and secure data storage solutions. Small and medium-sized enterprises often struggle with the high costs associated with upgrading their existing systems, leading to slower adoption rates. Cybersecurity risks also present a major challenge, as IIoT networks and cloud platforms are increasingly targeted by cyber threats, exposing critical asset data to potential breaches and malicious attacks.

Moreover, human factors and organizational resistance play a crucial role in the successful deployment of predictive maintenance solutions. Many industries still rely on traditional preventive or reactive maintenance strategies, and shifting to a data-driven, predictive approach requires significant cultural and operational changes, including workforce training and change management. Additionally, the effectiveness of DSS depends on their ability to provide actionable insights that align with real-world operational constraints, such as budgetary limitations and workforce availability, which can sometimes limit the practical implementation of AI-driven recommendations.

Lastly, while 5G and advanced connectivity are expected to revolutionize predictive maintenance by enabling real-time monitoring and remote diagnostics, their widespread adoption is still in progress, with many industrial regions lacking the necessary network infrastructure to support high-speed data transmission. Similarly, Digital Twin Technology, though highly promising, faces scalability challenges, such as creating accurate and high-fidelity digital replicas of complex industrial systems requires significant computational resources and domain expertise.

Addressing these challenges requires a collaborative effort between industry leaders, technology developers, and regulatory bodies to establish standardized frameworks, improve data governance, enhance cybersecurity measures, and develop user-friendly, interpretable AI solutions that align with real-world operational needs.

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Industry 4.0 technologies adopted by logistics companies for sustainability and competitiveness

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List of abbreviations

3PL	Third-party logistics service provider
AHP	Analytic hierarchy process
AI	Artificial intelligence
AWS	Amazon web services
BO	Best-to-others (method in BWM)
BSC	Balanced scorecard
BWM	Best–worst method
CAGR	Compound annual growth rate
CI	Consistency index
CPS	Cyber-physical systems
CR	Consistency ratio
CS	Customer satisfaction
DS	Data security
EI	Efficiency improvement
FL	Flexibility
IMARC	The name of a market research company
IoT	Internet of Things
MCDM	Multicriteria decision-making
ML	Machine learning
NDI	Nondestructive inspection
OW	Others-to-worst (method in BWM)
SCM	Supply chain management
SU	Sustainability
UPS	United parcel service
XR	Extended reality

13.1 Introduction

The global logistics industry is transforming significantly due to the rapid adoption of emerging technologies such as artificial intelligence (AI), the IoT, digital twins, blockchain, and autonomous vehicles. These technologies could revolutionize logistics operations by enhancing efficiency, reducing costs, improving customer satisfaction, and other ways. However, their adoption presents several challenges. For third-party logistics (3PL) companies, especially in diverse and competitive markets like the United Kingdom and China, integrating these technologies involves overcoming substantial hurdles, including high implementation costs, data security concerns, regulatory compliance, and workforce adaptation.

The core research problem examines the extent to which 3PL companies adopt these emerging technologies, the specific challenges they face in this process, and the overall impact on their operational efficiency and strategic competitiveness. This study aims to provide a comparative analysis of the adoption and impact of these technologies in the United Kingdom and China, drawing on insights from logistics experts in both countries. In doing so, the research seeks to identify best practices and strategic recommendations for optimizing technology integration in different market contexts.

Industry 4.0 and 5.0 have revolutionized manufacturing and industrial sectors by integrating advanced technologies to enhance productivity, efficiency, and flexibility. Key technologies driving Industry 4.0 and 5.0 include the IoT, Cyber-Physical Systems (CPS), big data analytics, AI, and cloud computing. In Industry 4.0, the IoT involves interconnected devices that collect and exchange data, allowing real-time tracking and monitoring of goods, thereby enhancing inventory management and reducing delays ([Sergi et al., 2021](#)). CPS combines physical processes with computational algorithms, enhancing automation and efficiency in logistics operations through advanced machinery and autonomous vehicles ([Rahman et al., 2022](#)). Big data analytics entails analyzing vast amounts of data to uncover patterns and insights, enabling logistics providers to optimize routes, forecast demand, and improve decision-making processes ([Chen et al., 2021](#)). AI automates and enhances demand forecasting, route optimization, and warehouse management by learning from data and making intelligent decisions ([Shee et al., 2021](#)). Cloud computing offers scalable and flexible IT resources, facilitating seamless collaboration, data sharing, and process integration across different locations and systems, ultimately enhancing operational agility and efficiency ([Ding et al., 2021](#)). For logistics service providers, these technologies collectively enable more efficient, responsive, and customer-centric operations, thereby reducing costs and improving service levels.

Understanding the adoption and impact of emerging technologies in logistics can be synthesized into two main areas. First, strategic competitiveness and operational efficiency are crucial in the logistics sector, which is marked by rapid growth and intense competition. Adopting technologies such as AI and IoT can substantially improve operational efficiency by optimizing routes, automating warehouse processes, and enhancing inventory management. These advancements reduce operational costs and improve service delivery, enabling companies to respond swiftly to changing market demands. However, the complexity and cost of implementing these technologies often pose significant barriers, especially for smaller firms lacking the resources of larger, multinational competitors.

Second, customer satisfaction and data security are essential to adopting new logistics technologies. In an era where customer expectations are constantly evolving due to the growth of e-commerce, technologies like digital twins and blockchain are crucial for enhancing service reliability, transparency, and security. Digital twins allow for real-time monitoring and predictive maintenance, significantly enhancing service quality and reducing downtime. Meanwhile, blockchain technology provides a robust solution for ensuring data integrity and security, which is increasingly important in a digitalized and interconnected world. However, implementing these technologies also presents data privacy and regulatory compliance challenges, particularly in regions with strict data protection laws.

Given these considerations, the research aims to bridge the gap in understanding how these emerging technologies can be effectively integrated into logistics operations across different markets. By focusing on the United Kingdom and China, the study provides a nuanced perspective on technology adoption's strategic and operational impacts, considering regional differences in market conditions, regulatory environments, and technological infrastructure. This understanding is vital for logistics companies looking to navigate the complexities of technology adoption and leverage these innovations to achieve sustained competitive advantage.

13.1.1 The current state of UK third-party logistics companies

The UK logistics service market is a crucial sector of the economy, characterized by dynamic growth and intense competition. In 2023 the market reached approximately USD 137.86 billion and is expected to grow at a compound annual growth rate (CAGR) of 2.91%, reaching around USD 163.77 billion by 2030 ("United Kingdom freight and logistics market size," [MarkWide Research, 2024](#)). This growth is fueled by several factors, including the expansion of e-commerce, technological advancements, and evolving customer expectations for faster and more efficient deliveries ([MarkWide Research, 2024](#)).

Key players in the UK logistics market include global giants such as DHL Group, DSV A/S, Kuehne + Nagel, United Parcel Service of America, Inc. (UPS), and Wincanton PLC ([MarkWide Research, 2024](#); [United Kingdom freight and logistics market size, 2024](#)). These companies offer a comprehensive range of services, including transportation, warehousing, freight forwarding, and supply chain management (SCM), constantly innovating to maintain a competitive edge. The competition is driven by service quality, pricing, geographic reach, technological capabilities, and customer relationships, with logistics companies increasingly adopting digital technologies such as AI, IoT, and automation to enhance operational efficiency and visibility ([MarkWide Research, 2024](#)).

The UK logistics market is segmented by transportation modes (roadways, seaways, railways, airways), with roadways currently dominating due to the extensive road network and the demand for rapid last-mile deliveries ([IMARC Group, 2024](#)). The market also varies by end-use sectors, with significant contributions from manufacturing, retail, and e-commerce ([United Kingdom freight and logistics market size, 2024](#)). Due to their strategic locations and well-developed infrastructure, regions such as North West England, London, Manchester, and Birmingham are key logistics hubs ([MarkWide Research, 2024](#)). The market dynamics are influenced by regulatory changes, economic conditions, and the need for

sustainable practices, with companies increasingly focusing on green logistics to reduce their carbon footprint (“United Kingdom freight and logistics market size,” [IMARC Group, 2024](#)).

13.1.2 The current state of Chinese third-party logistics companies

The logistics service market in China is a vital component of the economy, characterized by rapid growth and intense competition. By 2023, the market size had reached approximately USD 1.442 trillion and is expected to grow at an annual rate of 6.5%, reaching around USD 2.24 trillion by 2030. This growth is driven by several factors, including the rapid expansion of e-commerce, technological advancements, and rising customer expectations for faster and more efficient deliveries ([Zhang et al., 2019](#)).

The Chinese logistics market players include SF Express, JD Logistics, Cainiao Network, Deppon Logistics, and China Post. These companies offer a wide range of services, including transportation, warehousing, freight forwarding, and SCM, continuously innovating through technology to maintain a competitive edge. Competition is primarily driven by service quality, pricing, geographic coverage, technological capabilities, and customer relationships ([Özdağoğlu & Bahar, 2022](#)). Logistics companies increasingly adopt digital technologies such as AI, the Internet of Things (IoT), and automation to enhance operational efficiency and transparency.

The Chinese logistics market is segmented by modes of transport, such as road, sea, rail, and air, with road transport currently dominating due to the extensive road network and the demand for rapid “last-mile” deliveries. Additionally, the market is segmented by end-use industries, with manufacturing, retail, and e-commerce being major contributors. Cities like Beijing, Shanghai, Shenzhen, and Guangzhou have become key logistics hubs due to their strategic locations and well-developed infrastructure ([Dini et al., 2024](#)). Market dynamics are also influenced by regulatory changes, economic conditions, and the need for sustainable practices, with companies increasingly focusing on green logistics to reduce their carbon footprint.

The comparison of various aspects of the logistics sector between the United Kingdom and China is presented in [Table 13.1](#).

13.1.3 Research aim, objectives, and review of business problem

This chapter aims to investigate the adoption of certain new technologies from Industry 4.0 and 5.0 by 3PL companies, assess the impact of these technologies on various areas within these companies, and provide recommendations for applying these technologies to supply chains. To achieve this aim, the extent of the impact of new technologies on 3PL companies is determined by conducting a survey of experts in relevant fields in the United Kingdom and China and analyzing the survey results. The influence of different technologies are ranked and new technologies that are more effectively adopted by 3PL companies in different regions and sectors are identified. Based on the aim and objectives outlined above, the research questions are proposed as follows:

1. What are the key new technologies from Industry 4.0 and 5.0 that 3PL companies in the United Kingdom and China have adopted?

TABLE 13.1 Comparison of the logistics market between the United Kingdom and China.

Aspect	UK logistics market	China logistics market
Market size (2023)	USD 137.86 billion	USD 1.442 trillion
Expected market size (2030)	USD 163.77 billion	USD 2.24 trillion
CAGR (2023–30)	2.91%	6.50%
Key players	DHL Group, DSV A/S, Kuehne + Nagel, UPS, Wincanton PLC	SF Express, JD Logistics, Cainiao Network, Deppon Logistics, China Post
Main competitive factors	Service quality, pricing, geographical reach, technological capabilities, customer relationships	Service quality, pricing, geographical coverage, technological capabilities, customer relationships
Major logistics hubs	North West England, London, Manchester, Birmingham	Beijing, Shanghai, Shenzhen, Guangzhou
Market dynamics influences	Regulatory changes, economic conditions, sustainable practices.	
Key services	Transport, warehousing, freight forwarding, supply chain management	
Key end-use sectors	Manufacturing, retail, E-commerce.	
Dominant transport mode	Roadways	
Digital technologies adopted	AI, IoT, blockchain, digital twin, autonomous vehicles	

2. How do these new technologies impact different operational areas within 3PL companies?
3. Which technologies significantly influence the efficiency and effectiveness of 3PL operations in different regions and sectors?
4. What are the best practices for adopting these new technologies in supply chains within the logistics industry, considering regional differences between the United Kingdom and China?

Regarding research scope, this chapter covers three main research areas: new technologies in Industry 4.0 and 5.0, logistics service, and technology adoption in SCM. For the research gap addressed in this chapter, integrating emerging technologies, particularly those categorized under Industry 4.0 and 5.0, has been extensively discussed in the context of SCM. These technologies, including AI, the IoT, blockchain, digital twin, and autonomous vehicles, are acclaimed for their potential to revolutionize logistics by improving operational efficiency, enhancing data transparency, and reducing costs (Firoozi & Ajirlou, 2023; Rejeb et al., 2024). However, despite this general optimism, there is a significant divergence in perspectives regarding their adoption.

On the one hand, several studies and industry reports emphasize the transformative benefits of these technologies. For instance, AI is often highlighted for its ability to optimize

routing, predict maintenance needs, and improve decision-making processes within logistics operations (Rejeb et al., 2024). Proponents argue that adopting these technologies is crucial for maintaining a competitive advantage in an increasingly digital market.

On the other hand, some researchers and practitioners express concerns about the practical challenges associated with these technologies. These concerns include high implementation costs, integration challenges with existing systems, data security risks, and potential job displacement due to automation (Firoozi & Ajirlou, 2023). Additionally, there are questions about the technological readiness of logistics companies, especially in regions with varying levels of infrastructure development and regulatory support.

While these divergent views are well-documented, there is a noticeable lack of focused studies examining the specific impacts of these technologies on logistics companies. Recent literature reviews indicate that most existing research has either been theoretical or has focused on broader supply chain applications without exploring the unique challenges and opportunities within the logistics sector (Bentalha et al., 2023; Jain & Chou, 2023). Therefore, this study aims to fill this gap by examining the impact of emerging technologies in Industry 4.0 and 5.0 on logistics companies, considering both the potential benefits and the challenges these companies face in adopting these innovations.

This chapter is divided into six sections. Section 13.2 explores a range of new technologies, such as AI, the IoT, digital twins, blockchain, and autonomous vehicles, through a literature review and demonstrates that the impact of these technologies on 3PL companies can be quantified across six different areas. Section 13.3 details the methodology, which involves collecting primary data from experts in different countries using a questionnaire method and employing the best–worst method (BWM) to assess the impact of these technologies on logistics operations. Section 13.4 presents the results, specifically how these technologies affect operational efficiency, customer satisfaction, and other key performance indicators, focusing on regional differences between the United Kingdom and China. Section 13.5 discusses these findings, linking them to existing literature and providing strategic recommendations for integrating these technologies into logistics practices. Section 13.6 concludes the chapter by discussing the managerial implications of the research and suggesting directions for future studies.

13.2 Literature review

Based on the existing literature and statistical evidence, this study focuses on AI, blockchain, the IoT, digital twins, and autonomous driving as the five critical technologies. These technologies are central to Industry 4.0 and 5.0, significantly influencing various sectors and driving industrial evolution.

13.2.1 New technologies in Industry 4.0 and 5.0

The new technologies enable real-time data collection and analysis, facilitating improved decision-making and predictive maintenance. For example, implementing nondestructive inspection (NDI) systems in production lines aids in achieving zero-defect manufacturing by

leveraging IoT technologies to convert data from physical assets into valuable information (Martarelli et al., 2023). In the logistics service sector, NDI systems integrated with IoT technologies enable real-time monitoring and predictive maintenance of assets such as containers and vehicles, thereby enhancing operational efficiency and reducing the risk of disruptions (Meyendorf et al., 2023). Furthermore, AI and machine learning (ML) are crucial in processing vast amounts of data to optimize production workflows and develop smart applications (Lampropoulos, 2022). DHL employs AI algorithms to analyze vast amounts of data, including weather patterns, traffic conditions, and vehicle performance, to optimize delivery routes and predict potential delays. This approach has improved delivery efficiency and reduced fuel costs while also enhancing overall service reliability and customer satisfaction (Olaoye & Henry, 2024). Additionally, integrating these technologies into educational frameworks enhances the learning environment, promoting a collaborative and innovative approach (Periasamy & Umachandran, 2023). As Industry 4.0 continues to evolve, it promises significant advancements in digital automation and production systems, fostering a more connected and efficient industrial landscape (Jiang, 2023).

The term “Industry 5.0” began gaining recognition and acceptance around 2019. It was further solidified as a concept by the European Commission in January 2021 when they released a report outlining Industry 5.0 as a vision for a sustainable, human-centric, and resilient industrial future. This marked a more formal acceptance of the term in the context of industrial evolution (Gajdzik, 2023). The advent of Industry 5.0 marks the next phase in manufacturing and industrial evolution, emphasizing human-centric approaches and ethical considerations while leveraging advanced technologies. Key technologies driving Industry 5.0 include extended reality (XR), quantum computing, and next-generation connectivity, such as 5G. These technologies are crucial for developing a sustainable and advanced industrial ecosystem, enabling smarter and more efficient processes (Tyagi et al., 2024). These technologies enhance productivity and efficiency while prioritizing human well-being, sustainability, and product and service personalization. Collaborative robots are designed to work alongside humans, assisting with tasks requiring human dexterity and decision-making. These cobots enhance workplace safety and productivity by performing repetitive or hazardous tasks, allowing human workers to focus on more complex and creative activities (Smith et al., 2023). Advanced AI and cognitive computing enhance decision-making by understanding and reasoning contextually, leading to smarter, more adaptive manufacturing systems.

First, according to a report by *Tipping the scales in AI: How leaders capture exponential returns* (2021), AI is expected to add approximately \$13 trillion to the global economy over the next decade. AI’s data analysis, pattern recognition, and intelligent decision-making capabilities have been widely adopted across manufacturing, logistics, and service industries, significantly enhancing production efficiency and operational capabilities (*Tipping the scales in AI: How leaders capture exponential returns*, 2021). This technology optimizes existing workflows and enables the development of new business models. Furthermore, the IoT market is projected to reach \$1.6 trillion by 2025. It highlights its widespread application in real-time data collection and intelligent device interconnectivity, particularly in logistics and SCM, where it significantly improves operational efficiency and asset management (Statista, 2022).

Second, research on blockchain technology demonstrates its unique advantages in enhancing data security and supply chain transparency. A survey by [PwC \(2020\)](#) found that 84% of respondents believe blockchain will significantly increase transparency and security in information management. This is crucial in complex global supply chains, where the technology can substantially reduce fraud risk and operational costs ([PwC, 2020](#)). Meanwhile, digital twin technology is rapidly advancing, with the global market size expected to reach \$48.2 billion by 2026 ([Markets Markets, 2021](#)). The widespread adoption of this technology allows companies to monitor physical assets in real-time and conduct virtual simulations, optimizing maintenance strategies, reducing downtime, and enhancing production flexibility and resilience.

Lastly, advancements in autonomous driving technology are revolutionizing the transportation industry. Research by [Gartner \(2023\)](#) indicates that autonomous driving technology could reduce more than 25% of traffic accidents globally by 2030. Autonomous driving improves safety and efficiency and significantly reduces traffic congestion and carbon emissions, contributing to sustainable development goals ([Gartner, 2023](#)).

The advantages of five different emerging technologies are presented in [Table 13.2](#). Therefore, selecting these five technologies as the focus of this research is well-supported by extensive literature and statistical data, aligning with the current and future trends of industrial revolutions. The widespread application and continuous advancement of these technologies will continue to shape the future landscape of various industries, providing a solid foundation for achieving a more efficient, intelligent, and sustainable industrial ecosystem.

13.2.2 The impact of new technologies on logistics companies

The integration of new technologies in logistics is transforming the industry by improving efficiency, reducing costs, and enhancing customer satisfaction. Key technologies driving this transformation include autonomous vehicles, AI, IoT, digital twin, and

TABLE 13.2 Different technologies and their advantages.

Technology	Advantages
Artificial intelligence	Enhances production efficiency, optimizes workflows, enables new business models
Internet of Things	Improves operational efficiency, real-time data collection, intelligent device interconnectivity
Blockchain technology	Increases transparency and security, reduces fraud risk, lowers operational costs
Digital twin technology	Real-time monitoring of physical assets, optimizes maintenance strategies, reduces downtime
Autonomous driving technology	Improves safety and efficiency, reduces traffic congestion and carbon emissions

blockchain. For example, implementing AI and IoT in logistics enables real-time tracking, automated warehouse operations, and optimized fleet management, resulting in significant cost reductions and efficiency improvements (Frias et al., 2023). Additionally, the adoption of AI in logistics has affected labor demand, requiring new skill sets and presenting challenges related to workforce reskilling and unemployment (Wang et al., 2023). Digital technologies are crucial in reshaping business models and enhancing service delivery, providing competitive advantages to companies that effectively integrate these innovations (Gregori & Holzmann, 2020). Furthermore, IoT enables logistics companies to create integrated, flexible, and efficient supply chains tailored for e-commerce, enhancing productivity and safety through real-time data analysis (Gowri Gowri, 2022). Finally, technological advancements in IT systems and infrastructure facilitate better information flow and resource management, which is crucial for maintaining high service quality in logistics (Bazaras et al., 2023). Table 13.3 shows the applications of these technologies in logistics companies.

DHL Supply Chain has implemented IoT technology in its warehouse operations for Tetra Pak in Singapore. This smart warehouse, also functioning as a digital twin, continuously receives real-time data from physical assets. Integrating IoT allows DHL to optimize storage and retrieval processes, improving inventory accuracy and operational efficiency. This implementation has led to faster processing times, with goods stored within 30 minutes of receipt and ready for shipment in 95 minutes, enhancing overall productivity and safety (DHL warehouse image, 2019).

Maersk Tankers has successfully implemented digital twin technology to optimize vessel performance and reduce emissions. By creating a digital replica of each vessel, they can simulate and predict fuel consumption for specific voyages, allowing the selection of the most efficient routes and speeds. This approach has significantly reduced fuel consumption and greenhouse gas emissions, enhancing operational efficiency across their fleet of over 220 vessels (Dotzer, 2021).

DHL has implemented autonomous driving technology in their logistics operations, especially in warehousing and last-mile delivery. This technology has been key in enhancing operational efficiency and safety. For instance, DHL's use of self-driving vehicles in warehouses facilitates the transportation of goods without manual intervention, reducing human error, improving route optimization, and decreasing motoring costs and environmental impact. Consequently, DHL has reported significant improvements in productivity and cost-efficiency (DHL autonomous vehicles image, 2023). Additionally, integrating autonomous vehicles has enabled more flexible and reliable operations, supporting the growing demand and complexity in logistics services (Sullivan & Kern, 2021).

FedEx has adopted blockchain technology to revolutionize healthcare logistics, ensuring the integrity and security of sensitive medical shipments. Using blockchain, FedEx provides an immutable and transparent ledger for tracking the entire lifecycle of pharmaceutical products. This enhances traceability, reduces counterfeit drug risks, and ensures compliance with stringent regulatory standards. Blockchain implementation has improved supply chain data accuracy, increased stakeholder trust, and reduced fraud and errors (Hussien et al., 2021).

Amazon uses its AI-driven Package Decision Engine to optimize packaging, significantly reducing waste and improving efficiency. This AI model, built on Amazon Web Services

TABLE 13.3 The application of different technologies in logistics companies.

Company	IoT	Digital twin	Autonomous driving	Blockchain	AI
DHL Supply Chain	Warehouse	Predictive maintenance in logistics	Self-driving delivery robots	Supply chain transparency	Automated sorting and routing
Maersk	Smart shipping containers	Reduce vessel emissions		“TradeLens” for the supply chain	Predictive maintenance for ships
DHL	Connected vehicles	Real-time shipment tracking	Last mile	Secure data sharing	Route optimization
FedEx	Smart sensors for package tracking		Autonomous delivery vehicles	Blockchain for supply chain visibility	Healthcare logistics with AI
Amazon	Warehouse automation	Digital twins for warehouse optimization	Self-driving delivery vans	Blockchain for AWS services	Packaging and product recommendations with AI

(AWS) cloud, determines the best packaging for each product by analyzing dimensions, materials, and customer feedback. Since its implementation, Amazon has saved over 2 million tons of packaging material globally, enhancing sustainability and operational efficiency ([Amazon AI image, 2023](#)).

13.2.3 The importance and problems of new technology adoption

Digital technologies, including autonomous vehicles, AI, IoT, digital twins, and blockchain, significantly streamline logistics operations by enabling real-time tracking, automated warehouse management, and optimized delivery routes. These advancements increase productivity and customer satisfaction by ensuring timely deliveries and minimizing human errors ([Akyuz & Bicer, 2022](#)). Furthermore, digital twins in logistics enhance transparency and risk management by creating virtual replicas of physical processes, facilitating real-time monitoring and predictive maintenance ([Lin & Yao, 2022](#)). Integrating blockchain technology in logistics further enhances the transparency and sustainability of supply chains, improving information sharing and risk management ([Yontar, 2023](#)).

However, implementing these technologies comes with challenges. The initial costs of deploying advanced technologies can be high, and companies may face issues related to data security, system integration, and workforce adaptation ([Irannezhad, 2020](#)). For example, integrating blockchain technology in logistics aims to create a more secure and efficient system. Still, it faces problems due to its nascent stage and the complexity of integrating existing systems ([Huang, 2022](#)).

Additionally, the rapid pace of technological change can lead to job displacement, requiring ongoing training and development for employees to acquire new skills and competencies ([Krutova, 2022](#)). The COVID-19 pandemic has further highlighted the importance of technology in logistics by accelerating the adoption of logistics technologies to manage disruptions. However, it also introduced new challenges related to costs, safety, and legislative constraints ([Klapita et al., 2023](#)).

When logistics companies adopt new technologies, they face multiple challenges. For instance, in the collaboration between Waymo and UPS to pilot autonomous freight trucks, these vehicles have shown limitations in complex urban environments, like difficulty dealing with unexpected pedestrians and nonstandard traffic signals. Additionally, varying legal and regulatory landscapes across different states complicate interstate transportation compliance ([TechCrunch, 2021](#)). Although these autonomous trucks are equipped with advanced sensor suites and AI-driven navigation systems, they still require human oversight. During trial runs, each truck is accompanied by a safety driver and a technician to monitor the system's performance, indicating that the technology is not yet fully reliable for unsupervised operation ([Fox Business, 2021](#)). These factors highlight technical and regulatory challenges logistics companies encounter when integrating emerging technologies.

In this study, the impact of new technologies on 3PL companies (3PLs) is analyzed from six key perspectives: efficiency improvement, cost reduction, data security, customer satisfaction, flexibility, and sustainability. These dimensions encompass the primary application scenarios and benefits of new technologies in the logistics industry. However,

these aspects may only partially capture the full impact, and future research should explore other potential areas of influence.

Efficiency improvement: Efficiency improvement is a crucial aspect of how new technologies affect 3PLs. Logistics companies can optimize and automate processes to boost operational efficiency by leveraging AI, the IoT, and automation. For example, AI algorithms can process large volumes of logistics data to optimize transportation routes and warehouse management, reducing time and resource wastage (Ding et al., 2021). However, efficiency improvement extends beyond operational levels; it may also impact strategic decision-making and organizational agility, which require further investigation.

Cost reduction: Cost control is a primary concern for logistics companies, and new technologies provide various methods for reducing operational expenses. Blockchain technology, for example, can lower transaction costs and minimize fraud by reducing intermediaries and enhancing transaction transparency (Tsolakis et al., 2022). AI and ML technologies can also optimize inventory management and transportation planning, thereby reducing excess inventory and transportation costs. However, these technologies' high initial investment costs and implementation challenges are significant factors affecting overall costs, warranting further exploration.

Data security: Data security has become increasingly important in logistics, particularly when handling sensitive customer and business data. Blockchain technology enhances data security with its decentralized and immutable characteristics (Vaghani et al., 2022). Nevertheless, data security challenges are increasing with stricter data privacy laws and evolving cyber-attack methods. While data security is a significant benefit of new technologies, it only partially addresses the complexities of modern data environments.

Customer satisfaction: Customer satisfaction is crucial for logistics companies' reputation and long-term profitability. Through big data analytics and AI, logistics companies can better understand customer needs, offering personalized services and more effective customer support (Chung, 2021). Automated customer service systems and real-time cargo tracking can significantly enhance the customer experience. However, customer satisfaction also depends on factors like service stability and brand reputation, which should be considered when evaluating new technologies.

Flexibility: Flexibility is essential for logistics companies to adapt to market changes and unexpected events. Technologies like digital twins and autonomous driving enhance logistics systems' responsiveness, enabling them to quickly adjust operations to manage demand fluctuations or supply chain disruptions (Woschank et al., 2020). However, flexibility is not limited to operational adjustments; it also includes strategic adaptability and organizational change capabilities, which require more theoretical and empirical support.

Sustainability: With the global focus on sustainable development and environmental responsibility, logistics companies seek greener solutions. Technologies such as AI optimization and autonomous driving help reduce carbon emissions and energy consumption, fostering green logistics (Ghahremani Nahr et al., 2021). However, sustainability is not limited to environmental impacts; it also includes social and economic sustainability, such as fair trade and employee welfare. These broader sustainability goals need further exploration in the context of new technology applications.

Table 13.4 shows the impact of technologies on different performance areas of 3PL companies. In conclusion, these six aspects represent some of the primary areas where new technologies impact 3PL companies. Still, they may not fully capture the entire scope of these technologies' effects. Future research should investigate how these technologies influence other areas, such as organizational culture change, employee skill development, and the resilience of global logistics networks, to gain a comprehensive understanding of the potential and challenges of new technologies in the logistics industry (Zhang et al., 2021).

13.2.4 The best and worst method

In previous research, the best and worst method (BWM) has been applied in diverse management fields, such as green port management, municipal solid waste management, cloud-based e-learning provider evaluation, urban digitalization, and risk assessment in production-oriented projects (Khan et al., 2023; Li et al., 2021; Munim et al., 2020a; 2020b; Pour et al., 2020; Vieira et al., 2022). These applications demonstrate the versatility of the BWM in addressing complex decision-making scenarios across various sectors.

For instance, Munim et al. (2020a) and Munim et al. (2020b) combined BWM with the analytic network process to identify optimal governance models for green port management in India. In municipal solid waste management, Li et al. (2021) utilized BWM to determine the optimal scenarios for effective waste management. Pour et al. (2020) developed a framework for ranking cloud-based e-learning providers, showcasing BWM's utility in evaluating educational services.

TABLE 13.4 The impact of different technologies on six areas of third-party logistics (3PL) companies.

Impact area	Description
Efficiency improvement	New technologies like AI, IoT, and automation optimize processes, boosting operational efficiency. They also impact strategic decision-making and organizational agility.
Cost reduction	Technologies such as blockchain and AI reduce costs by minimizing intermediaries, enhancing transparency, and optimizing inventory management. Initial investment costs remain a challenge.
Data security	Blockchain enhances data security with decentralized, immutable features. However, evolving cyber threats and stricter data laws require ongoing attention.
Customer satisfaction	Big data analytics and AI improve understanding of customer needs, offering personalized services and enhancing customer support, though factors like service stability also play a role.
Flexibility	Technologies like digital twins and autonomous driving improve responsiveness and adaptability to market changes and disruptions, but strategic adaptability requires further study.
Sustainability	AI optimization and autonomous driving reduce carbon emissions, promoting green logistics. Broader sustainability goals include social and economic factors that need further exploration.

AI, Artificial intelligence; IoT, Internet of Things.

Furthermore, [Vieira et al. \(2022\)](#) employed BWM with cognitive mapping to measure urban digitalization, offering a multidimensional perspective on urban development. [Khan et al. \(2023\)](#) identified critical risk factors in production-oriented projects in the UAE using BWM analysis, whereas [Navaei et al. \(2023\)](#) explored knowledge management implementation in supply chains with a D-number integrated BWM approach.

[Dwivedi et al. \(2021\)](#) integrated BWM with the balanced scorecard (BSC) to evaluate the performance of an insurance company, demonstrating BWM's effectiveness in organizational performance assessment. [Nyimbili and Erden \(2021\)](#) conducted a comparative evaluation using GIS-based BWM for emergency facility planning, emphasizing its practical applications in crisis management. [Haseli et al. \(2021\)](#) introduced a novel group decision-making approach with G-BWM for SCM, while [Ecer and Pamucar \(2020\)](#) proposed an integrated fuzzy BWM and fuzzy CoCoSo model for sustainable supplier selection.

These studies highlight the broad applicability and robustness of BWM in addressing complex decision-making scenarios across various fields, reinforcing its status as a valuable tool for contemporary management and operational strategies.

13.3 Methodology

In this study, the impact of Industry 4.0 and Industry 5.0 technologies on 3PL companies is assessed through a systematic literature review and expert opinions. Additionally, the BWM is employed to rank the influence of different technologies on the overall competitiveness of 3PL companies as well as to analyze the impact of each technology across various operational areas within these companies. The BWM is preferred over other multicriteria decision-making (MCDM) methods in this research for three main reasons: (1) The best–worst method enhances computational accuracy and reduces the risk of bias arising from pairwise comparisons provided by decision-makers; (2) it utilizes a structured pairwise comparison, which results in more reliable and consistent outcomes; and (3) it is less time-consuming compared to the analytic hierarchy process (AHP), as it does not require a full pairwise comparison of all factors. Unlike AHP, which can result in inconsistency in pairwise comparison matrices and complicate result processing, the BWM provides a more straightforward, efficient, and dependable approach ([Youssef, 2020](#)).

While the BWM offers several advantages, it is not without limitations. One of the main challenges is that BWM can still face issues with inconsistency, particularly when there is a significant divergence in expert opinions ([Liang, Brunelli, & Rezaei, 2020](#)). In cases where the criteria are not clearly defined or uniformly understood by all decision-makers, the results may reflect these inconsistencies, thereby affecting the overall reliability of the findings ([Liang, 2021](#); [Li et al., 2021](#)). This inconsistency can be further exacerbated in a group decision-making context, where multiple experts provide input, potentially leading to conflicting judgments ([Guo & Qi, 2021](#)). Additionally, the method assumes a level of expertise and judgment from the decision-makers that might not always be present, potentially introducing bias or inaccuracies ([Malek & Desai, 2019](#)). Therefore, while BWM provides a more streamlined and often more reliable approach compared to AHP, its

effectiveness depends on the clarity of the criteria and the experience of the decision-makers involved.

By using this method, decision-makers assist researchers in identifying the most important (best) and least important (worst) factors that influence a logistics company's competitiveness and then compare these factors in pairs. This approach is straightforward to implement and computationally efficient. Compared to other MCDM techniques, such as TOPSIS, ANP, and AHP, the BWM provides more reliable and consistent results (Masoomi et al., 2022; Varchandi, Memari, & Jokar, 2024). Fig. 13.1 provides the methodological steps followed in this research.

The BWM is designed to be relatively simple, easy to understand, and capable of aggregating input from multiple decision-makers. In this study, the inputs from various experts are combined using a weighted average approach, ensuring that the consensus reflects the relative importance assigned by each expert, thereby enhancing the robustness of the findings (Rezaei, 2015; 2016; Mi et al., 2019).

The primary data for this study were obtained through a questionnaire survey. A total of 15 questionnaires were distributed, and all 15 were returned and deemed valid. The questionnaire indirectly captured experts' attitudes towards various technologies using a scoring method. The experts involved in this survey were either university professors or

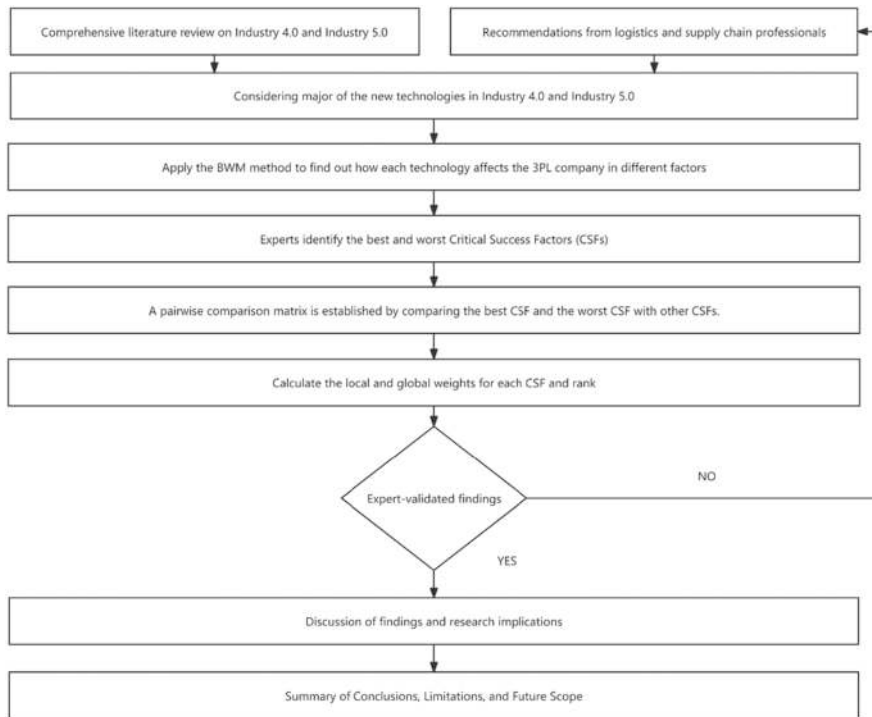


FIGURE 13.1 Figure methodological flow diagram.

professionals from relevant companies, each with over 10 years of experience in the fields of logistics and SCM. Due to the differing numbers of experts from the United Kingdom and China who participated in this study, some of the subsequent analysis will use an averaging method to ensure accurate comparison of the results. The questionnaire is included in Appendix 1, and the survey results provide the raw data needed for the subsequent BWM analysis.

The steps of the BWM method are as follows (Rezaei 2015, 2016; Gupta & Singh, 2024).

Step 1: Identify the critical success factors (CSFs) through literature review and discussions with decision-makers. The CSFs are denoted as (C1, C2, C3, ..., Cn).

Step 2: Decision-makers select the best (most important) and worst (least important) CSFs from the list identified in Step 1.

Step 3: Decision-makers compare the best CSF with others by forming a Best-to-Others (BO) vector using a 1–9 scale (Table 13.5), where 1 represents equal importance and 9 represents absolute importance over other criteria. The BO vector is expressed as

$$X_B = (x_{B1}, x_{B2}, \dots, x_{Bn}), \quad (13.1)$$

where x_{Bj} denotes the importance of best criterion B with criterion j .

Step 4: Decision-makers then compare the worst CSFs with others by forming an others-to-worst (OW) vector using a 1–9 scale, where 1 indicates equal importance and 9 represents absolute importance. The OW vector is expressed as

$$X_W = (x_{1W}, x_{2W}, \dots, x_{nW}), \quad (13.2)$$

where x_{jW} represents the importance of criterion j compared to over worst criterion W.

Step 5: The optimal weights (W_1^* , W_2^* , ..., W_n^*) of the decision criteria (CSFs) are computed to minimize the maximum absolute differences for all j within the following set:

$$\{ |W_B - x_{Bj}W_j|, |W_j - x_{jW}W_w| \}$$

TABLE 13.5 Scale used for comparison (Rezaei, 2015).

Value	Scale
1	Equal importance
2	Somewhat between equal and moderate
3	Moderately more important than
4	Somewhat between moderate and strong
5	Strongly more important than others
6	Somewhat between strong and very strong
7	Very strongly important than others
8	Somewhat between very strong and absolute
9	Absolutely more important than others

The min–max model is formulated as follows:

$$\text{Min max } j \{ |W_B - x_{Bj}W_j|, |W_j - x_{jw}W_w| \}$$

subject to,

$$\sum_j W_j = 1 \quad (13.3)$$

$$W_j \geq 0 \quad \forall j$$

Eq. (13.3-3) can be transformed into a linear programming problem as follows:

$$\text{Min } x,$$

$$\text{Subject to } |W_B - x_{Bj}W_j| \leq \xi \quad \forall j,$$

$$\sum_j W_j = 1,$$

$$|W_j - x_{jw}W_w| \leq \xi \quad \forall j, \quad (13.4)$$

$$W_j \geq 0 \quad \forall j.$$

Solving Eq. (13.3-4) yields the optimal weights for each criterion and the optimal value of the objective function ξ . A lower ξ indicates more consistency, while a higher ξ indicates less.

Once the optimal weights and the objective function ξ are obtained, it is crucial to assess the consistency of expert input using the CR, which measures the reliability of expert comparisons. The CR value ensures that the judgments are consistent rather than random.

The formula for calculating the CR is given by the following equation:

$$\text{Consistency Ratio (CR)} = \frac{\xi^*}{\text{Consistency Index (CI)}} \quad (13.5)$$

where

ξ^* represents the optimal value of the objective function obtained from the BWM (best–worst method) optimization model.

The consistency index (CI) is a predefined benchmark value that varies depending on the number of criteria considered. The CI values are derived from random index tables based on the number of elements being compared.

Following the previous process, the weight of each technology's impact on different aspects of 3PL companies can be calculated individually. By repeating this process, the respective weights for each technology can be determined. Consequently, it is possible to ascertain which aspect of 3PL companies is most significantly affected by each technology. This allows for further analysis to identify which technology is most crucial for 3PL companies.

Steps for calculating the consistency ratio:

- 1. Determine the consistency index:** The consistency index is obtained from a random index table, which provides a benchmark value based on the size of the matrix (number of criteria). This benchmark helps in comparing the consistency of the pairwise comparisons.

2. **Compute the optimal objective function value (ξ^*):** Using the BWM model, solve the linear programming problem to find the optimal value of the objective function ξ^* . This value reflects the level of inconsistency in the pairwise comparisons.
3. **Calculate the consistency ratio:** Divide the optimal value ξ^* by the corresponding CI for the given number of criteria. The resulting CR value provides a quantitative measure of consistency. A CR value of less than 0.1 (or 10%) is generally considered acceptable, indicating that the level of inconsistency is within reasonable bounds.

In summary, the BWM is used to determine the optimal weights of decision criteria by systematically comparing the most important (best) and least important (worst) criteria on a 1–9 scale. The method aims to minimize the maximum absolute differences between these comparisons through a linear programming model, yielding the optimal weights (W^*) and the objective function value (ξ^*). To ensure the reliability of these comparisons, the CR is calculated by dividing ξ^* by a predefined CI. A low CR value indicates a high level of consistency, confirming that the decision-making process is sound. This structured approach allows for a clear identification of the most influential criteria or technologies affecting 3PL companies.

13.4 Findings

13.4.1 Overview of the impact of new technologies on third-party logistics companies

After collecting and summarizing the questionnaires, [Table 13.6](#) presents the summary of inputs from experts. Due to the confidentiality agreement with the experts, it is not possible to display responses from each expert in detail. Additionally, the data in [Table 13.6](#) have been anonymized and are only used to illustrate the questionnaire response rate; they do not represent the actual data.

In [Table 13.6](#), each expert first selected the area they believed would have the greatest impact and then the area they thought would have the least impact on logistics companies. They then rated each area accordingly. An area that is either the same or of equal importance to another is rated as 1, while an area that is far more important is rated as 9. This process is repeated for each technology until all five technologies have been rated. Once summarized, a comprehensive base table is created, and all subsequent analyses are conducted based on this base table.

In the BWM calculation of the scores in the base table, an Excel spreadsheet is used with the table design shown in [Fig. 13.2](#). The table design follows the method proposed in Rezaei's (2016) paper. The spreadsheet is first divided into five separate sheets, each corresponding to a different technology type. The names of each field are entered into the top green table, followed by the scores given by the experts, which are filled into the middle green table. The resulting solutions are generated in the yellow table at the bottom.

After completing the calculations, the data in the table are automatically updated, and the bar chart below is simultaneously refreshed. Consistency ratio is also calculated in the table to ensure the accuracy of the results.

TABLE 13.6 Summary of some experts' questionnaire results.

Expert		1	2	3	4	5
Digital twin	Best	Sustainability	Efficiency improvement	Data security	Efficiency improvement	Flexibility
	Efficiency improvement	2	1	2	1	7
	Cost reduction	3	4	9	3	2
	Data security	5	1	1	4	9
	Customer satisfaction	9	1	3	7	7
	Flexibility	3	5	5	3	1
	Sustainability	1	9	5	9	8
	Worst	Customer satisfaction	Sustainability	Cost reduction	Sustainability	Data security
	Efficiency improvement	6	9	5	9	3
	Cost reduction	4	2	1	6	2
	Data security	6	9	9	5	1
	Customer satisfaction	1	9	6	3	3
	Flexibility	7	4	6	5	9
	Sustainability	9	1	5	1	3

The adoption of the BWM to rank the impact of emerging technologies on 3PL companies provides a structured and nuanced approach to understanding technological influences in the logistics sector. By engaging 15 seasoned decision-makers from China and the United Kingdom, this study gains insights from experts with a deep understanding of the industry. The diversity of perspectives, encompassing both academic and practical expertise, enhances the reliability of the findings.

After solving each table and aggregating the results, preliminary summary results similar to those in Table 13.7 are obtained. For digital twins, efficiency improvement has the highest weight at 3.668, followed by flexibility at 3.191. The lowest weight is sustainability, at 1.690.

The scores in Table 13.7 reflect the weight values assigned by each expert to the impact of different technologies across various domains within the company. This table uses the SUM formula at the bottom to calculate the total score for each expert within a specific domain. This score reflects the extent to which a particular technology is believed to impact that domain; a higher score indicates that the technology is considered more important within

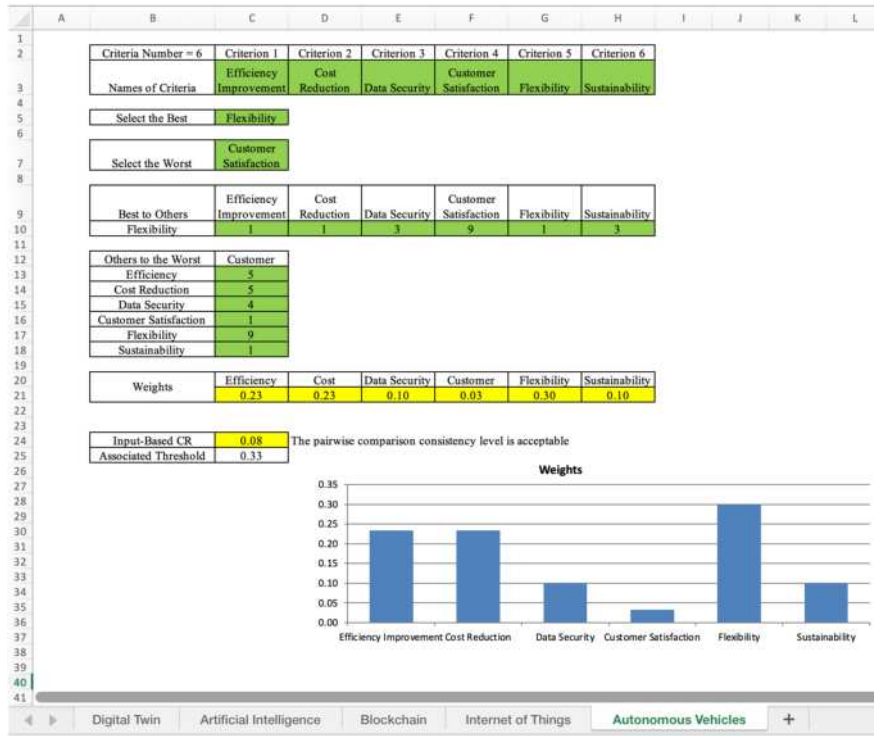


FIGURE 13.2 Best-worst method Excel calculation.

that domain. The values from all the tables for the five technologies are then consolidated to create Table 13.8.

The results reveal distinct trends across the six key operational areas for 3PL companies. The larger the value, the greater the impact of the technology on 3PL companies within that domain. For example, in terms of efficiency improvement, digital twins have the highest weight at 3.668, while autonomous driving has the highest weight at 2.569 in terms of cost reduction. The cells highlighted in yellow in Table 13.8 represent the maximum values in each column.

Table 13.8 shows that the technologies with the greatest impact on different areas of 3PL companies are listed on the right side of the table. The prominence of digital twin technology in efficiency improvement and flexibility suggests that the ability to simulate and optimize logistics processes in a virtual environment is increasingly critical. This technology enables 3PL companies to streamline operations, reduce downtime, and quickly adapt to changes, which is crucial in an industry where agility and precision are key competitive advantages.

In contrast, the dominance of autonomous vehicles in cost reduction and sustainability highlights a paradigm shift towards automation and eco-friendly practices. The potential of autonomous vehicles to reduce labor costs, fuel consumption, and emissions positions them as a transformative force in logistics. However, the lower impact of autonomous vehicles in other

TABLE 13.7 Illustration of results for digital twin technology.

Digital twin	Efficiency improvement	Cost reduction	Data security	Customer satisfaction	Flexibility	Sustainability
	0.224	0.149	0.090	0.030	0.149	0.358
	0.277	0.080	0.277	0.277	0.064	0.026
	0.238	0.032	0.381	0.159	0.095	0.095
	0.429	0.167	0.125	0.072	0.167	0.040
	0.084	0.203	0.055	0.084	0.499	0.074
	0.203	0.102	0.087	0.043	0.497	0.068
	0.149	0.149	0.460	0.036	0.085	0.120
	0.381	0.030	0.163	0.163	0.098	0.163
	0.471	0.187	0.042	0.080	0.140	0.080
	0.141	0.085	0.394	0.211	0.122	0.047
	0.381	0.030	0.163	0.163	0.098	0.163
	0.149	0.149	0.460	0.036	0.085	0.120
	0.203	0.102	0.087	0.043	0.497	0.068
	0.171	0.085	0.043	0.171	0.427	0.103
	0.165	0.307	0.031	0.165	0.165	0.165
Sum	3.668	1.857	2.861	1.733	3.191	1.690

TABLE 13.8 The total score of each technology in different areas.

	Efficiency improvement	Cost reduction	Data security	Customer satisfaction	Flexibility	Sustainability
Digital twin	3.668	1.857	2.861	1.733	3.191	1.690
Artificial intelligence	3.584	2.955	2.039	2.771	2.190	1.460
Blockchain	2.626	2.398	4.137	1.391	2.621	1.828
Internet of Things	3.480	2.815	1.797	2.729	2.628	1.551
Autonomous vehicles	3.049	3.192	1.605	2.270	2.286	2.598

domains, such as flexibility, may indicate that while these technologies excel in specific areas, they may not yet offer the same level of adaptability and integration as other technologies.

The strong performance of blockchain in data security underscores the growing importance of secure and transparent data management in the logistics sector. With the

increasing complexity of global supply chains, the ability to track and verify transactions with immutable records is becoming a cornerstone of trust and compliance. This suggests that 3PL companies recognize the need to invest in technologies that enhance the integrity and security of their operations.

AI's leadership in customer satisfaction further emphasizes the role of AI in enhancing customer experiences through predictive analytics, personalized services, and efficient problem-solving. AI's capability to process vast amounts of data and generate actionable insights allows 3PL companies to anticipate customer needs and respond proactively, which is essential in maintaining competitive service levels.

The aggregation of these results in Fig. 13.3 shows that new technologies have the greatest overall impact on efficiency improvement, with a high rate of 22%, with the 12% lowest impact on sustainability. This suggests that while efficiency gains are a primary focus for 3PL companies, sustainability initiatives may require further technological advancements or broader industry adoption to achieve similar levels of impact. The relatively lower emphasis on sustainability could reflect the current market dynamics, where cost-efficiency and operational effectiveness remain dominant drivers, despite increasing regulatory and societal pressures for greener practices.

By analyzing the best and worst technologies chosen by all experts, Table 13.9 is created to reflect the experts' preferences for different technologies across various domains. A higher number of selections indicates a greater perceived importance of that technology within the respective domain.

Digital twin technology is highly rated for efficiency improvement (5 "BEST" votes) and flexibility (4 "BEST" votes), highlighting its effectiveness in enhancing operations and adapting to various logistical needs. However, it is perceived poorly in customer satisfaction (0 "BEST" votes and 5 "WORST" votes), indicating that it does not directly improve

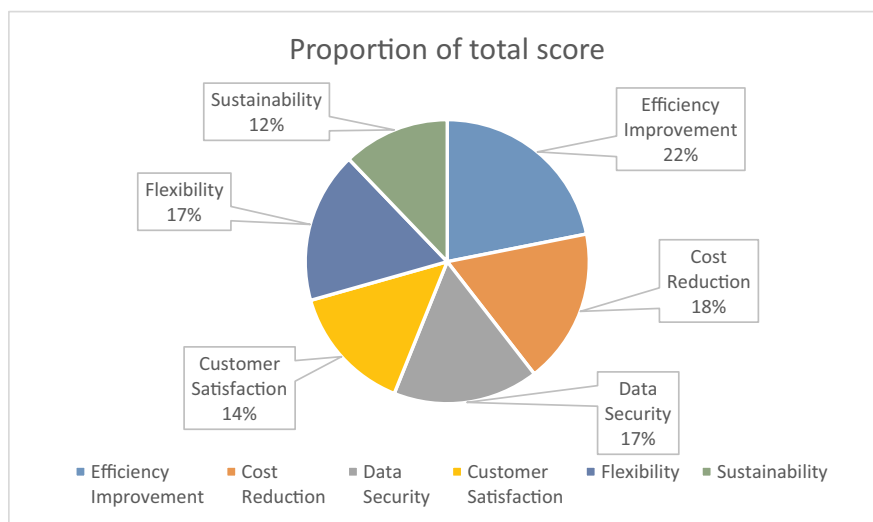


FIGURE 13.3 Proportion of total score.

TABLE 13.9 Experts' best and worst choices.

		Efficiency improvement	Cost reduction	Data security	Customer satisfaction	Flexibility	Sustainability
Digital twin	Best	5	1	4	0	4	1
	Worst	0	3	4	5	0	3
Artificial intelligence	Best	3	5	2	3	2	0
	Worst	0	3	4	2	2	4
Blockchain	Best	2	0	8	0	3	2
	Worst	0	4	0	5	0	6
Internet of Things	Best	5	4	1	3	1	1
	Worst	0	3	4	3	0	5
Autonomo- us vehicles	Best	5	4	0	2	1	3
	Worst	2	2	5	2	1	3

customer-facing outcomes. For cost reduction, data security, and sustainability, digital twin shows a balanced performance with moderate votes, suggesting that it provides some benefits but is not the leading technology in these areas.

AI is particularly valued for cost reduction (5 “BEST” votes) and efficiency improvement (3 “BEST” votes), reflecting its ability to lower operational costs and streamline logistics processes through automation. However, AI is less effective for sustainability (0 “BEST” votes and 4 “WORST” votes), indicating that it is not typically associated with environmental benefits. It shows mixed results in customer satisfaction and flexibility (3-2 “BEST” votes and 2-2 “WORST” votes), suggesting that while it has potential, it is not the primary technology for enhancing these areas.

Blockchain is highly regarded for data security (8 “BEST” votes and 0 “WORST” votes), making it the preferred choice for secure data management within logistics. However, it is not seen as effective for cost reduction (0 “BEST” votes and 4 “WORST” votes) or customer satisfaction (0 “BEST” votes and 5 “WORST” votes), indicating that it might not contribute significantly to reducing costs or enhancing customer experiences. Blockchain also shows a moderate impact on efficiency improvement, flexibility, and sustainability, with mixed votes indicating that while it offers some benefits, it is not a primary driver in these areas.

IoT is viewed as highly effective for efficiency improvement (5 “BEST” votes), reflecting its strength in connecting devices and improving operational processes. However, it scores low in data security (1 “BEST” vote and 4 “WORST” votes) and sustainability (1 “BEST” vote and 5 “WORST” votes), suggesting concerns about security risks and environmental impact. For cost reduction, customer satisfaction, and flexibility, IoT receives a mix of votes, showing that while it can offer some advantages, it is not the most effective technology in these categories.

Autonomous vehicles are highly rated for efficiency improvement (5 “BEST” votes) and cost reduction (4 “BEST” votes), indicating their potential for automating transport and

reducing labor costs. However, they score poorly in data security (5 “WORST” votes), highlighting concerns about cybersecurity risks and system vulnerabilities. The technology has mixed reviews in customer satisfaction, flexibility, and sustainability (2-1-3 “BEST” votes and 2-1-3 “WORST” votes), suggesting that while it has some advantages, it is not the most effective for these outcomes.

The next step involves focusing on the number of best choices and calculating their total. Sum the numbers in Table 13.8, which is 138. Then, the number of expert selections corresponding to each domain is determined. For instance, the number of expert selections for efficiency improvement is 41. By dividing this number by the total of 138, a weight of 0.297 is obtained. This weight represents the impact of the efficiency improvement domain on the overall company. By performing this calculation for each domain, the values presented in Table 13.10 can be derived.

Based on the data in Table 13.10, efficiency improvement has the highest impact weight of 0.297, indicating that it is the most critical factor for 3PL companies, accounting for nearly 30% of the overall influence. Flexibility follows with a weight of 0.225, underscoring its significant role in enabling companies to adapt to changing demands and contributing about 22.5% to the overall impact. Cost reduction and data security have moderate weights of 0.159 and 0.152, respectively, highlighting their importance in maintaining profitability and protecting sensitive information, with each contributing around 15% to the overall impact. Customer satisfaction has a lower impact weight of 0.101, suggesting that it is considered less critical, contributing about 10% to the overall influence. Sustainability has the lowest weight of 0.065, reflecting its lower priority in the current logistics landscape, with a contribution of just 6.5%. This distribution of weights suggests that logistics companies should prioritize efficiency and flexibility while also considering cost, security, and customer satisfaction, with sustainability being a lesser immediate concern.

The selection of all expert preferences in Table 13.9 and the resulting weights in Table 13.10 provide further insights into the strategic priorities of 3PL companies. The consistent favoring of digital twin technology across various domains highlights its versatility and potential as a cornerstone technology for the future of logistics. Meanwhile, the varying importance of technologies such as blockchain and AI across different domains suggests that while these technologies are recognized for their specific strengths, their broader application may still be evolving.

The final scores in Table 13.11 indicate that digital twin technology has the most significant overall impact, suggesting that its potential to drive efficiency and flexibility makes it a top priority for 3PL companies. The strong performance of the digital twin and IoT as the second and third most impactful technologies reinforces the trend towards

TABLE 13.10 The impact weight of each area on the company.

Efficiency improvement	Cost reduction	Data security	Customer satisfaction	Flexibility	Sustainability
0.297	0.159	0.152	0.101	0.225	0.065

TABLE 13.11 Rankings and ratings rankings for different technologies.

Ranking	Technology	Total weight
1	Digital twin	2.82
2	Internet of Things	2.72
3	Artificial intelligence	2.71
4	Blockchain	2.64
5	Autonomous vehicles	2.57

digitization and automation in logistics. The lower ranking of blockchain and autonomous vehicles, despite their specific strengths, suggests that these technologies may still be in the early stages of adoption or require further development to achieve their full potential in the logistics industry.

13.4.2 Validation of results and further analysis

The robustness of the results is further reinforced by the validation of the CR for each expert's input. Adherence to Rezaei's (2016) methodology ensures that the findings are not only statistically sound but also reflect a high degree of internal consistency among the experts' assessments. Fig. 13.4 reflects that consistency ratios were below the threshold for all experts, indicating a strong consensus and reliability in the evaluation process. This, in turn, provides confidence in the strategic insights derived from the study.

As the number of experts from China and the United Kingdom differs, the total score obtained by summing the weights of experts from each country needs to be averaged based on the number of experts. This ensures that all values are within the same range, making the processed data more intuitive and easier to analyze. The comparison of expert opinions from China and the United Kingdom in Table 13.12 and Table 13.13 reveals significant regional differences in the perceived importance of various technologies.

These differences may be attributed to several factors, including varying levels of technological infrastructure, regulatory environments, and market demands in each country. For example, the preference for digital twin technology in efficiency improvement among Chinese experts may reflect the country's focus on rapid industrial modernization and the need for advanced tools to manage complex logistics networks. In contrast, the British experts' preference for AI in the same domain could indicate a greater emphasis on leveraging AI for process optimization and decision support.

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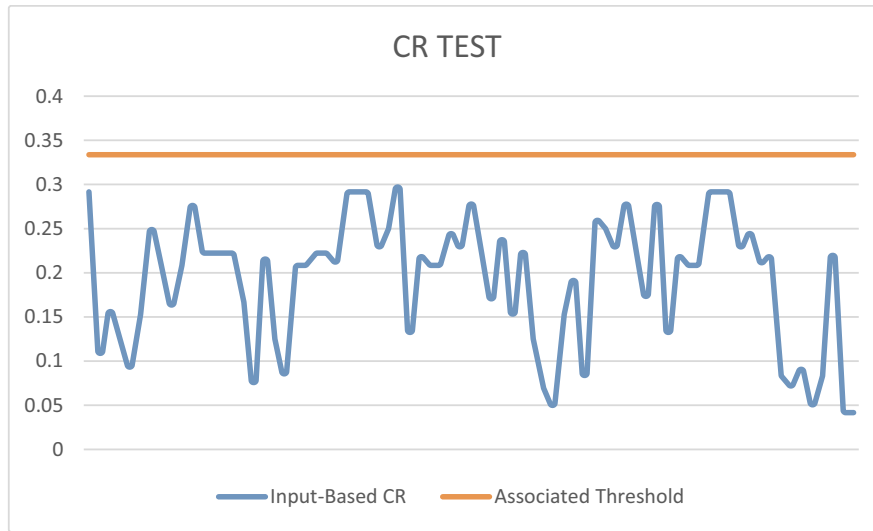


FIGURE 13.4 Experts' consistency ratio (CR) line chart.

TABLE 13.12 UK experts' weighted average.

United Kingdom						
	Efficiency improvement	Cost reduction	Data security	Customer satisfaction	Flexibility	Sustainability
Digital twin	0.168	0.196	0.037	0.168	0.296	0.134
Artificial intelligence	0.316	0.207	0.086	0.158	0.128	0.105
Blockchain	0.231	0.205	0.274	0.108	0.141	0.042
Internet of Things	0.158	0.229	0.091	0.263	0.152	0.106
Autonomous vehicles	0.179	0.311	0.112	0.135	0.162	0.100

British experts' preference for AI in the same domain could indicate a greater emphasis on leveraging AI for process optimization and decision support.

Based on the data from Table 13.12 and Table 13.13, a radar chart can be drawn to illustrate the impact of various technologies on different areas of 3PL companies. Fig. 13.5 and Fig. 13.6 represent the views of UK experts and Chinese experts on various technologies, respectively. In Fig. 13.5, it is evident that, for example, digital twin technology has a significant impact in the Flexibility area, as it stands out prominently in this domain.

TABLE 13.13 Chinese experts' weighted average.

China						
	Efficiency improvement	Cost reduction	Data security	Customer satisfaction	Flexibility	Sustainability
Digital twin	0.256	0.113	0.214	0.107	0.200	0.109
Artificial intelligence	0.227	0.196	0.144	0.189	0.149	0.096
Blockchain	0.167	0.153	0.276	0.090	0.180	0.134
Internet of Things	0.243	0.181	0.124	0.169	0.179	0.103
Autonomous vehicles	0.207	0.198	0.106	0.154	0.151	0.184

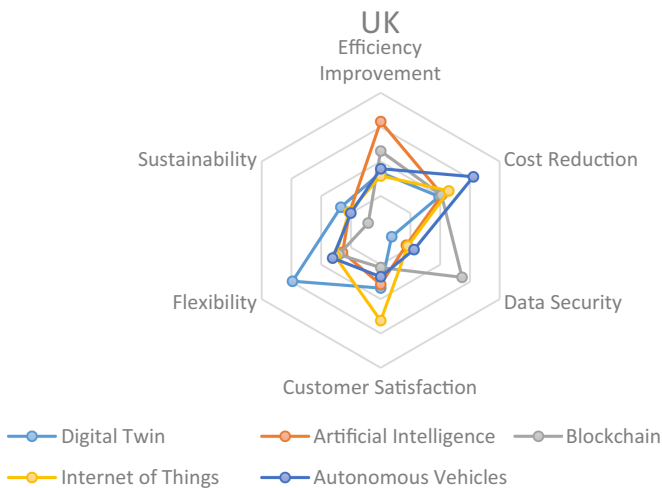


FIGURE 13.5 Radar chart for UK experts' weights.

These differences may be attributed to several factors, including varying levels of technological infrastructure, regulatory environments, and market demands in each country. For example, the preference for digital twin technology in efficiency improvement among Chinese experts may reflect the country's focus on rapid industrial modernization and the need for advanced tools to manage complex logistics networks. In contrast, the British experts' preference for AI in the same domain could indicate a greater emphasis on leveraging AI for process optimization and decision support. Similarly, Fig. 13.6 shows that blockchain technology has a substantial influence on data security for Chinese experts.

The consensus on the importance of autonomous vehicles for cost reduction in both countries suggests a shared recognition of the potential for automation to drive cost

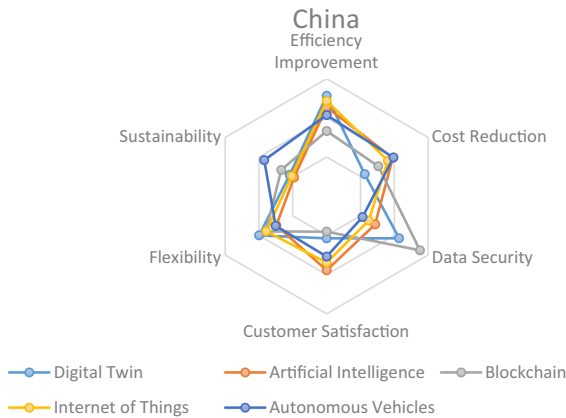


FIGURE 13.6 Radar chart for Chinese experts' weights.

efficiencies. However, the preferences for technologies in customer satisfaction and sustainability reveal different strategic priorities. For customer satisfaction, Chinese experts favor AI for its ability to enhance customer engagement, while British experts prefer IoT for its capability to provide real-time data and insights, which can improve service quality and responsiveness. Regarding sustainability, Chinese experts see autonomous vehicles as crucial for improving environmental performance, whereas British experts value digital twin technology for its role in optimizing resource use and reducing waste through predictive maintenance and better planning.

These regional variations underscore the importance of context in the adoption and impact of new technologies. For 3PL companies operating in different markets, it is crucial to tailor their technological strategies to align with local conditions and priorities. The findings suggest that while there is broad consensus on the importance of certain technologies, such as digital twin and AI, the specific applications and benefits of these technologies may vary depending on regional factors.

Overall, examining Fig. 13.5 and Fig. 13.6 reveals that UK experts tend to give higher ratings to a new technology within a specific domain, while Chinese experts provide more balanced scores across different domains. This difference could be attributed to regional variations arising from cultural differences and distinct logistics models or may be influenced by the differing numbers of experts from each country. This phenomenon could be explored further in future research.

In conclusion, the detailed analysis provided in this chapter highlights the critical role of emerging technologies in shaping the future of 3PL companies. As shown earlier in Table 13.11, digital twin technology has the greatest impact on 3PL companies, followed by AI. As indicated in Table 13.14, overall, digital twin technology is identified as the most influential for both efficiency improvement and flexibility. Autonomous vehicles are recognized as the leading technology for cost reduction and sustainability. Blockchain is highlighted as the key technology for enhancing data security, while AI is considered the most impactful for improving customer satisfaction. The study not only identifies the technologies with the most significant impact but also offers insights into the strategic considerations that 3PL companies must navigate as they integrate these technologies into

TABLE 13.14 Technologies that have the greatest impact in six areas of the company.

Number	Key performance area	Technology
1	Efficiency improvement	Digital twin
2	Cost reduction	Autonomous vehicles
3	Data security	Blockchain
4	Customer satisfaction	Artificial intelligence
5	Flexibility	Digital twin
6	Sustainability	Autonomous vehicles

their operations. The regional differences observed in expert opinions further emphasize the need for a nuanced approach to technology adoption, one that considers both global trends and local market dynamics. As 3PL companies continue to evolve in response to technological advancements, this study provides a valuable roadmap for understanding and leveraging these innovations to achieve sustained competitive advantage.

13.5 Discussion

This research provides a comprehensive analysis of the impact that emerging technologies—namely, digital twin, AI, IoT, blockchain, and autonomous vehicles—have on 3PL companies in the United Kingdom and China. Using the BWM (Rezaei, 2016) for evaluation, this study highlights the varying degrees to which these technologies influence critical operational aspects of logistics, including efficiency, cost management, data security, customer satisfaction, and sustainability. The findings broadly align with existing literature regarding the transformative potential of Industry 4.0 and Industry 5.0 technologies in the logistics sector. Industry 4.0 technologies, such as digital twin and AI, are widely recognized as key drivers for enhancing operational efficiency and customer experience. Meanwhile, Industry 5.0 further emphasizes the importance of human-machine collaboration, personalized services, and sustainability (Ghobakhloo et al., 2022). The integrated application of these technologies, as demonstrated in this research, aligns well with the insights and predictions found in the literature.

13.5.1 Detailed analysis of the application of new technologies

Digital twin technology emerged as the most significant among the technologies studied, particularly in terms of efficiency improvement and flexibility. The prominence of digital twin technology is supported by existing literature, such as Jones et al. (2020), who emphasized its role in enabling real-time simulation and optimization of logistics processes. This study corroborates those findings, demonstrating that digital twin technology not only enhances operational efficiency but also significantly reduces downtime and operational

disruptions. This impact is particularly pronounced in complex logistical environments where agility and precision are critical competitive factors. [Anderson and West \(2023\)](#) also highlighted the ability of digital twin technology to improve flexibility, allowing logistics companies to adapt swiftly to changing market demands—a conclusion further supported by this research. The ability to conduct predictive maintenance and optimize resource allocation underscores the role of the digital twin as a cornerstone technology for modern logistics.

AI demonstrated a substantial impact on customer satisfaction, reflecting its critical role in enhancing customer service and experience. This research corroborates [Anderson and West \(2023\)](#) findings, which highlighted AI's role in improving customer satisfaction through predictive analytics and personalized services. AI's capability to process and analyze vast amounts of data allows logistics companies to offer more personalized services, improve delivery accuracy, and predict customer needs with greater precision. The study further illustrates how AI-driven tools, such as predictive analytics, chatbots, and dynamic routing systems, contribute to higher customer satisfaction by ensuring timely deliveries, reducing errors, and providing real-time updates ([Singh, 2023](#)). Furthermore, AI's role in demand forecasting and inventory management is pivotal, as it helps companies better anticipate market fluctuations and manage supply chain disruptions, thus maintaining service quality even in volatile conditions.

Blockchain technology stood out in the domain of data security, aligning with the literature that recognizes blockchain's potential to revolutionize data security and transparency in supply chains ([Yontar, 2023](#)). The research findings indicate that blockchain's decentralized and immutable ledger system is highly effective in enhancing the transparency and security of transactions within the logistics sector. This technology is particularly crucial in a globalized supply chain environment where the integrity and traceability of data are paramount. The ability of blockchain to provide a secure and transparent record of all transactions mitigates the risks associated with fraud, data breaches, and compliance failures.

Autonomous vehicles were identified as crucial for cost reduction and sustainability, findings that align with the literature's perspective on their potential benefits ([Sullivan & Kern, 2021](#)). Autonomous vehicles, particularly in last-mile delivery and intrawarehouse transportation, have the potential to drastically reduce labor costs and improve fuel efficiency. The research suggests that by minimizing human intervention and optimizing routing, these vehicles can lead to substantial cost savings and lower environmental impact through reduced emissions. However, similar to findings by [Bonab et al. \(2023\)](#), this study also identifies significant challenges in their broader integration, such as technology reliability, regulatory hurdles, and public acceptance. These challenges suggest that while autonomous vehicles are seen as a transformative force in logistics, their full potential will only be realized when these barriers are addressed through further technological advancements and supportive regulatory frameworks.

IoT, though slightly less dominant compared to the other technologies, plays a critical role in creating interconnected and smart logistics systems. The IoT enables real-time monitoring of goods, fleet management, and warehouse operations, which enhances overall operational visibility and control. This research highlights the IoT's contribution to improving supply chain integration and efficiency, particularly through its ability to collect

and analyze data from various touchpoints across the logistics network. The IoT's role in predictive maintenance and asset tracking further underscores its importance, especially in enhancing operational reliability and reducing downtime (Gayialis et al., 2020).

Furthermore, this research adds a critical layer of analysis by exploring regional differences in technology adoption between United Kingdom and Chinese experts, an area that has been relatively underexplored in existing literature. While both regions recognize the importance of these technologies, the emphasis on different technologies for various operational goals suggests that regional market dynamics and regulatory environments play a crucial role in shaping technological priorities. For example, Chinese experts prioritize digital twin technology primarily for its role in enhancing operational efficiency, likely reflecting China's broader industrial focus on rapid modernization and the optimization of complex supply chains. In contrast, UK experts place greater emphasis on AI for its ability to refine and optimize processes, suggesting a more mature market focus where operational fine-tuning and customer engagement are key drivers.

13.5.2 Strategic integration of emerging technologies in global logistics operations

The integration of emerging technologies into logistics operations presents profound implications for companies striving to maintain competitiveness in an increasingly digital and automated global market. Digital twin technology stands out as a critical tool for logistics companies, offering unparalleled advantages in simulating and optimizing logistics processes within a virtual environment. This capability not only streamlines operations and reduces downtime but also enhances a company's ability to adapt swiftly to changes in market demand or supply chain disruptions. For instance, a recent study by Tao et al. (2019) demonstrates how digital twin technology can significantly improve supply chain resilience and flexibility by providing real-time insights and predictive analytics. Companies investing in digital twin technology can expect significant improvements in both operational resilience and flexibility, enabling them to respond more effectively to the dynamic challenges of the logistics industry.

In parallel, AI plays a pivotal role in transforming the customer experience. AI's ability to process vast datasets and generate actionable insights allows logistics companies to offer more personalized services, which are crucial in maintaining high levels of customer satisfaction—a key competitive differentiator in the logistics sector. According to a study by Kuo and Smith (2020), AI-driven solutions have been shown to enhance customer satisfaction through improved service delivery and demand forecasting. By leveraging AI, companies can optimize their operations from demand forecasting to dynamic routing, ensuring that services are both timely and accurate, thereby enhancing overall customer satisfaction and loyalty.

IoT and blockchain technologies, while still evolving, are equally important in creating integrated, transparent, and secure supply chains. The IoT's role in real-time monitoring and management of logistics operations enhances operational visibility and control, contributing to more efficient and responsive supply chains. Ivanov et al. (2021) highlight the significant impact of IoT on enhancing the efficiency and responsiveness of supply chains through real-

time monitoring and predictive maintenance. Blockchain, with its decentralized and immutable ledger system, significantly enhances the security and transparency of data across the logistics network. This is particularly important in managing the complexity of global logistics, where the integrity and traceability of information are paramount for compliance and risk management.

However, despite these clear benefits, the adoption of these advanced technologies is not without significant challenges. The initial investment required for deploying technologies such as digital twin and AI is substantial, often demanding considerable capital and a long-term strategic commitment from companies. This financial burden can be a barrier, particularly for small to medium-sized enterprises (SMEs) in the logistics sector. Moreover, the integration of these technologies into existing legacy systems poses additional challenges, including potential disruptions during the transition phase and the complexity of ensuring compatibility with current operations. [Raut et al. \(2019\)](#) discuss the challenges and financial implications of integrating advanced technologies into logistics, particularly for SMEs, and emphasize the need for strategic planning and phased implementation to mitigate risks.

Data security concerns, especially with IoT and blockchain, further complicate the adoption process. As logistics operations become increasingly digital, the risk of cyber threats escalates, necessitating robust security measures to protect sensitive data and maintain the integrity of supply chain operations. Companies must also address the challenge of workforce adaptation, as the successful implementation of these technologies requires employees to develop new skills and competencies. This necessitates ongoing training and development initiatives, which can be resource-intensive and time-consuming. [Mittal et al. \(2022\)](#) emphasize the importance of cybersecurity in logistics and the need for continuous workforce training to manage the challenges posed by digital transformation.

The regional differences highlighted by this research underscore the importance of contextualizing technology adoption strategies. The preferences expressed by experts in the United Kingdom and China reveal how local market dynamics, regulatory environments, and industrial priorities shape the adoption and implementation of these technologies. For example, Chinese experts' preference for digital twin technology reflects the country's focus on rapid industrial modernization and the optimization of complex supply chains. In contrast, UK experts emphasize AI's role in refining and optimizing processes, suggesting a more mature market approach that prioritizes operational fine-tuning and customer engagement. [Zhang et al. \(2020\)](#) explore the regional variations in technology adoption within the logistics sector, highlighting the different strategic priorities in China and the United Kingdom.

For logistics companies operating across multiple regions, it is crucial to tailor their technological strategies to align with these local conditions. This requires a deep understanding of regional market demands, regulatory frameworks, and industrial objectives to ensure that technology integration is both effective and efficient. By doing so, companies can better navigate the challenges associated with technology adoption and leverage the unique advantages offered by each technology in different contexts. This approach is supported by a study by [Gupta and Venkatesh \(2019\)](#), who recommend a localized strategy for technology adoption to maximize the effectiveness and return on investment.

Strategic recommendations for logistics companies based on these findings include prioritizing the adoption of digital twin and AI technologies, given their broad impact across multiple operational areas. A phased approach is recommended, starting with technologies that offer the quickest return on investment. For instance, AI can be leveraged to enhance customer satisfaction through improved service delivery, while digital twin technology can be deployed to optimize operational efficiency. As these technologies become more embedded within company operations, further investments in IoT and blockchain can be pursued to strengthen data transparency, security, and overall supply chain resilience. Autonomous vehicles, although promising, should be adopted with caution. Pilot programs in controlled environments are advisable to refine the technology and address potential challenges related to reliability, regulatory compliance, and public acceptance. Once these challenges are mitigated, broader implementation can be considered. This strategic roadmap will enable logistics companies to capitalize on the benefits of emerging technologies while managing the associated risks, ensuring a sustainable and competitive edge in the rapidly evolving logistics landscape. This phased approach to technology adoption is further supported by the findings of [Zhou et al. \(2021\)](#), which suggest that logistics companies should initially focus on technologies that offer the highest potential for ROI before expanding their technological investments.

13.6 Conclusion

The primary contribution of this research lies in its examination of the impact of emerging technologies within the frameworks of Industry 4.0 and Industry 5.0 on 3PL companies. By focusing on key technologies such as digital twin, AI, IoT, blockchain, and autonomous vehicles, this study provides a nuanced understanding of how these innovations are reshaping the logistics sector. At the same time, these technologies are ranked according to their importance, from most to least important: digital twins, the IoT, AI, blockchain, and autonomous vehicles. For instance, [Giri and Manohar \(2021\)](#) highlight the role of digital twins, AI, and IoT in enhancing operational efficiencies in 3PL companies, further supporting the findings of this study. The analysis offers a strategic framework that logistics companies can utilize to prioritize the adoption of these technologies, thereby enhancing operational efficiency, customer satisfaction, data security, and sustainability.

A secondary, yet significant, contribution is the exploration of regional differences in technology adoption between the United Kingdom and China. By shedding light on how local market dynamics, regulatory environments, and industrial priorities influence the adoption of these technologies, the research enriches the existing body of knowledge on global logistics strategies. [Wang et al. \(2020\)](#) provide evidence of how China's regulatory environment shapes the adoption of blockchain in logistics, underscoring the regional nuances discussed in this research. This comparative analysis is particularly valuable for multinational logistics companies, as it underscores the importance of tailoring technology implementation strategies to align with regional contexts.

Despite these valuable insights, the research is not without its limitations. A key limitation is the reliance on expert opinions, which, while providing depth and specialized

insights, may introduce bias due to the subjective nature of expert judgment. The relatively small sample size of experts further exacerbates this issue, as it may not fully capture the diversity of perspectives within the logistics industry. Expert-driven studies often face challenges in achieving broad generalizability (Kache & Seuring, 2017), a concern that is relevant here. Additionally, the focus on the United Kingdom and China, while providing important regional insights, limits the generalizability of the findings. The specific technological infrastructures, regulatory frameworks, and market conditions in these countries may not be reflective of other regions, particularly those with different levels of technological development or distinct regulatory challenges.

Another limitation relates to the dynamic nature of technology adoption. The rapidly evolving landscape of Industry 4.0 and 5.0 technologies means that the findings of this study may quickly become outdated as new technologies emerge and existing ones mature. Recent research by Schwab (2020) echoes this concern, noting that the pace of technological advancement poses a significant challenge for longitudinal studies. Furthermore, the study does not fully address the implementation challenges associated with integrating these technologies into existing logistics operations, such as the need for legacy system compatibility and the potential for operational disruption during the transition phase.

Lastly, the study touches only briefly on the ethical implications of adopting advanced technologies, such as data privacy concerns. As logistics companies increasingly rely on automation and data-driven decision-making, these ethical considerations will become increasingly important. For example, Smith and Anderson (2022) discuss the ethical challenges posed by automation in logistics, particularly in terms of data privacy concerns, which highlights the need for deeper exploration in future research. Future research should delve deeper into these areas, exploring strategies for ensuring robust data protection measures are in place.

In summary, while this research makes substantial contributions to understanding the impact of emerging technologies on logistics, it is essential to recognize its limitations. These limitations suggest several avenues for future research, including expanding the geographic scope, increasing the diversity of expert opinions, and exploring the long-term implications and ethical challenges associated with these technologies. By addressing these areas, future studies can build on the foundation laid by this research, offering even more comprehensive insights into the evolving logistics landscape.

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Leveraging Industry 4.0 technologies for smart and sustainable wastewater treatment

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14.1 Introduction

Recently, the world has been confronted with a triple planetary crisis due to the interrelation of climate change, biodiversity loss, and environmental pollution due to water contamination (Gernaey et al., 2004). As a crucial resource for the process industry and energy supply, water has become one of the most critical resources due to shortage and pollution (Lowe et al., 2022). A global assessment of future clean water has projected that about three billion people will encounter water scarcity by 2050 because of nitrogen pollution that contributes to water scarcity in basins worldwide (Li et al., 2021). Unless properly tackled, the interlinked issues can put the contribution of the United Nations Sustainable Development Goal (UN SDG#6) in jeopardy.

For example, clean water and sanitation have become more essential to stopping the spread of disease and improving sustainability as the population rapidly grows in urban areas globally. Traditional grid-based water fails to meet the challenge of water supply in many areas (Guo et al., 2015). Furthermore, they are the main contributors to climate change. Additionally, the high level of organic carbon in municipal wastewater presents challenges and bottlenecks for denitrification. When external carbon sources are included for denitrification, errors arise due to the lack of accuracy and timely quality prediction. Furthermore, an overconsumption of water resources, loss of nutrients, and the failure to expand urban services to vulnerable populations also imply the urgency for a wastewater treatment revolution. Hence, it is vital to synergize various treatment approaches time efficiently and effectively to ensure that the UN SDGs remain on track, entailing the growing need for collaborative work across sustainable development aspects (Sundui et al., 2021).

Digitalization may play a vital role in this aspect (Fig. 14.1).

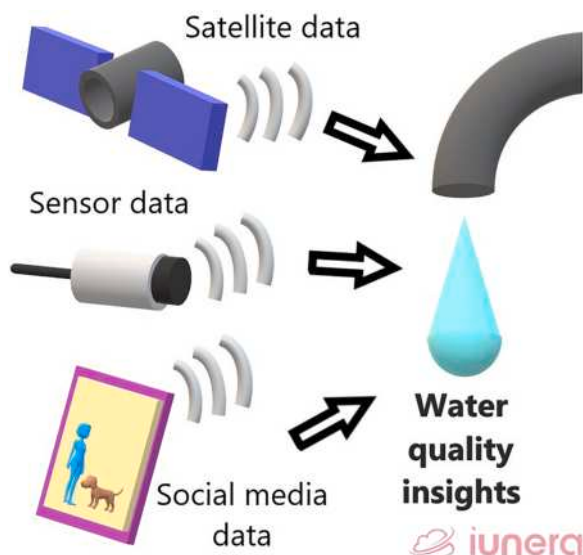


FIGURE 14.1 Digitalization in wastewater treatment.

If industrial water management can be integrated into onsite management, process efficiency can be increased, circularity solutions become possible, and the transformation toward a sustainable water industry advances (Bernardelli et al., 2020). Water treatment operators can simulate the increasing demands on system dynamics in real time, while adapting production and securing decisive competitive advantages. The increased demands on the security of supply and system efficiency can be provided through a digital transformation of conventional water treatment (Kovacs et al., 2022).

In addition, a close integration of the circular economy and industrial water treatment strengthens the competitiveness of wastewater treatment plants (WWTP) and locations, reducing the risk of failure in operation. The increasing water stress in process industry locations implies that business success depends on an efficient industrial water treatment (Wang et al., 2021). Hence, wastewater treatment needs to consider process development. For aqueous residual streams, new approaches are required to recover chemical energy and valuable materials such as nutrients. In addition to its conventional role in industrial production, wastewater as a resource has increasingly become the focus of a circular economy. Wastewater treatment needs to be transformed from water purification to the use of the ingredients and the energy it contains through resource recovery (Zhu et al., 2022).

As many aspects of water treatment reflect the cyclical nature of water, designing treatment processes with no waste, keeping products and materials in use, and regenerating natural systems can make water treatment circular (Syah et al., 2021). By aligning with the UN SDG#12 on “Sustainable production and consumption,” a circular water treatment closes a water loop by designing new technologies that can recover resources and energy from wastewater. This approach moves away from conventional treatment options for water streams to focusing on their simultaneous treatment and value addition to resource recovery (Wang et al., 2022).

The fourth Industrial Revolution, commonly coined “Industry 4.0,” presently transforms the water sector through an integration of advanced digital technologies like artificial intelligence (AI), machine learning (ML), Internet of Things (IoT), big data (BD) analytics, and advanced robotics (Zhang et al., 2022). The emerging smart technologies could be deployed to improve ongoing services such as wastewater treatment, power network, as well as mitigate water pollution via real-time monitoring (Lowe et al., 2022).

While current debate centers on the potential economic impacts of digitalization, the Industry 4.0 holds significant implications for sustainability across environmental, social, and economic dimensions. On one hand, the digital technologies introduce new capabilities for energy and resource efficiency, process optimization, circular business models, near-zero waste manufacturing, and evidence-based sustainability (Fan et al., 2018). On the other hand, simply adopting the digital technologies does not guarantee sustainability benefits. If improperly managed, they pose risks related to job losses and rebound effects that need to be addressed through integrative frameworks (Malviya & Jaspal, 2021). Therefore there is a critical need to examine the nexus of Industry 4.0 and sustainability to develop novel solutions that maximize resource recovery, while mitigating risks (Zhang et al., 2021).

The latest developments in digitalization of water sector provide public utilities with the opportunity to share how digital tools are utilized by water sector and to provide a new environment for the digitalization to be involved in water industry. Currently, water industry is in the midst of a digital transformation, with new technologies being developed and deployed to improve efficiency, reduce costs (chemicals, energy, residuals, and labor), while enhancing the overall treatment processes (Nourani et al., 2018). One of the most promising new technologies is digital solutions, a virtual model of a physical system, using live data feeds that can be used for analysis, optimization, and prediction (Al Aani et al., 2019).

To bridge the knowledge gaps, this work provides a multidisciplinary perspective in engineering domains to direct the Industry 4.0 toward enhanced sustainability in the water sector by highlighting the need for new approaches such as AI and ML to optimize water treatment, while improving efficiency and reducing treatment costs as a catalysator for sustainable development. Furthermore, this work aims to explore the potential of digitalization in achieving sustainable water treatment and its contribution to UN SDG#6 “Clean water and sanitation” by providing an overview of the significance of sustainable wastewater treatment solutions.

By leveraging digitalization for the UN SDG#6, it is expected that this work would advance best practices at a crucial intersection of digital transformation and sustainable development in the water sector (Nicolae et al., 2021). It is also projected that real-time monitoring and predictive analytics would enable proactive decision-making, ensuring timely interventions to prevent water pollution from taking place. Data-driven approaches facilitate resource allocation, enabling an efficient water treatment and its conservation (Dogo et al., 2019).

14.2 Variety of digital technologies in water sector

Recently, the growing utilization of AI, BD, and ML has become a subject of controversial debates. In this regard, the United Nations Environmental Program (UNEP) has highlighted

ways through which AI can be used to tackle global societal challenges such as biodiversity loss, water pollution, as well as solid waste. To this end, in 2022, the UNEP launched the World Environment Situation Room, a digital platform that leverages AI's capabilities to gather, aggregate, visualize, and interpret complex and multifaceted datasets (Yasin et al., 2020).

Recently, AI, BD, and ML have emerged as powerful tools that can revolutionize the way the world tackles climate change by providing data-driven insights, optimizing decision-making processes, and facilitating the development of sustainable economic and financial strategies. Despite the AI being uniquely positioned to tackle societal challenges, no consensus has been reached so far in the body of literature to what extent the mechanism could transform BD into sustainable economic and financial solutions to climate change. With respect to this concern, Salam and Salam (2020) found that AI can establish 134 targets across the 17 UN SDGS and inhibit 59 other targets. Focusing on the environmental targets (climate action, life below water, and life on land), there are evidences from their study that AI promotes better understanding of climate change and extrapolating its impacts, while supporting low-carbon energy, and improving the health of the ecosystem.

Moreover, Júnior et al. (2021) highlighted the role of AI in promoting circular economy practices in the water treatment industry. Aligning with them, Jagtap et al. (2021) underscored BD and AI as two key digital technologies for a sustainable circular economy in the water sector. It is also worth mentioning the role of AI in fighting climate change (Hakak et al., 2020). The results of their work suggest that AI can be employed to obtain complex data on emissions and climate effects and to strengthen planning and decision-making, while optimizing processes, supporting collaborative ecosystems, and encouraging climate-positive behaviors. It is asserted that climate change needs to become a key factor within government policy to address technology-specific opportunities and risks in the fight against climate change (Dogo et al., 2019).

Some of the benefits of the use of digitalization in the water and wastewater sector include improved efficiency, predictive maintenance, process optimization, time-relevant and actionable decision-making, and better safety control (Senthil Rathi & Senthil Kumar, 2022). Digitalization can help water and WWTPs optimize their operations by providing real-time insights and data analysis. This can lead to a higher treatment efficiency and cost reduction. Additionally, digitalization has the ability to simulate different scenarios at the same time and predict the results of various operational settings. This helps minimize the risks of optimizing processes, while improving an overall performance (Chang et al., 2021).

With respect to users, digitalization can provide water treatment operators with real-time data and insights, which can help them rapidly to make more informed decisions. This can lead to better performance and more effective management of wastewater treatment processes. Digitalization can also be used to simulate potential safety hazards and assess the risks related to a variety of operational scenarios. This can help to identify potential safety problems before they take place and to take measures to prevent them (Mahmoud et al., 2021).

14.3 Data-driven water treatment for energy gain: the way forward

The water and wastewater treatment industry is in the midst of a digital transformation, with new technologies being developed and deployed to improve efficiency, reduce costs

(chemicals, energy, residuals, and labor), and enhance the overall effectiveness of treatment processes (Sundaresan et al., 2021). One of the most promising new technologies is the digital twin, which is a virtual model of a physical system, using live data feeds that can be used for analysis, optimization, and prediction. Currently, WWTPs around the world are using digital technologies to become more energy efficient. Digital technologies can facilitate them to prepare for a low-carbon future by optimizing their processes. Water treatment requires energy, but it also generates energy (Thakur et al., 2021).

Wastewater utilities use new technology to enhance their energy efficiency and sustainability. Digitalization can help WWTPs optimize their operations by providing real-time insights and data analysis. This can lead to greater efficiency and cost savings. Today, WWTPs have ways to lower their energy consumption, increase their energy production, and improve their circularity (Sriyono, 2020). For example, they can convert sludge into biogas. Digitalization can help them achieve better results. Cloud computing, smart algorithms, and AI work together with existing wastewater treatment technologies, such as membranes, filters, chemistry, and biological treatment, to create a system that combines chemistry with a digital platform for automated dosing, energy optimization, and compliance with stricter regulations (Bakalar et al., 2012).

Maximizing water treatment efficiency, improving sustainability performance, and ensuring compliance with regulations and standards are the essential goals in water management (Burgués et al., 2021). Utilizing a combination of high-quality chemicals and digital technologies can help achieve the objectives. By integrating digital technologies and data-driven chemistry management, water treatment plants can benefit from real-time monitoring, process control and optimization, and predictive analytics (Burgués et al., 2022). The solutions provide insights into the treatment process, enabling operators to make informed decisions and take proactive actions (Cancela et al., 2019).

Real-time monitoring allows for continuous monitoring of key parameters, such as water quality indicators, flow rates, and chemical dosages. Digitalization can be used to monitor the health of equipment and either provide early notification of problems or predict when maintenance or repairs will be required. This can help reduce downtime and extend the life of equipment. This helps in identifying any deviations or anomalies in the process, allowing for immediate corrective actions to be taken (Lally et al., 2019).

Advanced process control and optimization utilize algorithms and automation to optimize the water treatment process. Digitalization can simulate different scenarios and predict the results of various operational changes (Vellemu et al., 2021). This can help reduce the risks of optimizing processes and improve overall performance. By continuously analyzing data and adjusting process parameters, the technology can improve efficiency, reduce chemical usage, and enhance overall performance. Predictive analytics leverages historical and real-time data to identify patterns, trends, and potential issues during leachate treatment. By applying ML and statistical models, it becomes possible to predict equipment failures, optimize maintenance schedules, and prevent operational disruptions (Das et al., 2014).

Furthermore, digital technologies enable enhanced transparency and communication within the WWTP (Li et al., 2023). Digitalization can provide operators with real-time data and insights, which can help them rapidly make more informed decisions. This can lead to better overall performance and more effective management of water and wastewater

treatment processes. Stakeholders can access real-time data, reports, and analytics, promoting collaboration and enabling informed decision-making (Abegaz et al., 2018). By leveraging the power of high-quality chemicals and digital technologies, landfill leachate treatment can become more efficient, sustainable, and compliant with regulations. This integration allows for continuous improvement, optimized resource utilization, and proactive management of water treatment.

Digital technologies can be used to simulate potential safety hazards and assess the risks associated with various operational scenarios. This can help to identify potential safety problems before they occur and to take measures to prevent them. For this purpose, WWTPs need to integrate physical equipment with cloud-based solutions and software, so they can have better plant-wide controls and predictive analytics. One example is soft sensors (Park et al., 2020). Soft sensors are digital only. They are calibrated to the physical sensors of a system, and they use predictive monitoring to give WWTP operators a better view of more of the system. This allows automated dosing, real-time feedback, and helps operators prepare for dynamic situations. Other benefits include energy savings from lower suspended solids in the centrate, as well as dryer sludge, which reduces sludge hauling and disposal costs (Qu et al., 2013).

Utilities and larger private water companies are using digital technologies early, and they are enjoying the benefits. Well-managed systems can cut energy use by 40% (Angelakis & Snyder, 2015). However, smaller WWTPs are behind due to resources or simple resistance. Municipal wastewater treatment facilities choose physical sensors only, as they do not want their data in the cloud, or they think that sensors and AI are advanced (Nair et al., 2022).

Modern computational facilities and ML approaches have made it easier to deal with BD and solve complex problems. This progress has helped to handle difficult problems in water resource management, such as hydrological simulation, fluid flow in different media, and detailed characterizations of surface and subsurface. Therefore ML methods have been widely used to make use of BD from sensors, drones, and geographical data and to explore the relationship between influencing parameters (Afridi & Mukhopadhyay, 2022).

Recently, there has been more research interest in using the recycle, reuse, recovery (3Rs) strategy to promote food security. Globalization and interconnectivity between water infrastructures and resources have enabled water reuse as a key part of circular economy (CE) and changed the nexus of water, energy, and food systems. Unlike the linear model from product-to-use-to-disposal, a CE paradigm maximizes resource recovery used in the economy to reduce pressure on finite resources, while protecting the environment and improving long-term sustainability (Khan et al., 2021). For wastewater to be integrated with a CE, there is a growing need to restore local social fabrics with respect to the circular relationships between water resources, target nutrients, and people through digitalization via instrument interconnectivity (Gopavanitha & Nagaraju, 2017).

It is expected that digitalization would drive an economically driven decarbonization scenario from 2020 to 2050, a period relevant to meet the 2015 Paris Agreement target. Indonesia's GHG emissions could decrease by 15% from 447 Mt CO_{2eq} in 1990 to 380 Mt CO₂ in 2030 if there is a shift from an industrial economy to a digitalization-focused economy in food, energy, and water nexus (Kruse, 2018).

The water sector needs a revolution to face the challenges of the next decades. In Southeast Asia, the industrial water and wastewater treatment market is expected to grow

beyond US\$5 billion by 2024 (Yaroshenko et al., 2020). As the largest economy in the region, Indonesia has the biggest potential market. However, there is a misunderstanding in the water sector that digitalization is hard and expensive to do because of the automated and continuous process. However, digitalization is affordable and easy to implement in the existing systems. Digitalization helps the water utility sector to improve operations without making any changes or a huge financial overhaul related to an upgrade (Raich, 2013). Digitalization offers practical and effective benefits with respect to specific needs when dealing with security and access to audit logs for recording (Ailamaki et al., 2003).

Digitalization is everywhere, and it changes how the water sector works, delivering value to public utilities around the world. As municipalities are seeking for ways to lower their carbon footprint and reduce their environmental impacts, digitalization transforms the water sector by using data to lower energy use, raw material consumption, and carbon intensity. Saving energy in a water treatment process and optimizing chemical consumption are smart solutions that WWTPs can use to achieve their environmental goals. Sludge dewatering is another area where water utilities can enhance performance. Sludge is hard to dewater, handle, and dispose of (Koppanen et al., 2022). For water utilities that start a digitalization journey, key benefits can be gained in optimizing primary treatment and sludge dewatering through efficiencies. Since using smart solutions, dry solids have increased 21% (v/v) (Alferes & Vanrolleghem, 2016). Over time, drier sludge leads to less disposal costs and a lower carbon footprint (Winkler et al., 2004).

Water sector has become more sustainable and fair through digital transformation. Digitalization has had impact on the world quickly. As digital maturity grows, it leads to an enhanced ability to use digital technologies innovatively, creating opportunities to develop new business models. With sensors and analyzers in place, digitalization can help plant operators to see the benefits of water treatment.

This new development involves disruptive technologies such as human-machine interface. AI has transformed applications, such as waste recycling and water treatment (Cong & Yu, 2018). AI deals with computer intelligence simulations. AI and computer vision are used for decision-making activities to provide enough water supply. Specifically, water systems can use data and information to make better decisions to improve the delivery of services, optimize investment capital, and lower operational expenses, such as environmental implications (Yaroshenko et al., 2020).

Water utilities often follow other industries, especially energy, without understanding the principles and consequences of incorporating information and communications technology in their management. IoT devices can measure the pH and total dissolved solids contribution of different water types using AI-based Arduino programming language. An AI-based leak detection approach uses hydrophone technology sensors to detect even small leaks in water pipes by noise. By using ground and light sensors, AI development solutions for water supply systems can properly estimate the amount of water and fertilizers needed in the fields. By recognizing microorganisms, AI can improve current systems. This technology is better than the current way of identifying harmful microbes using biochemical chips (Adu-Manu et al., 2017).

The application of AI, digital data, and faster connectivity and networks could change the whole structure of water industry, because of the huge growth in data collection, storage capabilities, and computing power. Digitalization has changed how people interact with

the water sector, bringing impacts on efficiency and accuracy in the field (Hellweger et al., 2004). The technological revolution has made computing storage technology available at low cost. Digital technology, which was not available to water industries before, has become affordable recently for developed countries (Brando & Dekker, 2003).

BD also transforms business processes, products, and services. As a global industry, water treatment operations need rapid digitalization. Enhanced connectivity is key for digitalization to be effective. Data is useless if it is locked away in instruments and users cannot access it. Without data, it is not possible to get insight from it or make any quick changes to processes that may be needed during drinking water treatment (Harvey et al., 2015). It can be challenging to deliver the results when facing issues such as connectivity, increased regulations, market demands, and productivity. The powerful tools have been widely used to assess contaminant toxicity and environmental risks, evaluate the health of water and wastewater infrastructure, examine the fate and transformation of pollutants in different environments, optimize treatment technologies, identify and characterize pollution sources, model wastewater treatment, predict contaminant activity in treatment systems or in the environment, and perform lifecycle analysis (Vrieling, 2006).

Digitalization has transformed the global water industry by setting a new standard for water treatment design. It leverages the advances in AI, data mining, ML, and BD, powered by algorithms and computing capacity, to tackle water pollutants effectively. Digitalization can also help cope with the climate change impacts that link SDGs such as food–water–energy nexus with urban development. It can enhance the efficiency of resources and information, making clean water more accessible and affordable. This supports global efforts to achieve the UN’s SDG#9 “Industry, Innovation and Infrastructure” (Yunus et al., 2020).

Like AI, ML is a potentially disruptive technology that enables a program to learn from data, examples, and experience without predefined rules. ML has been applied to the management and operation of water treatment systems, contributing to the sustainability of water technology and its resources (Kumar & Hong, 2022).

14.3.1 Wastewater treatment plant operation and management

One of the main challenges in WWTP operation and management is to reduce the high cost of energy and chemicals required to meet the stricter effluent standards. ML can help managers to optimize costs and operations by providing solutions. A study (Usali & Ismail, 2010) used ML algorithms to analyze a database of WWTPs and identify key variables affecting energy cost. They (Mabwoga et al., 2010) proposed a Bayesian method to calculate the individual payments of contributors, which facilitated the management of the construction, regulation, and operation of a WWTP.

14.3.2 Process optimization and reactants design

Wastewater treatment involves complex interactions among various parameters, and it is hard to pinpoint the key parameters. Glasgow et al. (2004) used the random forest (RF) model to examine the factors affecting the removal of five heavy metals and found that the

pH and the flocculant dosage were the most important, and the average molecular weight was the main factor among the flocculant characteristics. [Morgan et al. \(2020\)](#) applied the RF algorithm to predict the reduction of micropollutants during ozonation, and the model was successfully used to optimize the O₃ dose for the desired removal of MPs. The cases show that ML can provide valuable information for the optimal design of reagents, operations, and reaction devices.

14.3.3 Effluent quality monitoring and prediction

The water quality of a WWTP is influenced by various parameters and changes over time in a nonlinear way. ML models have been shown to be useful for predicting and monitoring the effluent quality in a WWTP. [Vellemu et al. \(2021\)](#) used artificial neural networks (ANN) algorithms to predict the total nitrogen (TN) concentration of effluent from a WWTP in Ulsan (Korea) with a 1-day interval. [Sibanda et al. \(2021\)](#) achieved the online monitoring of chlorine in real time based on ML, and their findings offered guidance for the design and development of water quality monitoring systems. ML has created new opportunities in wastewater treatment, and its application will likely become more widespread in the future ([Safeer et al., 2022](#)).

It was obvious that digitalization has improved the speed, efficiency, and accessibility of water operations recently. Data and digital technologies create multiple benefits, as digital solutions allow economic transformation aligned with human, social, and environmental progress. For water operations, AI technologies (5 G, cloud computing, ML, digitalization, virtual reality) have been increasingly used to turn data into knowledge to enhance the performance of water cycle infrastructures and facilitate the operation and maintenance of decision-making ([de Lima et al., 2021](#)).

To achieve this, modeling is used for automation. The common AI techniques in water treatment include adaptive network-based fuzzy inference systems (ANFIS), ANNs, decision trees (DT), and fuzzy inference systems. The techniques are expected to provide benefits in wastewater treatment. The advantages, limitations, and applications of frequently used AI techniques for modeling, simulating, and predicting the water treatment processes, such as ANFIS, ANNs, DT, genetic algorithm, support vector machine, and RF. The algorithms have been proven to be highly accurate in predicting material properties and reaction efficiencies with a relatively low demand for the dataset ([De Keukelaere et al., 2023](#)).

Water industries are interested in new possibilities of computer-aided decision-making at operational levels, but they face technical challenges with BD in terms of variety and veracity ([Salam, 2020](#)). Therefore human intelligence is still needed to classify, homogenize, and convert data into useful information. This step accounts for 40% of the costs in data science of the wastewater treatment sector due to the need to separate useless data from data fit for purpose, avoiding the “Garbage-In Garbage-Out” problem. The scientifically informed policy-making process has become more popular, but people’s views, inspirations, and pathways to carbon neutrality are poorly understood. Although the digitalization policy-making process is designed with global recognition, its implementation pathways are inherently local. Therefore bridging local condition with global transformation is vital ([Martin et al., 2018](#)).

14.4 Concluding remarks

This study has demonstrated that the integration of digitalization in sustainable wastewater treatment represents a pivotal step forward in the global pursuit of UN SDG #6, while concurrently aligning with carbon neutrality objectives. Through the adoption of digital technologies and innovative approaches, wastewater treatment processes can be optimized to not only enhance water quality but also minimize environmental impact and contribute to carbon neutrality goals. By leveraging real-time monitoring, predictive analytics, and automation, digitalization enables more efficient resource utilization, reduced energy consumption, and proactive maintenance in wastewater treatment facilities.

Moreover, the implementation of digitalization empowers stakeholders to make informed decisions, improve operational efficiency, and enhance system resilience. This transformation toward digitalized wastewater treatment not only addresses immediate challenges related to water quality and sanitation but also lays a basis for a sustainable and resilient infrastructure for future generations. However, it is crucial to acknowledge the challenges and barriers associated with the widespread adoption of digitalization in wastewater treatment, including initial investment costs, cybersecurity concerns, and the need for skilled workforce development. Addressing these challenges will require collaborative efforts from governments, industries, and research institutions to foster innovation, provide incentives, and ensure capacity building.

In light of the urgency to achieve SDG #6 and mitigate the impacts of climate change, it is imperative to accelerate the deployment of digital solutions in wastewater treatment, while ensuring inclusivity and equity in access to clean water and sanitation services. By embracing digitalization as the way forward, the world can not only promote environmental sustainability and achieve carbon neutrality goals but also pave the way for a more resilient and equitable future for all.

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Industry 4.0 and the circular economy: toward new business models

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15.1 Introduction

The convergence of Industry 4.0 (I4.0) and the circular economy (CE) represents a transformative shift in how businesses operate and create value. Not surprisingly, the intersection of I4.0 and CE is a rapidly evolving research area, with growing empirical evidence suggesting that digital transformation plays a crucial role in accelerating sustainable business practices (Lopes de Sousa Jabbour et al., 2018; Toth-Peter et al., 2023). As global sustainability challenges intensify, organizations are seeking ways to transition from linear economic models to circular business strategies. I4.0 technologies, including big data, artificial intelligence (AI), and the Internet of Things (IoT), offer unprecedented opportunities to revolutionize business operations and serve as key tools to facilitate the CE transition.

However, integrating these I4.0 technologies into circular business models presents both opportunities and challenges, requiring significant adjustments in business strategies, policy frameworks, and workforce capabilities. With that in mind, this chapter explores the role of I4.0 in enabling circular business models, critically analyzing the benefits, challenges, and future directions of this transition. Therefore, in this chapter, we unpack the synergy between I4.0 and CE by exploring how digital technologies enable new business models, streamline operations, and optimize resource loops. It also investigates the limitations of these technologies, particularly the challenges businesses face in terms of financial feasibility, skills gaps, and interoperability of systems.

Beyond technological considerations, this chapter highlights the broader implications of I4.0-enabled circularity, emphasizing its role in redefining value creation. Traditional business models that prioritize ownership-based consumption are assumed to be replaced by service-based and product-as-a-service models in the CE, which emphasize

environmental sustainability alongside financial considerations. Such transformations necessitate rethinking supply chains, consumer behavior, and regulatory landscapes. We explore the extent to which businesses can leverage I4.0 innovations to create economically viable circular models and assess whether these technologies can truly deliver on their sustainability promises.

Ultimately, this chapter provides a comprehensive overview of the intersection between I4.0 and CE, offering both theoretical insights and practical applications. It discusses emerging trends, showcases real-world examples, and presents a nuanced perspective on the potential pathways and roadblocks that businesses encounter when transitioning toward the CE. By bridging digital transformation with sustainability principles, we shed light on the evolving nature of business in the era of I4.0 and CE, making the case for a strategic, integrated approach that aligns technological advancements with long-term environmental and economic goals.

In a nutshell, we show that while I4.0 technologies offer promising solutions to support the CE by enhancing resource efficiency and waste reduction throughout the product lifecycle, their adoption—despite being a strong driver of business model innovation—is often constrained by economic, technical, and regulatory barriers.

15.2 Theoretical background

15.2.1 Circular economy: a new economic model

The articulation of the CE concept started in the 1960s to address and alleviate the negative impacts of the linear, capitalist system. To understand what the CE is, it is important to delineate it from what it is not. Since the first industrial revolution (1760–1820), the world economy has adopted a linear “take-make-use-dispose” system. Under this paradigm, profit was a driver for large-scale industrialization and scientific and technological advancement. This further intensified the linear processes, leading to high productivity, new design concepts, and the proliferation of cheap resources. This has led to increased growth and wealth at an unprecedented scale, and “more is better” became the guiding principle, aiming for accumulation, more profit, more value, and more market share, which established the basics of capitalism and the market economy system (Bonciu, 2020). However, in the linear economy, the concept of economic development was associated with short-term gains at the cost of ecological impacts. Thus the capitalist system created secondary effects that cannot be solved by operating within the same system that induced them.

Therefore the CE appears as an alternative to the traditional linear economy, and it emphasizes closed-loop systems, resource efficiency, and sustainable production. Core principles of the CE include waste minimization, product life extension, and the integration of renewable materials into production processes (Ellen MacArthur Foundation, 2017). Transitioning to circular business models requires innovation in product design, manufacturing processes, and consumer engagement strategies to facilitate recycling, remanufacturing, and product-as-a-service models, among others. Accordingly, the transition entails

circular business model innovation as shifting from ownership-based consumption to service-based solutions, such as leasing, sharing, and pay-per-use arrangements, requires a different way of looking at how value is created, by reintegrating the same value into the economy.

Although [Ellen MacArthur Foundation \(2017\)](#) proposed a definition for the CE and summarized three key principles commonly used in the literature, it is important to highlight that, due to the high number of conceptualizations already discussed, the CE means different things to different people, as [Kirchherr et al. \(2017\)](#) claim. Their study collated 114 CE definitions to provide an overall understanding of the concept (reanalysed in 2023 with 221 definitions). Thus, for us, we used Kirchherr and colleagues' definition of the CE as follows:

"an economic system that is based on business models which replace the 'end-of-life' concept with reducing, alternatively reusing, recycling and recovering materials in production/distribution and consumption processes, thus operating at the micro level (products, companies, consumers), meso level (eco-industrial parks) and macro level (city, region, nation and beyond), with the aim to accomplish sustainable development, which implies creating environmental quality, economic prosperity and social equity, to the benefit of current and future generations." ([Kirchherr et al., 2017](#), pp. 224–225)

Building on this definition, it is essential to explore the strategies businesses can adopt to implement CE principles. In the next section, we show some key conceptualizations of CE. By examining these strategies, we can better understand how organizations can transition from traditional linear models to more circular and resource-efficient practices.

15.2.2 Circular economy principles and business models

15.2.2.1 A hierarchy of circular economy strategies

A common way to apply CE principles is through the waste hierarchy, often called the R-hierarchy or R-framework. It starts with the well-known 3Rs: reduce, reuse, and recycle, which are basic waste management concepts. Over time, additional strategies have been added, such as recover, remanufacture, and redesign, expanding the framework to 4R, 5R, and 6R models. The 9R and 10R frameworks go even further, incorporating actions like rethink, repair, refurbish, repurpose, and refuse ([Potting et al., 2017](#)). While these models suggest a hierarchy and priority order for managing resources, some scholars argue that the relationships between these strategies are not strictly hierarchical—some work as trade-offs, while others create synergies ([Blomsma et al., 2019](#)). This evolving perspective highlights both the complexity of implementing CE strategies and the value of these strategies as a practical guide for companies to explore their options and adapt them to their specific business context.

15.2.2.2 Resource management strategies

Another way businesses can manage resources effectively is by adopting strategies that focus on slowing, closing, and narrowing resource loops—key principles of CE business models ([Bocken et al., 2016](#)). These approaches help companies preserve material value,

maximize product utility, and improve efficiency while integrating sustainability into their operations.

Narrowing resource loops means using fewer materials in production to minimize waste, which requires rethinking product design from the start. However, some argue that this is more about improving efficiency than achieving true circularity. Slowing resource loops, on the other hand, extends the lifespan of products by emphasizing durability, upgradeability, and optimized maintenance. Strategies such as reuse, repair, refurbishing, and remanufacturing play a crucial role in keeping products in circulation for as long as possible. Closing resource loops takes this further by creating closed-loop systems where waste from one process becomes input for another. This can involve industrial symbiosis, where multiple businesses collaborate to repurpose materials, or the development of eco-industrial parks that facilitate large-scale resource-sharing networks. Design, for instance, plays a critical role through the resource loops, with eco-design principles ensuring that materials are designed at the beginning of the life so that they can be effectively recovered and reintegrated at the end of a product's life.

More recently, these strategies have been expanded to include regeneration (which is also the third key principle of the CE), which highlights the importance of renewable energy and cleaner production, and information-driven innovation, which leverages digital technologies to inform circular business practices (Konietzko et al., 2020). Together, these approaches provide businesses with a broader understanding and implications for embedding CE principles. As these resource management strategies prioritize using fewer materials and extending product lifecycles, service-based models and servitization emerge as key mechanisms for reducing consumption while maintaining value creation.

15.2.2.3 Servitization and service-based models

The shift from selling products to offering services, and the concept of servitization (Vandermerwe & Rada, 1988), is a key characteristic of the CE. Instead of focusing solely on physical goods, service-based models prioritize digital solutions, performance, and functionality. This shift changes how people consume, moving from traditional ownership to virtual, access-based, and shared-use models in a service-based economy.

In this approach, companies retain ownership of their products while providing them as services—whether through leasing, subscriptions, or pay-per-use models. Rather than selling a product outright, businesses take on the role of service providers, ensuring that goods are maintained, upgraded, and used efficiently. This shift not only reduces waste but also encourages resource efficiency and durability by extending product lifespans and minimizing the need for constant production of new items.

By embracing this model, businesses can create new value streams while consumers benefit from access to high-quality products without the burden of ownership. Ultimately, this transformation supports a more sustainable economy by reducing material consumption and promoting responsible resource management. However, this shift fundamentally changes business-as-usual and current value chain characteristics and how companies create value.

15.2.3 Transitioning to circular economy

Transitioning to CE requires more than just adopting sustainable practices—it demands a fundamental shift in how businesses create, deliver, and capture value (Teece, 2010). This transformation starts with embedding circular principles into a company's value proposition, ensuring that products and services align with both sustainability goals and customer needs. To achieve this, businesses must first understand their target customers, analyze their behavior, and tailor circular offerings that genuinely resonate with them. The success of CE adoption depends on demonstrating that circular solutions are not just environmentally responsible but also practical and beneficial for consumers.

Beyond redefining value propositions, companies must rethink how they create and deliver value. This means decoupling economic growth from the depletion of finite resources and finding innovative ways to recover and repurpose materials. When businesses shift toward circularity, their financial models inevitably evolve as well. Capturing value in a circular system is crucial for long-term viability—without a sustainable financial model, the transition to CE cannot succeed. For circular strategies to be widely adopted, they must prove economically attractive, balancing profitability with sustainability.

However, this transition is far from simple. Many businesses struggle to integrate circular principles due to operational and technological challenges. This is where digital technologies, particularly I4.0 tools, could play a transformative role. Smart technologies such as AI, IoT, blockchain, and digital twins enable businesses to track materials, optimize resource use, and implement closed-loop systems more effectively. By bridging the gap between digitalization and circularity, companies can streamline processes, reduce inefficiencies, and make circular business models more scalable and accessible.

To fully unlock the potential of CE, businesses must deepen their understanding of how digital technologies can facilitate this shift—turning circular strategies from theoretical concepts into practical, value-generating solutions. However, this is particularly challenging given that I4.0 itself is still an evolving concept, with new tools, systems, and processes continuously emerging and disrupting business processes, making it difficult for businesses to keep pace and integrate them effectively into circular models.

15.2.4 Industry 4.0: the new industrial revolution

Following the paradigm shifts of the first three industrial revolutions, I4.0 introduced a new wave of smart objects that dominate manufacturing systems and processes. On the one hand, I4.0 is considered to be application-pulled, triggered by social, economic, and political changes, including short development periods or time to market, on-demand individualization, flexibility, decentralization, and resource efficiency. On the other hand, I4.0 is technology-pushed, driven by increasing mechanization and automation (to enable independent control and optimization), digitalization, networking, and miniaturization. Ghobakhloo (2020) discussed the fundamental design principles of I4.0, including decentralization, horizontal integration, interoperability, modularity, product and service individualization, real-time capability, service orientation, smart factory, smart product, vertical integration, and virtualization. Further, they also identified 16 different areas where I4.0 could positively impact economic, environmental, and social sustainability.

The new principles and digital transformation of I4.0 rely on implementing and integrating various technologies, ranging from simple to advanced information, digital, and operation technologies. Indeed, the I4.0 technologies vary according to different interpretations. Broadly, they embody advances in the IoT, cloud computing, additive manufacturing (AM) or 3D printing, wireless sensor networks, big data analytics, AI, advanced robotics and autonomous systems, augmented reality (AR) and virtual reality (VR), horizontal and vertical system integration, simulation, cybersecurity, and blockchain (Demir & Cicibaş, 2019).

There are different ways to classify these technologies. For example, Dalenogare et al. (2018) grouped them into product development (expected to improve product performance, such as 3D printing), manufacturing (expected to improve operational performance, such as AM), and integration technologies that are at the intersection of the two categories (such as cloud services and big data). In another conceptual framework, Frank et al. (2019) separated front-end technologies that address operational and market needs, in which smart manufacturing plays a central role and base technologies (such as the IoT, cloud, big data, and analytics) that enable integration and connection across front-end technologies. Similarly, Bai et al. (2020) grouped I4.0 technologies into physical (AM, sensors, or drones) and digital technologies (cloud computing, blockchain, big data analytics, simulation).

This evolving landscape highlights the diverse ways in which I4.0 technologies can drive innovation and sustainability, ultimately offering businesses the tools to rethink how they operate, produce, and deliver value. By integrating these technologies, companies can improve not only efficiency and productivity but also their environmental and social impact, to support sustainable development (Lopes et al., 2023). For example, using real-time data analytics can help optimize resource usage, while 3D printing can reduce material waste and enable more customized production. Therefore the adoption of I4.0 technologies can unlock new business models, facilitate collaboration across industries, and pave the way for a more sustainable future. As businesses embrace this new digital era intersection with the CE era, they must also be prepared to continuously evolve and adapt to stay competitive in an ever-changing market.

15.3 Industry 4.0 toward the circular economy

Given the diverse role that I4.0 plays in advancing the CE, we put together a table to show how different digital tools support specific CE strategies. Each I4.0 tool has its own unique function, offering businesses distinct opportunities to enhance their operations. The way these tools are integrated and utilized will vary depending on the needs and expectations of different industries. In this section, we explore each I4.0 technology (presented in alphabetical order), highlighting its key features, benefits, and how it aligns with the core principles of the CE and business models. We have drawn on insights from existing literature, alongside examples from our own research in 2023. A summary of these technologies is provided in Table 15.1

TABLE 15.1 Summary of Industry 4.0 characteristics, benefits, and contributions to the circular economy.

Industry 4.0		Characteristics	Benefits and contributions
Additive manufacturing		Digital design and modifications 3D PRINTERS ADDITIVELY BUILD UP PRODUCTS	Reduces material waste and processing time; enables resource-efficient manufacturing; facilitates spare part production, repair, refurbishment, and remanufacturing; complex and customizable designs
Advanced and autonomous robots		Replicate human actions PERFORM REPETITIVE AND COMPLEX TASKS AUTONOMOUSLY OR IN COLLABORATION WITH HUMANS	Enhances efficiency, safety, and precision in manufacturing; reduces human labor in hazardous environments; extends product life through automated repair and maintenance processes
Artificial intelligence		Machines that mimic human intelligence; key aspects: analytics, big data, cloud, domain expertise, and evidence-based learning	Enables smart manufacturing and predictive maintenance; improves process optimization and failure detection; supports decision-making with scenario analysis; enhances resource efficiency and lifecycle assessment
Augmented and virtual reality		Creates virtual and mixed environments for data interaction and simulation	Supports product design, workforce training, and remote maintenance; enables virtual prototyping and optimization of repair/refurbishment processes; enhances decision-making in product lifecycle management
Big data		Processing and analyzing large volumes of structured and unstructured data	Supports real-time decision-making, predictive analytics, and lifecycle tracking; enables efficient resource management and failure detection; enhances traceability of products and materials
Blockchain		Decentralized, tamper-proof digital ledger; smart contracts for automation	Ensures transparent and secure supply chains; improves product traceability and authentication; facilitates carbon footprint tracking; enhances trust in material reuse and supply chains
Cloud computing		Network-based digital services; enables data sharing and connectivity	Provides remote access to shared data; optimizes resource use and recovery; reduces the need for physical infrastructure; enables collaborative platforms for circular business models

(Continued)

TABLE 15.1 (Continued)

Industry 4.0		Characteristics	Benefits and contributions
Cybersecurity		Protective measures against cyber threats and data breaches	Secures digital infrastructure, intellectual property, and critical operations; prevents cyberattacks on smart systems; safeguards consumer and business data
Drones		Aircraft without human pilots, equipped with sensors for data collection	Enhances surveillance, monitoring, and logistics; supports emergency response in hazardous or remote areas; aids environmental monitoring and compliance tracking
Internet of Things		Network of connected devices with sensors, radio-frequency identification tags, and smart chips	Enables real-time tracking of materials and products; facilitates smart inventory and supply chain optimization; improves energy efficiency and waste reduction
Simulation		Virtual representation of real-world systems for predictive analysis	Optimizes resource use and energy efficiency; enables scenario testing for circular design improvements; supports maintenance, cleaning cycles, and process adjustments
System integration		Connecting diverse software, hardware, and data systems for seamless operations	Enables interoperability between I4.0 technologies; enhances data sharing and collaboration across industries; supports closed-loop supply chains and circular business models

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15.3.1 Additive manufacturing

AM, also known as 3D printing, is a revolutionary production method that builds products layer by layer. This process allows for digital modifications to products without needing to create them physically, which helps reduce the use of resources, tools, and processing time. Unlike traditional manufacturing, AM enables on-demand production, meaning businesses can produce items only when they are needed, minimizing excess inventory and optimizing resource use. This capability makes AM particularly valuable in the CE, as it supports flexible product design, adaptability, and upgradability, while also facilitating easier maintenance.

Companies can incorporate AM into operations to enhance repair and refurbishment efforts by producing spare parts on demand, which reduces storage costs and extends product lifecycles. This approach can support situations where a company needs to secure enough spare parts during the warranty period, ensuring that products continue to function well without

unnecessary waste. This way, AM fosters resilience and rapid response in supply chains. Furthermore, AM's ability to accommodate complex design changes means that manufacturers can improve their products with minimal resource input, further boosting circularity in production. When combined with digital tools like simulation and data analytics, AM enables design improvements before physical production even begins. This reduces waste from prototyping and optimizes material use, making it a powerful tool for the CE.

However, AM does have its challenges. For instance, the cost of 3D printing can sometimes be higher than traditional manufacturing methods, especially for large-scale production. Additionally, disassembling products and separating materials can be difficult, particularly when different materials are fused together in a single print. Despite these challenges, companies are working to overcome these limitations by developing new technologies and materials that enhance AM's versatility. With continued advancements in speed, scalability, and material efficiency, AM is well-positioned to become a key enabler of resource-efficient, on-demand, and CE-driven manufacturing.

15.3.2 Advanced and autonomous robots

Advanced robotics, including autonomous robots, is revolutionizing industries by supporting automation in line with I4.0. These robots mimic human actions and handle repetitive or complex tasks with varying degrees of autonomy, often driven by AI and machine learning. Companies increasingly use automation and robotics to enhance operational efficiency and extend product lifecycles. Robotics plays an essential role across sectors like manufacturing, defense, healthcare, mining, and agriculture, boosting efficiency, flexibility, and safety. For example, robots are commonly used for tasks like product inspection, welding, painting, and pick-and-place operations (Goel & Gupta, 2020).

One of the growing uses of robotics is waste management, where AI-driven robots are being tested to automate waste sorting, replacing human spotters in hazardous environments. These robots work alongside automated conveyor systems and separation technologies such as density-based screens, magnets, and anticurrent extractors for ferrous and nonferrous metals. This not only reduces the risk of human exposure to dangerous environments but also enhances recycling efficiency by working with technologies that separate materials like metals.

Additionally, AI-powered autonomous monitoring systems are being deployed in industrial settings to oversee exclusion zones and prevent accidents involving heavy machinery. These innovations significantly improve workplace safety by reducing human exposure to dangerous conditions and optimizing material recovery processes. However, while robots have proven effective in automating tasks, their full potential in areas like demand forecasting, product optimization, and quality control has yet to be fully explored. Either way, building on this progression, robot-human collaboration is expected to be a hallmark of the next phase, I5.0, enhancing workplace safety and productivity.

15.3.3 Artificial intelligence

AI refers to the development of machines that can mimic human behavior, helping industries to improve efficiency across various tasks. AI is used in fields like image

processing, natural language understanding, robotics, and machine learning, which allows systems to learn and evolve from experience and large datasets. One framework that defines industrial AI is the “ABCDE” model, which covers five core elements: analytics, big data, cloud technology, domain expertise, and evidence (Lee et al., 2018). These elements together drive AI’s value and learning capabilities, empowering industries to optimize their operations. Machine learning, a subset of AI, enables systems to improve outcomes by continuously learning from data, which is particularly useful in manufacturing and maintenance, where it can predict failures and reduce the strain on human workers.

AI is also transforming service optimization and automation. For instance, digital twins and simulations powered by AI are helping industries enhance operational efficiency. In healthcare, AI supports the maintenance of complex medical equipment, ensuring smoother operations with fewer interruptions. AI-enabled drones are being deployed for infrastructure inspections, making it possible to detect issues in real-time and reduce reliance on manual checks. In waste management, AI-driven optical separators and high-definition cameras help sort materials more efficiently, minimizing downtime and improving productivity. As AI continues to evolve, collaborations with research institutions are expanding its applications across diverse sectors, making it a key player in transforming industries.

Moreover, AI plays a crucial role in measuring and assessing sustainability. AI-powered tools can calculate sustainability metrics by analyzing procurement data, applying methods like natural language processing and lifecycle analysis to evaluate environmental and social impacts, including CE-driven metrics. These tools help businesses identify risks, prioritize actions, and optimize their strategies for reducing Scope 3 emissions. By utilizing AI-generated insights, companies can refine their sustainability efforts and make better decisions, supporting CE goals. These AI systems act as digital assistants as they offer mitigation strategies, provide the ability to compare scenarios, and suggest efficient maintenance cycles—all contributing to CE business practices.

15.3.4 Augmented and virtual reality

AR and VR are groundbreaking technologies that enhance human capabilities by integrating digital tools into our interactions with the world. These technologies provide real-time information, map value chains, and offer computer-generated representations of real-world objects or digital twins. AR and VR have the power to create both partial and entirely virtual environments, allowing users to engage with data from the physical and digital worlds simultaneously. While AR presents real-world environments as they are, VR immerses users in simulated surroundings, replacing reality with digital constructs. Both AR and VR have significant applications across industries, including product and plant design, decision-making, workforce training, quality assurance, and maintenance.

While AR and VR have yet to be fully implemented or may not directly contribute to CE practices, their potential is widely acknowledged. AR could be particularly useful in repair services, enabling remote collaboration across different locations, assisting with repair guides, and even aiding in equipment installation through holographic displays. AR also holds promise in enhancing decision-making and safety training. It could help workers make more informed decisions on the job or create more engaging safety training materials,

like immersive safety videos. However, AR is still in development, with challenges, including high costs and the need for specialized technical skills to integrate it into existing systems. Despite these hurdles, AR's potential to transform industries remains clear, and it shows potential for the CE.

15.3.5 Big data

Big data refers to the immense amount of data being generated every day, with a vast variety and complexity. This data can be processed and analyzed using cloud computing, which allows for real-time access and enables more informed decision-making. Big data plays a crucial role in product development and demand forecasting within supply chains, helping to create more agile and responsive systems. By analyzing large datasets, big data analytics has become an essential tool in the advanced application of I4.0 technologies. However, handling big data comes with its own set of challenges. The volume, diversity, and value of the data, along with the need for robust infrastructure to process it, make it difficult to extract meaningful insights using traditional methods. While big data holds immense potential, the complexity of managing and interpreting it requires ongoing advancements in technology and methodology.

In the context of the CE, big data plays a vital role in identifying potential failures early and supporting timely product repair and maintenance. By using data intelligently, businesses can ensure the longevity of their products and materials. A key challenge in this process is the need for structured data—data that is organized and standardized in a way that allows actionable insights to be extracted. Industry-wide initiatives to standardize such data are still lacking worldwide, making it a significant hurdle to overcome.

Big data also helps uncover alternative uses for materials, offering exciting opportunities for sustainability. For example, in waste management, digital tools can track the location of waste in landfills, opening the door for material recovery in the future. Materials once deemed unsuitable for recycling can now be repurposed for new applications, such as using laminated timber as fuel in power stations to replace coal. While treated timber still has environmental concerns, this innovation provides a way to give the material a second life and reduce reliance on fossil fuels. As technology evolves, AI tools are continuously improving their ability to process and interpret big data, with advancements like ChatGPT showcasing how data can lead to even greater efficiency and sustainability.

15.3.6 Blockchain

Blockchain technology, introduced in 2008 alongside cryptocurrencies like Bitcoin (Nakamoto, 2008), revolutionized the way we manage economic transactions. At its core, blockchain relies on distributed ledger technology, where transaction records are stored in encrypted blocks that are securely linked together, making them immutable. This decentralized network facilitates online transactions and the management of digital assets, ensuring transparency, traceability, and protection against data tampering (Ajwani-Ramchandani et al., 2021). In the context of I4.0, blockchain addresses critical concerns around confidentiality, privacy, and security—issues that arise as automation and cyberattacks become more prevalent.

Moreover, blockchain can enable the autonomous execution of business operations through smart contracts, which automatically carry out predefined conditions.

One of the most exciting potentials of blockchain lies in its ability to transform supply chain management by providing real-time data sharing and greater visibility. This can enhance the resilience of businesses by improving how goods and services are tracked, especially in industries like agriculture and waste management. For example, blockchain could track food products from farm to supermarket, allowing consumers to distinguish between traditional and regenerative farming methods. This transparency could also streamline certification processes, ensuring that products meet sustainability standards. Similarly, in waste management, blockchain could offer ecosystem-based solutions to better monitor the lifecycle of materials, providing valuable insights into their reuse and recycling.

In terms of the CE, blockchain can play a crucial role in decarbonization efforts. By offering a secure and verifiable method for tracking emissions across supply chains, it can enable businesses to make more informed, data-driven decisions. This capability could revolutionize how companies measure the environmental impact of their products and improve methods for reducing emissions.

However, challenges remain in implementing blockchain in certain industries. For instance, tracking materials once they have been mixed or aggregated—such as those sent to smelters or exported for manufacturing—remains a significant hurdle. Moreover, while blockchain solutions are explored in various sectors, challenges related to regional adoption and scalability continue to pose obstacles to widespread implementation. Despite this, the potential of blockchain to create transparent, secure, and efficient supply chains remains clear.

15.3.7 Cloud computing

Cloud computing and manufacturing are interconnected digital services that enable products equipped with sensors, processors, and software to connect via the cloud. This technology offers on-demand, remote access to a shared pool of resources, improving resource management and monitoring. It also holds the potential for resource recovery by enabling the recirculation of reused and refurbished components through a shared network, connecting new buyers with available resources. Cloud manufacturing builds on technologies such as AM.

Cloud computing serves as a foundational enabler of company processes, improving data resource management and scalability. It provides a common platform for suppliers, clients, governments, and large organizations to access and store data, creating a more efficient and interconnected ecosystem. In the context of the CE, cloud computing facilitates the sharing of information among key players, contributing to resource efficiency. For example, cloud-based solutions can optimize systems like hospital monitoring by running software remotely, reducing the need for on-site data centers and lowering energy use and CO₂ emissions. These solutions also contribute to establish more sustainable infrastructure.

However, the adoption of cloud computing in the CE transition faces several challenges. Issues such as unclear regulations, privacy concerns, and resistance to transparency—particularly regarding sensitive business information—can complicate its integration. Additionally, in rural areas with limited internet access, the use of cloud computing is restricted, limiting its application in sectors like agriculture where connectivity may be less robust.

15.3.8 Drones

Drones, or unmanned aerial vehicles, are another exciting development in automation. These aircraft, which do not require a human pilot, are equipped with sensors that gather data for surveillance and monitoring. Their applications are vast, ranging from logistics, such as last-mile package delivery, to assisting in safety operations in remote or hazardous areas. Drones have also found a place in agriculture, where they are used to monitor crops and prevent diseases. This innovation is part of the broader trend of Agriculture 4.0, which integrates AI, IoT, and GPS to create smart farming systems.

In the CE, drones are powerful tools for data collection and forecasting. For example, companies use GPS-equipped drones to monitor landfills, manage stockpiles, and track environmental conditions. In weather forecasting, drones have replaced traditional balloon-based sensors, providing more precise data while minimizing waste. In agriculture, drones are used for precision spraying, conducting automated flights to spray crops based on sensor readings. However, ensuring the quality of the data collected by these drones remains a key challenge in fully realizing their potential for sustainable industrial applications.

15.3.9 Internet of Things

IoT refers to a network of interconnected digital devices, manufacturing processes, and value streams that facilitate information exchange within factories. It enables the creation of smart products, improving decision-making by providing more accurate insights into product conditions. Through this, IoT systems make operations more reliable, transparent, and efficient, enhancing agile supply chains and aligning logistics processes. The IoT relies on technologies like radio-frequency identification tags, sensors, and chips for tracking and identifying objects. The Industrial IoT refers to the hardware systems working together within the IoT to improve manufacturing processes (Bai et al., 2020).

In the context of the CE, the IoT plays a pivotal role in extending product lifecycles through enabling remote maintenance and repair. IoT systems offer software updates and diagnostic data, allowing businesses to accurately assess when products need repairs based on context-specific information. This optimizes product usage, reduces premature failures, and enhances product longevity. For example, IoT sensors can evaluate whether a product qualifies for repair or recycling based on usage patterns, facilitating the reintegration of a product into the economy. However, full integration into CE models is still in its early stages, with not all products globally connected across value chains and markets.

In sectors such as agriculture and waste management, IoT helps optimize resource efficiency. For instance, in agriculture, sensors in irrigation systems enable precise water control, reducing consumption by activating pumps only when needed. Moreover, satellite imagery monitors soil health by analyzing microbiology, acidity, and chemical composition, supporting more sustainable farming practices. In landfill management, IoT-enabled GPS trackers optimize truck routes and equipment movements, improving operational efficiency and environmental outcomes. However, limitations in infrastructure, especially in rural areas, hinder the full potential of IoT. Widespread adoption is needed to fully realize its benefits in advancing resource efficiency and supporting CE objectives.

15.3.10 Simulation

Simulation technologies replicate real-world systems and processes virtually, enabling companies to optimize resource use and support decision-making across various industries. These simulations can be applied in areas such as knowledge transfer and simulated teaching games. Simulation is often linked to digital twins—integrated multiphysics, multiscale, and probabilistic systems that allow for smart production and precision management. The key difference between simulations and digital twins is the level of data integration, with simulations serving as an enabler for implementation.

Simulations and digital twins can significantly contribute to the CE by supporting lifecycle optimization, improving product design, and enhancing operational efficiency. In construction, for example, Building Information Modeling is used to simulate the entire lifecycle of infrastructure, from design and material selection to maintenance and end-of-life management. This allows businesses to proactively assess various design alternatives and their long-term impacts. In agriculture, digital twins are utilized to track activities such as paddock rotation and livestock movements, enabling more effective management of natural resources and ecosystem functions. By simulating carbon sequestration and biodiversity credits, farmers can enhance land management practices and generate additional income streams. These technologies also play a role in waste management, where drone-collected data optimize landfill operations and lifecycle planning.

In manufacturing, simulation and digital twin technologies allow companies to test designs virtually, reducing the need for physical prototypes, which saves time and resources. This approach aligns with CE principles by minimizing material waste and promoting more sustainable production. However, challenges persist in fully implementing these technologies across different regions and industries, such as limited access to digital tools and the need for integration with real-time data, and the operational and maintenance challenges associated with handling large datasets. Despite these challenges, the potential of simulations and digital twins to support the CE and lifecycle optimization remains significant across various sectors.

15.3.11 System integration

System integration is the key to unlocking seamless communication and collaboration across various technological components—be it software, hardware, or data systems. Think of it as the glue that binds different systems together, allowing them to work in harmony. This integration can take different forms: vertical integration (connecting systems within a single company), horizontal integration (bridging systems across companies), and end-to-end integration (linking physical systems with virtual ones). The ultimate goal of system integration is interoperability—ensuring that systems, data, and people communicate effortlessly, creating a smooth flow of operations that transcends technological boundaries.

In the context of the CE, system integration plays a pivotal role in unlocking the full potential of interconnected technologies. Take, for example, a recycling center: integrating Operational Technology and Information Technology systems enables the smooth collection and processing of data from various sensors throughout the facility. Instead of working in silos, previously independent systems can now collaborate, driving improved operational

efficiency and maximizing the value of resources. Similarly, in the world of 3D printing, linking printers to internal networks helps synchronize production, supporting a broader ecosystem of connected devices that work together seamlessly. These examples illustrate how system integration is not just a technical necessity but a cornerstone for driving productivity and innovation in complex environments.

The need for integration is further amplified in the development of AI-powered platforms and data management systems, where Application Programming Interfaces connect different machines and systems. This allows for real-time data sharing and enables remote control and optimization of operations. At the heart of the CE transition lies the seamless flow of data across the entire value chain, and system integration is crucial to ensuring interoperability among diverse technologies. While achieving perfect integration remains a complex challenge, it is clear that continued advancements in integration technologies are essential for businesses striving to optimize operations and stay ahead in an increasingly interconnected world.

15.4 Future prospects

The future of I4.0 is poised for a dramatic shift, where human–machine interaction takes center stage. While I4.0 is often associated with smart technologies, automation, and the seamless exchange of data, the emerging concept of I5.0 promises a more human-centric approach. I5.0 envisions a future where machines do not simply replace human labor but collaborate alongside humans, empowering them to unlock new possibilities and achieve higher levels of efficiency, creativity, and sustainability. In fact, the Japanese government introduced the idea of Society 5.0—a vision that integrates advanced technologies into every aspect of daily life, making them more accessible, intuitive, and, importantly, human-centered. Though I5.0 remains in its nascent stages, this paradigm holds the promise of transforming industries and human experiences, blending technological progress with human well-being.

This transition is particularly relevant to the CE, as I5.0 supports both digital, green, and social transformations, aligning well with I4.0 technologies to create a sustainable, people-centric future. As we continue to explore and implement I4.0 within organizations, it becomes evident that human involvement is a critical factor in the success of these technologies. By embracing I5.0 principles, businesses can integrate CE principles into their models while prioritizing human well-being—ensuring that technology works not only for the benefit of businesses but also for society as a whole.

The intersection of I4.0 and I5.0 is particularly exciting as it opens up new avenues for technological advancements. The rise of AI and generative models like ChatGPT has already begun to shape sectors ranging from healthcare to education, promising to revolutionize how industries and societies operate. In healthcare, AI is enabling breakthroughs in personalized medicine, accelerating drug discovery, and improving large-scale data analysis. Similarly, the use of AI in education, scientific publishing, and entrepreneurship offers unprecedented opportunities to spark innovation (Davidsson & Sufyan, 2023).

From a CE perspective, AI can play a pivotal role in advancing our understanding of climate change and environmental trends. AI models, such as those powered by ChatGPT, can significantly enhance climate projections, providing more accurate predictions and enabling deeper insights into environmental behaviors. These insights can then be used to optimize resource management and sustainability practices within the CE framework, helping businesses make data-driven decisions about their environmental impact.

However, as with any powerful technology, it is essential to apply I4.0 cautiously, as it also raises important ethical considerations and the potential risks of overrelying on these tools. It is important to be mindful of the environmental footprint created by the increased data processing and I4.0 adoption. The key to ensuring CE goals in the face of digital transformation is to balance the power of I4.0 with a commitment to minimizing its ecological impact.

As we look ahead, it is important to address a few critical points about the implications of these technologies. First, we must consider how the deployment of I4.0 technologies influences different levels of society and business—macro, meso, and micro. On the macro level, these technologies have the potential to reshape entire economies by driving CE transformations and fostering sustainability at a global scale. On the meso level, businesses and industries can leverage digital tools to optimize operations, improve supply chains, and reduce waste. At the microlevel, individuals and workers can benefit from the collaboration between humans and machines, enhancing productivity and enabling more sustainable practices. More interdisciplinary research is needed to understand the interplay between business strategy, environmental policy, and technological development in supporting large-scale CE adoption.

Yet, the ultimate value of these technologies lies not just in monitoring or collecting vast amounts of data but in changing behaviors. If we simply digitalize existing wasteful practices without rethinking how we use resources, we risk falling into the trap of perpetuating the same inefficiencies, albeit in a more technologically advanced form. Technologies like IoT, AI, and cloud computing can provide real-time insights into product usage and resource consumption, but unless they lead to tangible behavior change—whether it is reducing waste, optimizing energy use, or embracing circularity—they are unlikely to fulfill their true potential. The real challenge lies in how we use these technologies to not only collect data but also to drive a cultural shift toward the CE, encouraging businesses to adopt smarter, more responsible behaviors and corporate purpose (Torres de Oliveira et al., 2023). Therefore it is critical to evaluate the extent to which I4.0 remains beneficial to the CE progress.

This brings us to an important point, often overlooked, the holistic assessment of CE principles across different levels of business and society. Service-based models, while pivotal in the CE to support dematerialization, are heavily impacting both consumer behaviors and business models. Importantly, these service-based models require a shift in value propositions, altering how businesses engage with consumers. As companies adopt new CE principles, they impact the entire lifecycle of products, creating a ripple effect across the supply chain, by narrowing, slowing, and closing resource loops. Circular design, which spans from initial product creation to end-of-life management, necessitates collaboration across various stages of the supply chain. Additionally, reverse flows—mechanisms that enable the retrieval, return, and circularity of products—highlight the interdependent

nature of CE. To effectively close the loop, businesses and consumers must work together, establishing a collaborative approach across industries. This interconnectedness reinforces the need for integrated systems to support CE consumption patterns and ensure that technology's benefits extend throughout the entire product lifecycle (Toth-Peter et al., 2023).

As we continue to explore the integration of I4.0 and CE, it is clear that this requires a systemic approach, where the interlinked nature of technology, business models, design, and consumer behaviors plays a pivotal role. A focus on collaborative innovation across supply chains, the use of IoT and blockchain to integrate stakeholders, and the importance of product lifecycle management all contribute to the creation of a more sustainable, circular world. However, as we move forward, it is critical to remain vigilant about the potential trade-offs, such as increased energy consumption and the tension between customization and standardization in design. These tensions must be navigated carefully to avoid falling into the trap of optimizing processes at the cost of environmental impact. Through system-wide innovation, we can pave the way for a future where technology not only drives efficiency but also supports the goals of a more sustainable CE.

15.5 Conclusion

This chapter has explored the profound impact of I4.0 technologies on advancing CE principles, illustrating both their potential and the challenges that businesses face in their adoption. By leveraging I4.0 tools such as AI, blockchain, big data analytics, and IoT, businesses can optimize resource use, extend product lifecycles, and transition from linear to circular business models. These technologies serve as key enablers in driving efficiency, sustainability, and resilience across industries.

One of the central insights from this discussion is that I4.0 enables businesses to narrow, slow, and close resource loops, thereby reducing waste and improving material recovery. Of some of the examples presented, technologies like AM allow for on-demand production and repair, minimizing excess inventory and extending product longevity. AI-driven predictive maintenance further enhances circularity by reducing premature product failures and optimizing repair cycles. Potential technologies, like blockchain, strengthen supply chain transparency, ensuring material traceability and enabling better circular resource management. Collectively, these innovations contribute to a more efficient and sustainable industrial ecosystem and the establishment of local circular ecosystems.

However, while the technological potential is clear, practical implementation remains complex. Economic barriers, regulatory constraints, and knowledge gaps often limit businesses from fully integrating I4.0 solutions. High upfront costs, fragmented data ecosystems, and cybersecurity risks pose significant challenges to firms aiming to transition to I4.0-enabled business models. Additionally, the evolving nature of these technologies requires continuous adaptation, which can be particularly difficult for SMEs with limited resources and capabilities.

Another critical takeaway is the shift from ownership-based consumption to service-oriented models. While product-as-a-service approaches present great potential in the CE, enabling consumers to access goods without direct ownership, the business-as-usual model

is not (yet) equipped for this shift and requires fundamental change. As the CE transition unfolds, businesses more often than not opt for lower hierarchy CE strategies (the low-hanging fruit) such as recycling and remanufacturing instead of fully embracing service-based solutions, as this requires a more disruptive change in their value chain. Nevertheless, these models show promise in driving systemic change, and new policy frameworks could encourage and shape both consumer and corporate engagement with circular practices.

Looking ahead, the successful integration of I4.0 into CE requires a multistakeholder approach. Collaboration between businesses, policymakers, and technology providers will be essential in overcoming barriers to adoption and ensuring that digital innovations align with CE goals. Governments must play a proactive role in establishing supportive policies, incentivizing circular business models, and investing in digital infrastructure, while cautiously looking out for unintended consequences of such measures. Similarly, firms need to invest in workforce upskilling to bridge the digital skills gap and enable employees to navigate the complexities of emerging technologies, including understanding the unintended consequences and potential negative impact of overreliance on I4.0 tools.

As we move toward a future shaped by digitalization and sustainability imperatives, the intersection of I4.0 and CE will continue to evolve. While challenges remain, the potential for innovation and transformation is significant. Businesses that proactively embrace this shift, leveraging I4.0 technologies and CE principles into their operations, will be well-positioned to thrive in an increasingly resource-conscious and digitally driven economy. Ultimately, the path to a CE is not just about technological advancement—it is about realizing a systemic shift in how we design, produce, and consume in ways that align with both economic prosperity and environmental responsibility while keeping up with innovation and progress.

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Aligning Industry 4.0 technologies with sustainability: the strategic role of circular open innovation and circular ambidexterity

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16.1 Introduction

The Fourth Industrial Revolution (Industry 4.0) has ushered in a paradigm shift in global industrial systems through the pervasive integration of advanced digital technologies. Innovations such as artificial intelligence (AI), the Internet of Things (IoT), blockchain, and digital twins are redefining production processes, enabling real-time data analytics, autonomous decision-making, and hyperconnected supply chains (Bai et al., 2022; Hadi et al., 2025; Khan et al., 2025; Nara et al., 2021; Yavuz et al., 2023). These technologies

collectively enhance operational efficiency by automating repetitive tasks, optimizing resource allocation, and minimizing waste—capabilities that have allowed organizations to achieve significant cost reductions and productivity gains (Al-Okaily et al., 2024; Bag et al., 2020; Moch, 2024). For instance, AI-driven predictive maintenance systems reduce unplanned downtime in manufacturing, while IoT-enabled sensors monitor energy consumption in real time, enabling dynamic adjustments to minimize waste (Ejsmont et al., 2020; Ghobakhloo, 2020; Lee et al., 2018). However, amid these advancements, a pressing question looms: does Industry 4.0 inherently foster sustainability, the harmonization of technological progress with ecological preservation, social equity, and long-term economic viability—or does it merely perpetuate efficiency-driven, linear production models under a veneer of modernization? While proponents argue that Industry 4.0 technologies hold unprecedented potential to catalyze circular innovation—such as enabling closed-loop manufacturing through blockchain-tracked material flows or AI-optimized remanufacturing, their actual contribution to systemic sustainability remains contested (Beltrami et al., 2021; Khan et al., 2025; Yun et al., 2025). Critics highlight that many industries adopt these tools incrementally, focusing narrowly on short-term operational gains rather than reimagining value chains for regenerative outcomes (Nara et al., 2021; Yavuz et al., 2023). This tension is exacerbated by mounting global crises, climate change, biodiversity loss, and resource scarcity—that demand urgent transitions away from extractive, linear economic models toward circular systems prioritizing resilience and renewal (Drofenik et al., 2025; Hadi, 2024; Uwuigbe et al., 2025).

The circular economy (CE) emerges as a transformative framework to address these challenges, advocating for a systemic overhaul of traditional "take-make-dispose" models. By emphasizing resource efficiency, waste reduction, and closed-loop production cycles, CE principles align closely with sustainability imperatives, promoting strategies such as product life extension, material reuse, and regenerative design (Agrawal et al., 2025). Industry 4.0 technologies are often positioned as enablers of this transition; for example, digital twins can simulate product life cycles to identify reuse opportunities, while blockchain ensures transparency in reverse logistics (de Sousa Jabbour et al., 2022; Lei et al., 2023). Yet, empirical evidence reveals a critical disconnect: the mere adoption of digital tools does not guarantee circularity or sustainability. Instead, their impact hinges on how deeply they are embedded within holistic, innovation-driven business strategies (Dantas et al., 2021; Laskurain-Iturbe et al., 2021; Rosa et al., 2020). Recent studies underscore this paradox—organizations frequently deploy Industry 4.0 technologies to streamline existing processes (e.g., automating assembly lines or optimizing inventory) but fail to leverage their full potential for disruptive circular innovations, such as product-as-a-service models or industrial symbiosis networks (Banihashemi et al., 2024; Ilić et al., 2022; Okorie et al., 2023). Dantas et al. (2021) caution that without strategic alignment with circular objectives, Industry 4.0 risks reinforcing linearity under the guise of digital progress. For instance, while AI might enhance energy efficiency in a factory, its benefits remain confined to operational silos unless coupled with systemic changes, such as redesigning products for disassembly or collaborating with cross-sector partners to recover end-of-life materials. This misalignment underscores a broader theoretical and practical gap: the absence of frameworks that integrate technological capabilities with CE principles to drive scalable, sustainable transformation.

A predominant assumption in contemporary literature posits that sustainability inherently accompanies digital transformation, with scholars often conflating technological adoption with sustainable outcomes (Khan et al., 2025; Rosa et al., 2020). However, this perspective overlooks critical intermediary mechanisms that mediate the relationship between Industry 4.0 and sustainability, a gap that this study seeks to address. While Industry 4.0 technologies undeniably provide the infrastructural backbone for modern industrial systems, their capacity to drive sustainability, defined as the integration of ecological, social, and economic resilience into digital transformation, remains contingent on their strategic embedding within circular innovation ecosystems (Bai et al., 2022; Hadi, 2024). Such ecosystems transcend isolated technological deployments, fostering synergies between stakeholders, policies, and regenerative business models. As Banihashemi et al. (2024) emphasize, the absence of a unifying framework to bridge digital transformation with CE adoption has resulted in fragmented progress, where organizations prioritize efficiency gains over systemic sustainability. To resolve this, our research introduces Circular Open Innovation (COI) as a pivotal moderator that enables organizations to harness Industry 4.0 for circular ambidexterity (CA), the dynamic equilibrium between refining existing circular processes (circular exploitation) and pioneering disruptive models (circular exploration) (Hadi, 2024; Katou et al., 2023). This dual focus ensures that technological investments yield not only incremental improvements but also radical innovations, such as closed-loop supply chains or product-as-a-service systems.

COI redefines traditional innovation paradigms by fostering collaborative, cross-industry ecosystems where knowledge, resources, and risks are shared to accelerate circular transitions (Hadi, 2024; Perotti et al., 2025). Unlike closed innovation models, which silo intellectual property and restrict external collaboration, COI thrives on open networks that integrate diverse stakeholders—from suppliers and competitors to academia and policy-makers—into cocreating regenerative solutions (Köhler et al., 2022; Sgambaro et al., 2025). For instance, platforms like the Ellen MacArthur Foundation's CE100 network exemplify COI in action, enabling multinational corporations like Unilever and Google to collaborate on blockchain-enabled material traceability or AI-driven waste reduction strategies (Barrie & Kanda, 2020). The moderating role of COI in linking Industry 4.0 to CA is threefold. First, while digital technologies provide real-time data and automation, their potential for circular innovation remains latent without external collaboration. For example, IoT sensors may optimize energy use in a factory (circular exploitation), but COI partnerships with recyclers and designers are essential to reimagine products for disassembly (circular exploration) (Lei et al., 2023; Yu et al., 2022). Second, COI facilitates the integration of advanced tools like blockchain for transparent resource tracking or digital twins for simulating circular supply chains, thereby embedding circularity into core operations (Jesus & Jugend, 2023; Sahoo et al., 2025). Third, COI mitigates barriers to circular digitalization—such as high R&D costs and regulatory fragmentation—by pooling resources and fostering standardized frameworks (Lorenc & Schadt, 2024; Trevisan et al., 2023). Without COI, organizations risk perpetuating “islands of efficiency” within linear systems, as seen in automotive firms using AI solely for predictive maintenance rather than battery lifecycle management (Danvers et al., 2023).

This chapter advances academic and practical discourse by proposing a novel conceptual framework that elucidates the indirect relationship between Industry 4.0 and sustainability

via COI and CA. Departing from prior works that treat digital tools as standalone solutions, our model positions COI as the linchpin that unlocks Industry 4.0's regenerative potential. For academia, this bridges a critical theoretical gap, offering a systemic lens to analyze how technological, organizational, and ecosystem-level factors interact to drive sustainability (Kandasamy et al., 2023; Okorie et al., 2023). Practically, the framework equips industry leaders with actionable strategies, such as forming cross-sector consortia for AI-driven material recovery or adopting open-source platforms for circular data sharing—to align digital investments with circular objectives. Policymakers, too, can leverage these insights to design incentives for collaborative innovation, such as tax breaks for COI-driven projects or mandates for blockchain-based supply-chain transparency (de Sousa Jabbour et al., 2022; Laskurain-Iturbe et al., 2021). Ultimately, this research challenges the prevailing narrative of Industry 4.0 as a mere efficiency engine, recasting it as a catalyst for long-term sustainability when synergized with COI and CA. By transcending isolated optimizations and embracing ecosystem-wide collaboration, industries can transition from linear exploitation to circular resilience, ensuring that technological progress aligns with planetary boundaries and societal well-being.

16.2 Why, Industry 4.0 alone not a panacea for sustainability?

Industry 4.0 technologies (such as advanced robotics, big data analytics, and cloud computing) provide the infrastructural backbone for sustainable and circular industrial practices (Hadi et al., 2025). They equip firms with fine-grained monitoring and control over processes, enabling higher efficiency in the use of energy and materials (Ghobakhloo, 2020; Khan et al., 2025; Moch, 2024; Silvestri et al., 2020). They also open new possibilities for innovation: for instance, data analytics might reveal opportunities to recirculate waste as input, and connectivity can support new service-based business models (Bag et al., 2020; Yavuz et al., 2023). In essence, Industry 4.0 greatly enhances a firm's capabilities—its ability to measure, optimize, and manage complex systems which are foundational for any sustainability initiative. Empirical research underscores the potential: companies adopting digital technologies have shown improved ability to implement sustainability measures like aligning production with renewable energy supply and reducing surplus production (Beier et al., 2022; Khan et al., 2025).

While Industry 4.0 technologies are powerful enablers, their deployment does not automatically equate to a transition from linear to circular models. Several challenges and observed shortcomings highlight the gap between technological potential and actual sustainable outcomes:

- **Efficiency versus circularity:** Most companies' initial forays into Industry 4.0 focus on operational efficiency and cost reduction, rather than systemic circularity (Banihashemi et al., 2024; Dantas et al., 2021). Digital tools are often applied in isolated projects, for example, installing sensors to save energy in one process, or using data analytics to speed up throughput—without altering the fundamental business model or supply-chain structure. These efficiency gains, while beneficial, may simply enable a company to

produce the same linear outputs with fewer resources, not to change what is produced or how value is delivered. In other words, a firm can become a leaner version of its linear self. A textile dyeing factory, for instance, might employ IoT sensors to cut water and energy use in production, yet still source virgin materials and ignore end-of-life recovery. This yields a one-time improvement in resource intensity but falls short of closing loops or reducing the overall material footprint of the product line.

- **Rebound and incrementalism:** Efficiency improvements risk being offset by rebound effects or scaled-up production (Aydoğan et al., 2024; Ghobakhloo & Fathi, 2021; Khan et al., 2025). If Industry 4.0 makes manufacturing cheaper or faster, the firm might expand output and potentially stimulate more consumption, undermining net sustainability gains (a phenomenon noted in CE contexts as the rebound effect) (Ferrante et al., 2024). Moreover, incremental waste reductions (e.g., 10%–20% less scrap) are helpful but insufficient for the “transformational shift” needed to achieve true circularity (Hadi, 2024). Even after deploying advanced automation and analytics, a company might still rely on continuous input of new materials and generate waste, albeit at a slightly reduced rate. Such marginal improvements, while commendable, do not meet the scale of change required to mitigate climate change or resource depletion. The mere digitalization of production processes will not suffice for a sustainable transition. Without deeper changes, Industry 4.0 could even reinforce the dominant linear paradigm by enabling companies to continue business-as-usual more efficiently.
- **Lack of strategic alignment:** Technology initiatives often operate in silos, unmoored from a broader sustainability strategy (Masood & Sonntag, 2020; Okorie et al., 2023). Many firms implement Industry 4.0 projects without clear long-term environmental goals or without integrating them into a CE roadmap. For example, a company might digitize its inventory management or introduce robots for automated sorting of products, but if these moves are not guided by circular design principles or paired with plans for product take-back, their sustainability impact remains limited. In short, technology needs direction—a purposive strategy that prioritizes circular outcomes is necessary to steer Industry 4.0 applications away from shallow gains and toward transformative ones.

These observations make clear that Industry 4.0 is a necessary but not sufficient condition for sustainable industrial transformation. On its own, it provides the tools and capabilities—what can be done—but it does not dictate why and to what end those tools are used. As an analogy, one can think of Industry 4.0 as a powerful engine: it can drive progress, but the course and destination depend on the steering and fuel. The “steering” in this context is strategy, ensuring that the engine’s power is harnessed in the right direction. This is where CA becomes crucial: it is the strategic orientation that determines how Industry 4.0 is applied, balancing improvements to current operations with innovation for future, more circular business models. And the “fuel” is collaboration, drawing in external knowledge, partnerships, and shared initiatives to accelerate and amplify change, which is the role of COI. In summary, Industry 4.0 offers the technological engine for a sustainable industry with unprecedented means to monitor, optimize, and potentially reinvent industrial processes for lower environmental impact. Yet without the guiding hand of circular-oriented strategy and the catalyzing effect of collaborative innovation, this engine may idle or even drive in the wrong direction.

16.3 Circular ambidexterity: strategic duality for circular economy transformation

Transitioning to a circular and sustainable industrial model requires firms to simultaneously pursue two kinds of efforts: on one hand, incremental improvements that make current products and processes more sustainable (e.g. reducing waste, improving energy efficiency, increasing recyclability), and on the other hand, radical innovations that fundamentally change the business model or value proposition towards circularity (e.g. shifting from selling products to providing services, or developing entirely new products that eliminate waste by design). In organizational theory, this dual pursuit is captured by the concept of ambidexterity, which is the capability to balance exploitation (refinement, efficiency, execution) and exploration (innovation, experimentation, search for new opportunities) at the same (Chaudhuri et al., 2022; Katou et al., 2023). Traditionally, organizational ambidexterity has been studied as a key to long-term success: firms that exploit existing capabilities while exploring new ones are better able to adapt to change and avoid (stagnationieomsociety.org). Here, we extend this concept to the domain of CE and sustainability, introducing CA as the strategic capacity of an organization to concurrently optimize its current operations for sustainability and innovate new circular business models for the future.

CA entails balancing two critical and complementary strategic orientations:

- **Circular exploitation—optimizing and refining existing processes and products for sustainability.** This involves leveraging Industry 4.0 and other tools to improve eco-efficiency in current operations, eliminate waste in the supply chain, increase the use of recycled or renewable inputs, and generally “do better with what we already do.” Circular exploitation is essentially about operational excellence in sustainability: identifying opportunities for incremental improvements that cumulatively can yield significant environmental benefits (Latan et al., 2024; Silvestri et al., 2020). For example, a manufacturing firm might use AI-driven analytics to optimize machine settings and reduce energy consumption, or implement IoT-based tracking to ensure higher reuse of packaging materials. These actions align with what in sustainability literature is often termed “eco-efficiency” or the pursuit of less resource use and pollution per unit (outputieomsociety.org). Industry 4.0 technologies are particularly adept at enabling this side of ambidexterity. Predictive maintenance powered by AI can extend equipment lifespans and reduce material waste, real-time data from IoT can pinpoint inefficiencies in water or energy use for correction, and digital twins can help tweak processes to minimize scrap. Such efforts typically build on existing business models and infrastructure, enhancing their sustainability performance without drastically altering the firm’s core product-service offering or revenue logic. We can view circular exploitation as “low-hanging fruit” that captures immediate gains (cost savings, compliance with environmental standards, incremental reputation benefits) while preparing the ground for deeper changes.
- **Circular exploration—pioneering new business models, products, or services that are inherently circular.** This corresponds to the more radical, innovative side of sustainability strategy: investing in the development of offerings and value delivery models that

break from the linear mold. Circular exploration may involve designing products for longevity and modularity, creating take-back and remanufacturing programs, shifting from ownership to service-based delivery, or entering entirely new lines of sustainable products (Bocken & Konietzko, 2023; Bocken, 2024). These initiatives often require embracing uncertainty, experimentation, and potentially cannibalizing or overhauling established ways of doing business; hence, they align with the classic notion of exploration as the pursuit of new knowledge and opportunities. A salient example is the move from selling products to Product-as-a-Service (PaaS) models, which many manufacturing firms are trying to retain ownership of products and ensure they are maintained, recovered, and reused. Philips Lighting's "Lighting as a Service" offering is a case in point: instead of selling lightbulbs, Philips (now Signify) provides illumination as a service contract, installing IoT-enabled lighting systems and charging customers for the performance (light output) while retaining ownership of the equipment. Under this model, Philips remains responsible for maintaining the lights, upgrading them for energy efficiency, and taking them back for recycling at the end of life—aligning the incentives for longevity and circular material flows. This kind of circular business model innovation is a hallmark of circular exploration. It often leverages Industry 4.0 as an enabler—in Philips' case, IoT connectivity and data analytics are crucial for monitoring usage and optimizing lighting service, making the service model viable. Circular exploration also covers R&D into new circular products (for example, developing a fully recyclable or biodegradable product line, or new materials that eliminate hazardous waste) and into systems like reverse logistics and recycling technologies that might not yield immediate profit but are essential for future competitiveness in a CE. Exploration is inherently riskier and typically requires a long-term vision, as the financial returns may take time to materialize while costs and organizational challenges are front-loaded. However, it is crucial for achieving "next-generation" sustainability innovations that go beyond incremental change (Hadi, 2024). Studies have noted that incremental changes (exploitation) alone "may not suffice for this transition" to circular models, which calls for significant transformations and new architectures of products and services (Hadi, 2024; Snihur & Markman, 2023). In short, circular exploration is about reinventing the business with circularity at its core, rather than as an add-on.

The premise of CA is that firms must engage in both circular exploitation and circular exploration and find the right equilibrium between them over time (Hadi, 2024). Too much focus on exploitation can lead to a "competency trap" ieomsociety.org—the firm becomes so good at its current (partially improved) processes that it neglects the shifts in market and technology that require new business models, potentially being left behind in a future where deeper circular practices are the norm (Chizaryfard et al., 2022; Stekelorum et al., 2021). For example, an automaker might lean heavily into using IoT and AI to improve manufacturing efficiency and reduce emissions per car, but if it never invests in exploring models like car-sharing, electrification, or remanufacturing, it may fail to transition in time to meet future regulations or consumer preferences for sustainable mobility. This risk is evident in cases where incumbents optimize a product (like improving fuel efficiency in combustion engines) but are then disrupted by a radical innovation (like electric vehicles and mobility services) that they were slow to embrace (Katou et al., 2023; Stekelorum et al., 2021). On the

other hand, overemphasis on exploration without maintaining excellence in current operations can be financially unsustainable and operationally chaotic. If a company pours resources into experimental circular ventures but lets its core business falter, it may undermine its own capacity to continue innovating. A balance is therefore critical. Ambidexterity theory suggests organizations need structures or cultures that allow them to separate or integrate these dual activities effectively—some companies create dedicated innovation units for exploration while others foster a culture where employees divide their time between exploitative and exploratory projects ([Hadi, 2024](#)).

In the context of Industry 4.0, CA ensures that the new technological capabilities are used to serve both sides of the sustainability agenda. On the exploitation side, it means using Industry 4.0 tools to maximize the sustainability of existing operations (for instance, using AI for process optimization as noted, or using digital twins to tweak current product designs for slightly better recyclability). On the exploration side, it means leveraging Industry 4.0 to enable or accelerate the development of those novel circular models (e.g.e, IoT connectivity making a pay-per-use model feasible, or advanced manufacturing enabling a profitable take-back program through cost-effective refurbishing of returned products). Industry 4.0 can thus be thought of as providing the means for both exploitation and exploration activities, but CA is about deciding how to allocate attention and resources between the two. A practical illustration of CA in action could be a company like Renault: while optimizing the efficiency of its current car production with digital tools (exploitation), it simultaneously launched the Refactory, a facility dedicated to vehicle remanufacturing, battery recycling, and new mobility services (exploration). This dual approach allows Renault to improve its environmental performance in the short term and also invest in the capabilities and business models that will drive long-term circular value ([Renault, 2023](#)).

It is important to recognize that circular exploitation and exploration are interdependent. Efficiency gains from exploitation can free up resources (capital, talent, and even materials via waste reduction) that support exploratory initiatives. Conversely, successful circular innovations from exploration can eventually be scaled up and folded into the company's routine operations, becoming new sources of efficiency and competitive advantage. This dynamic is sometimes described as a continuum rather than a strict dichotomy ([Hadi, 2024](#)). For example, if a pilot project in circular exploration (say, a new product-service system) proves viable, it may transition into the exploitation mode as it gets rolled out and optimized. The organization must then possibly find the next exploratory project to keep pushing the frontier. In academic terms, ambidexterity can be structural (different units focusing on each mode) or contextual (same teams switching modes as needed), but in either case, leadership and strategy play a crucial role in maintaining the balance ([Hadi, 2024](#)). Top management needs to set an ambidextrous strategy by articulating clear sustainability objectives that include both incremental targets (e.g., “reduce carbon intensity by X% each year”) and transformative goals (e.g., “develop one new circular business line by year Y”) ([Redelinghuys et al., 2020](#); [Wang et al., 2022](#)). This guides different parts of the organization and helps resolve resource allocation conflicts.

To underscore why CA is necessary, consider some scenarios: a firm that only focuses on circular exploitation might achieve lean, eco-efficient operations but miss out on innovation, for instance, a packaging manufacturer might use all the latest AI and IoT to minimize waste in production, yet still produce single-use plastics in a world moving towards reusables and

new materials; eventually that business could decline. Conversely, a startup or business unit that only does bold circular exploration (say, investing heavily in a futuristic recycling technology) might struggle to stay afloat if those ideas cannot be monetized quickly, especially without a stable core business generating profits—many clean-tech startups face this challenge of bridging to profitability. Therefore, CA also has a temporal aspect: it helps firms manage the present and future concurrently, ensuring short-term wins on sustainability do not preclude long-term pivots, and vice versa.

Crucially, CA by itself still has limits. A company might internally balance and commit to both refining its current sustainability performance and exploring new circular innovations, but it could fail to scale these innovations or integrate them into the broader system if it works in isolation. One major limitation is that many CE solutions require collaboration beyond the firm's boundaries. For example, a manufacturer may design a recyclable product (exploration) and improve its processes to produce it efficiently (exploitation), but if there is no external ecosystem to take back, recycle, or provide secondary materials, the impact remains small. This is evident in cases where firms piloted circular initiatives that did not gain traction because they lacked partnerships for reverse logistics, customer engagement, or supportive policy. The snippet of a fashion company launching a rental service is illustrative: a clothing retailer might introduce a rental or take-back program (circular exploration) to reduce textile waste, and optimize its supply chain for using returned clothes (exploitation), yet without collaborating with textile recyclers, cleaning services, or municipal waste managers, the program might not scale or might face operational bottlenecks. In short, a firm can be ambidextrous and still fall short in impact if it remains too insular. This points to the need for the third element of our framework, COI, which complements CA by linking the firm's efforts with external innovation and collaboration networks.

The idea of applying ambidexterity to sustainability is supported by emerging literature. Recent studies suggest that ambidexterity (exploration–exploitation balance) is a key mediating mechanism for sustainability performance and circular outcomes ([Hadi, 2024](#)). For instance, [Katou et al. \(2023\)](#) found that organizations with ambidextrous leadership—fostering both incremental and radical innovation cultures—achieved better sustainability performance, with ambidexterity enabling CE practices as a bridge between leadership and outcomes. This resonates with the concept of CA as a mediator linking a firm's strategic intent to actual circular results ([Hadi, 2024](#)). Additionally, a dynamic capabilities perspective suggests firms need to develop “sensing” and “reconfiguring” capabilities specific to circular opportunities, effectively the ability to sense when to exploit and when to explore in the context of CE shifts. such circular dynamic capabilities underpin ambidexterity, allowing the firm to pivot between modes as needed. In conclusion, CA provides the strategic steering for Industry 4.0's engine, ensuring that the power of new technologies is harnessed in a balanced way, improving the sustainability of today's operations while innovating for tomorrow's circular business. It makes sustainability an integral part of corporate strategy rather than a one-off project. However, to fully realize CA, firms often must reach beyond their own walls. The next section discusses COI, the “collaborative fuel” that propels and magnifies the effect of ambidextrous strategies on a broader scale.

16.4 Circular open innovation: collaborative networks as a catalyst for sustainability

The scale and systemic nature of sustainability challenges demand solutions that no single organization can develop or implement alone. Whether it's creating a circular supply chain for electronics or establishing a new reuse business model in the fashion industry, collaboration across companies and sectors is often essential. Open innovation, a concept pioneered by Henry Chesbrough, refers to the paradigm where firms transcend their boundaries to cocreate and share ideas, intellectual property, and solutions with external partners. Instead of the traditional closed innovation model (relying solely on internal R&D), open innovation leverages inflows and outflows of knowledge—firms can license technology in or out, engage in joint development, crowdsource ideas, or build innovation ecosystems. This approach has proven effective in accelerating innovation in many fields, and in recent years it has been increasingly applied to address sustainability and CE issues (Hadi, 2024). We define COI as the application of open innovation principles specifically to CE and sustainability initiatives. COI involves the collaborative generation, sharing, and implementation of circular solutions among a network of diverse stakeholders—including companies (incumbents and startups), academia, government bodies, and even consumers or grassroots innovators. It is essentially an ecosystem approach to innovation with the explicit goal of advancing CE transitions.

COI plays a **moderating and enabling role** in our framework: it connects the technological potential of Industry 4.0 and the strategic drive of CA to the wider system, ensuring that innovations can scale and that best practices diffuse quickly. Several aspects illustrate how COI contributes to sustainability goals:

- **Cross-industry and supply-chain collaboration:** A CE often requires creating closed loops that cut across the traditional linear supply chain. For example, one company's waste might be another's raw material (industrial symbiosis), or a product take-back program might involve retailers, logistics providers, and recyclers working in concert. COI provides a mode for coordinating these activities by fostering partnerships. Companies can enter into consortia or platforms to collectively tackle challenges like recycling infrastructure or material standards. A case in point is the automotive sector: Renault's Refactory project in France exemplifies an open-innovation ecosystem approach. At the Flins Refactory—Europe's first CE factory for vehicles—Renault has brought together multiple partners, from high-tech startups to recycling specialists and training institutes, under one roof to drive circular innovation. The site includes an open innovation hub that welcomes startups developing circular solutions for mobility, enabling external innovators to collaborate directly with Renault's teams. Through such partnerships, Renault benefits from fresh ideas (e.g., new battery recycling techniques or digital platforms for car-sharing) and the startups gain access to data, facilities, and a path to scale. This kind of collaborative ecosystem greatly enhances the impact of any single innovation by embedding it in a supportive network. Notably, Industry 4.0 technologies are a common thread linking partners: for instance, a tech startup might provide an AI-based sorting system for used parts, while Renault integrates

it into the Refactory's digitalized operations. Thus open innovation ensures that Industry 4.0 is integrated into circular ecosystems, not just individual firms.

- Knowledge sharing and collective learning:** Sustainability transitions involve steep learning curves and uncertainty. COI allows organizations to share knowledge, data, and even intellectual property to surmount common hurdles. In some cases, companies have made patents related to green technology openly available or formed precompetitive research alliances. For example, a group of electronics companies might share research on designing for disassembly or pool funds to develop a recycling technology that none could justify alone. By sharing the costs and risks of R&D, open innovation can speed up the development of circular solutions (Hadi, 2024). A literature review by Jesus and Jugend (2023) finds that open innovation contributes significantly to CE adoption by opening avenues for reusing, remanufacturing, and recycling through stakeholder collaboration. They note that openness—in terms of sharing technologies and expertise—has the capability to “close the loop of product life cycles” and drive the shift to circular business models. This aligns with Bogers et al. (2019) who emphasize that combining open innovation with dynamic capabilities can strategically enhance innovation outcomes. In practice, knowledge-sharing platforms (physical or digital) have emerged, such as the Ellen MacArthur Foundation's CE100 network, which convenes businesses to exchange case studies and even collaborate on pilot projects in CE. By participating in such networks, a firm practicing CA internally can gain access to external ideas for its exploration initiatives and benchmark its exploitation practices against peers. In other words, COI broadens the solution space: it prevents firms from “reinventing the wheel” and helps propagate effective circular practices across industries.
- Pooling resources and scaling up:** Many circular innovations struggle to achieve scale due to resource constraints or the need for industry-wide adoption. Open innovation can pool resources—financial, technological, human—from multiple actors to give an innovation the critical mass it needs. For instance, consider the development of a blockchain-based material tracking system to enable circular supply chains. If only one company adopts it, the utility is limited, but if an entire industry (competitors included) collaborates to implement a shared blockchain standard for, say, tracking plastic resin from production to recycling, it creates a network effect benefiting all participants (Murphy & MacArthur, 2022). A real-world example is the Circularize consortium in the plastics industry, where competitors team up to use a common blockchain platform for tracing recycled content in products, thereby creating an industry-wide transparency system. This exemplifies COI as “collaborative fuel”—it ignites wider adoption and scales localized successes to the system level. Another domain is renewable energy or materials marketplaces: companies might jointly develop a platform (using Industry 4.0 elements like IoT and cloud) to exchange surplus materials or waste heat, which only yields significant environmental benefit once many actors join. By engaging in COI, firms also share the narrative and marketing of circular innovations, helping to shape consumer awareness and demand. If multiple major brands cooperate to promote product-service systems or standardized reuse models, consumers are more likely to accept the change (e.g., seeing multiple companies offer refillable packaging creates a norm).
- Policy and multistakeholder alignment:** COI is not limited to private companies—it often involves government agencies, cities, research institutes, and NGOs in a quadruple

helix of innovation. Policymakers can be key partners by providing regulatory sandboxes, incentives, or public procurement that supports circular solutions. Conversely, firms collaborating under COI can more effectively advocate for supportive policies or standards. For example, an alliance of firms might work with the government on setting standards for recycled content in products or take-back requirements, which in turn encourage more circular innovation. COI thus helps align the institutional environment with technological and business innovation. The moderating effect of COI is evident in that it ensures other enablers (like policy, public awareness, and cross-sector infrastructure) coevolve with the firm-level innovations. In our framework, COI provides the glue that connects a firm's ambidextrous strategy and Industry 4.0-enabled initiatives with the broader societal transition to sustainability. It can also mitigate the risk of firms "going it alone" on circular innovations that require collective action. For instance, if a company develops a breakthrough biodegradable material (exploration) and refines it to be cost-competitive (exploitation), COI could involve licensing that material to other companies or colaunching an industry initiative to use it, thus creating demand and economies of scale that make the innovation viable. Without such openness, the innovation might fail commercially if the firm tries to monopolize it in a niche application. There are documented cases where companies realized that sharing certain sustainability innovations was more beneficial overall—for example, Tesla's decision a few years ago to open its electric vehicle patents to accelerate the EV industry is a notable parallel in the sustainability space, illustrating that making an innovation open can enlarge the market for everyone and solve infrastructure challenges (like charging networks) faster.

However, just like Industry 4.0 and CA, COI on its own is not a silver bullet. If firms engage in extensive collaboration but lack internal strategy or technological capacity, those collaborations may not lead to meaningful implementation. For instance, a company might join a multistakeholder circular initiative and attend knowledge-sharing workshops (COI), but if it has not internally invested in the needed technologies or aligned its strategy (lacks Industry 4.0 integration and ambidexterity), it may not be able to act on the ideas generated. Open innovation can yield many possibilities, but firms need absorptive capacity—the ability to internalize and apply external knowledge—to benefit, which comes from strong internal capabilities (often tied to having the right technology and skills in place). Additionally, managing open partnerships requires its own set of skills and sometimes new business models (for sharing value creation and IP). Hence, COI works best in tandem with a clear strategic framework (like CA) and modern technical infrastructure (Industry 4.0) that together enable a firm to seize the opportunities that open innovation presents.

The interplay can be seen this way: Industry 4.0 provides the connective digital infrastructure that often underpins collaborative networks (e.g. data platforms, blockchain, etc.), CA ensures the firm knows what knowledge or innovation it seeks (either to improve operations or to reinvent them), and COI provides access to that knowledge or innovation from outside and a pathway to implement it at scale. When all three operate together, a powerful synergy emerges.

The importance of open collaborative approaches for CE is well-recognized in recent research. Köhler et al. (2022) call for frameworks that combine dynamic capabilities and open innovation to foster CE, highlighting that firms need both internal agility and external

collaboration to succeed. Studies have also documented that open innovation correlates with better corporate social responsibility and environmental performance (Hadi, 2024). The “Radical innovation for sustainability” framework by Kennedy et al. (2017) posits that open innovation, coupled with strategic commitment, can yield the kind of radical solutions needed for sustainability transitions. This is fully consonant with our argument: COI (open innovation) and CA (strategic commitment to exploration) together steer technology towards breakthrough sustainability outcomes. To illustrate COI with another concrete example, consider the case of shared renewable energy micro-grids: multiple companies in an industrial park might share a solar/wind energy system and exchange power through IoT-managed micro-grids. This requires coordination, trust, and a business model for sharing costs and benefits—all facilitated by open innovation agreements and platforms. Each firm on its own might not invest in large renewable systems, but together they can, thus decarbonizing their operations more effectively.

In summary, COI acts as the collaborative catalyst that fuels and sustains circular transformation beyond the boundaries of any single firm. It harnesses the collective intelligence and resources of networks to overcome barriers, achieve scale, and spread innovative practices. With Industry 4.0 as a common enabler (providing data and connectivity) and CA guiding each firm’s contributions and uptake of new ideas, COI ensures that the whole becomes greater than the sum of the parts in the quest for sustainability. It is the third vital component, alongside technology and strategy, in delivering a holistic and effective approach to Industry 4.0-powered sustainability.

16.5 Integrating Industry 4.0, circular ambidexterity, and circular open innovation: a holistic framework for sustainable transformation

In this section, we synthesize the three distinct elements, that is, Industry 4.0, CA, and COI, into an integrated framework and examine how they interdependently drive sustainable transformation. As illustrated in Fig. 16.1, the central thesis is that sustainability-oriented Industry 4.0 (the engine), guided by CA (the steering mechanism) and amplified by COI (the fuel), creates a self-reinforcing system for continuous and scaled-up sustainability improvements. When aligned, these components enable a circular, sustainable industrial paradigm that is dynamic and responsive to both internal and external opportunities.

To detail the integration: consider how a new sustainability initiative might progress through the combined framework.

- **Sensing and conception (COI→CA):** Through open innovation networks, a firm becomes aware of an emerging opportunity—for instance, a startup in its industry has developed an AI-enabled system for refurbishing used products. This knowledge enters the firm via COI channels (perhaps the firm participated in a joint pilot or learned of it at a consortium meeting). The firm’s leadership, having a CA mindset, “senses” this as an exploration opportunity (dynamic capability of sensing in a circular context [mdpi.com](https://www.mdpi.com)). Strategically, they incorporate this into their ambidextrous approach: a decision might be made to

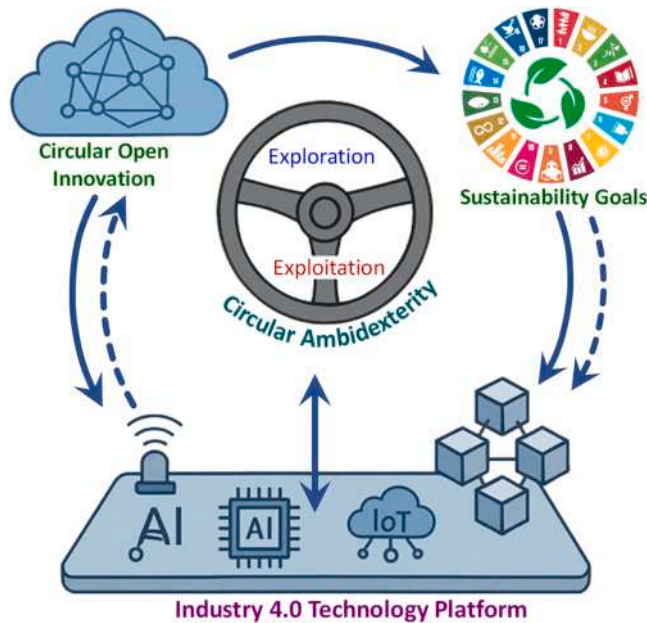


FIGURE 16.1 Schematic of a conceptual integrated framework, where Industry 4.0 forms the base (technology platform), CA is depicted as a steering wheel or control tower within the firm, and COI as a network or cloud feeding into the system, all aiming towards sustainability goals (like an overarching direction). The flow of influence is circular: external ideas (COI) inform strategy (CA), which directs technology use (Industry 4.0), which produces results and data that can be shared back into the network (COI), and so on. This framework model underscores feedback loops: external collaboration informs internal strategy, internal strategy guides technology deployment, technology deployment yields innovations that can be externally shared, etc. CA, Circular ambidexterity; COI, circular open innovation.

collaborate with the startup to experiment with a refurbishment business model. Here, open innovation has sparked a strategic choice—CA comes into play by allocating resources to explore this idea while ensuring current operations continue to improve.

- Development and implementation (Industry 4.0↔CA↔COI):** The firm works with the startup (COI) to integrate the refurbishment technology into its operations. Industry 4.0 tools are crucial in this stage: the firm might use IoT sensors and digital twins to adapt its production line for handling returned products, and use data analytics to assess the quality of used items for refurbishment. The exploration side of CA is executed using these technologies (for example, setting up a small automated cell for refurbishing, guided by AI inspection). Meanwhile, the exploitation side of CA ensures the firm's existing production keeps improving—they might concurrently use AI to reduce scrap in the manufacturing of new products, sharing some of the lessons learned from the refurbishment process (e.g., design tweaks that make both new manufacturing and refurbishing easier). Throughout development, COI continues as an enabler: the firm might share intermediate results with the consortium, get feedback or additional support from a university (maybe to solve a tricky materials issue in refurbishment), and involve a key supplier or recycler in codesigning the process. This **cocreation** ensures that when the new model is implemented, partners are ready to play their roles (supplier provides spare parts for refurb, recycler takes rejects, etc.).
- Scaling and diffusion (COI←Industry 4.0):** Suppose the refurbishment model proves successful in a pilot, significantly reducing waste and generating a viable profit stream. To scale up, the firm uses Industry 4.0 connectivity to network multiple facilities—perhaps cloud platforms coordinate refurbishment activities across regions, and blockchain

is used to track product histories (so any facility in the network can refurbish an item with full knowledge of its service record). The firm's ambidextrous strategy now shifts more towards exploitation of this new model (making it efficient and standardizing it) while possibly identifying a new exploration (maybe looking into a service model to bundle refurbished products). Crucially, through COI, the firm diffuses this practice: it might help set industry standards for refurbished goods, or even spin off a joint venture that offers refurbishment services to other companies' products. The knowledge gained (technical know-how, business model insights) is fed back into the open innovation ecosystem—for example, the firm publishes a case study with data on environmental benefits, contributing to collective learning. Other companies, seeing this success, may adopt similar approaches, perhaps even partnering with the firm or the startup for their own contexts. In this way, a single innovation does not remain confined—COI channels ensure it influences the broader transition.

Within the firm, the continuous loop of CA means that the gains from this innovation (reduced material costs due to using reclaimed components, higher customer loyalty from offering sustainable options) are reinvested into further sustainability efforts, keeping the engine running. The Industry 4.0 infrastructure that was put in place (sensors, data systems, etc.) can now also be leveraged for other purposes, such as improving the logistics of take-back programs or analyzing product life cycles for better design.

This integrated perspective highlights a few key interdependencies:

- **COI enhances CA:** Open innovation provides a broader pool of ideas and knowledge that feeds the exploratory side of ambidexterity. It also offers benchmarks and external pressure that can spur a firm to set more ambitious strategic goals. If peers in a network are all aiming to eliminate certain waste streams, a firm is pushed to explore solutions in that area too. Moreover, partnerships can reduce the risk and cost of exploration, making it more feasible for a firm to pursue radical ideas as part of its strategy. At the same time, open innovation helps exploitation by sharing best practices—for instance, companies in a cluster might share data on energy efficiency measures, effectively raising the baseline of operational sustainability for all.
- **CA guides COI:** A firm with a clear ambidextrous strategy will enter collaborations with clarity on what it needs. It can then seek specific partners or knowledge flows to fill those needs. For example, if a company's strategy is to develop a circular service model (exploration) while greening its supply chain (exploitation), it can focus its open innovation efforts on finding service platform partners and sustainable material suppliers. This prevents the firm from engaging in "random acts of collaboration" and instead aligns external engagements with internal priorities. Also, by demonstrating internal commitment (CA), the firm is a more attractive partner in open innovation networks—others see that it's serious about implementing ideas, not just talking. This can foster deeper trust and more meaningful collaboration.
- **Industry 4.0 energizes both CA and COI:** The advanced technologies of Industry 4.0 act as an enabler and accelerator in both domains. Internally, they provide the data and capabilities that allow an ambidextrous organization to succeed—for instance, digital dashboards can simultaneously track exploitative KPIs (like waste reduction in current processes) and exploratory project milestones, giving management real-time insight to

manage both. Externally, Industry 4.0 platforms (like shared data spaces or interoperability standards) often form the backbone of collaborative initiatives. A simple example is a shared data platform for circular supply chains—without modern cloud and IoT tech, such collaboration would be cumbersome. Another example is digital marketplaces for secondary materials enabled by Industry 4.0, where multiple firms transact waste-as-resource; these require robust digital infrastructure. Thus, technology is the common language that different collaborators use to connect their efforts. Additionally, digital communication and modeling tools (videoconferencing, virtual twins, etc.) make it easier for geographically dispersed partners to coinnovate, which is a very practical facet of COI.

- **COI drives technological adoption (Industry 4.0) and innovation diffusion:** Through networks, firms may gain access to technologies they wouldn't develop alone. For instance, a small enterprise might adopt IoT sensors as part of a larger retailer's circular program—effectively, the collaboration brought technology into the smaller player's operation. At an industry level, open standards or consortia often accelerate the adoption of certain Industry 4.0 solutions (like an industry-wide blockchain platform for traceability) because multiple actors agree to it, reducing uncertainty and providing mutual assurance. This collective push can drive faster diffusion of sustainable tech solutions than market competition alone would.
- **Feedback loops:** The framework creates a positive feedback cycle: as more firms adopt the Industry 4.0 + CA + COI approach, successes accumulate and are shared via COI, raising the bar for all and encouraging further innovation (a bandwagon effect towards circular solutions). Over time, whole value networks can transform. For example, consider the evolution of battery recycling for electric vehicles: initially, one or two automakers (with partners) develop digital-enabled recycling plants (Industry 4.0 + CA leading them there, COI with recycling firms). As they share results and regulations tighten, others join collaborative efforts, maybe even sharing those facilities or knowledge, leading to an industry norm where every battery is tracked and recovered. At that point, sustainability practices have effectively scaled, and Industry 4.0 tools like digital passports and AI sorting are standard across the sector—a far cry from the starting point, which might have been one firm's experiment.

Illustrative integrated example: Consider the food packaging industry, facing the challenge of plastic waste. A packaging company (Firm A) adopts an Industry 4.0 solution: IoT sensors and machine learning to improve its production efficiency, cutting material waste by 15% (tech for exploitation). But it does not stop there. Guided by CA, the firm invests in exploring a new business model: a refillable packaging service, in partnership with a major food brand. It prototypes smart dispensers (leveraging digital tech) and durable containers tracked by RFID (Industry 4.0, enabling exploration). To do this, it engages in COI by partnering with the food brand, a tech startup for dispenser design, and a recycling company to handle damaged returns. The pilot is a success at a small scale, drastically reducing single-use package waste. Through the industry association, Firm A shares the model and even the underlying tech (perhaps open-sourcing the RFID tracking

software). Several competitors and brands collectively discuss setting standards for refillable packaging systems (COI scaling the idea). Meanwhile, Firm A uses data from the pilot (captured via IoT and user apps) to refine its processes and improve the user experience, making the service more efficient (exploitation of the new model). Over a few years, multiple companies have adopted similar refill systems, interoperable thanks to those shared standards—consumers can refill different brands' products in standardized smart containers. The outcome: an entire portion of the industry moves toward circular packaging, supported by Industry 4.0 (smart tracking, automation in cleaning refills, etc.), driven by each firm's strategic choice to innovate (CA) and enabled by their willingness to collaborate on infrastructure and knowledge (COI). This narrative demonstrates how a combination of internal initiative and external collaboration, all underpinned by technology, can achieve what no company could alone: a new, more sustainable normal.

16.6 Conclusion and outlooks

The convergence of advanced digital technologies, ambidextrous strategy, and open, cross-sector collaboration offers the most credible pathway for realigning industrial development with planetary boundaries: Industry 4.0 supplies the data-rich engine for deep eco-efficiency and real-time circular resource flows; CA steers that engine by obliging firms simultaneously to optimize today's operations and explore tomorrow's regenerative business models; and COI furnishes the collaborative fuel that diffuses successful experiments, pools risk and investment, and establishes the shared standards without which even the best-designed circular solutions wither in isolation. Taken together, these three mutually reinforcing levers create a self-renewing feedback loop in which external knowledge continually refreshes strategic intent, strategy channels technology toward both incremental and radical sustainability goals, and the resulting performance data flows back into wider innovation ecosystems, accelerating industry-wide learning. Realizing this potential, however, demands that firms embed explicit circular metrics into core KPIs, that policymakers synchronize incentives across technology adoption, business model innovation, and partnership platforms, and that educators equip the workforce not only with digital skills but also with systems thinking and alliance management. Future research should therefore test the performance pay-offs of CA and open-innovation network participation across sectors, develop maturity tools that diagnose misalignments among the three pillars, and examine the governance mechanisms—intellectual-property regimes, benefit-sharing models, and Global South inclusivity—needed to sustain long-term, multiactor collaboration. By reframing Industry 4.0 as a sociotechnical transformation rather than a productivity upgrade, and by coupling it with strategic duality and collaborative openness, industry can move from incremental greening toward the systemic circularity demanded by climate stability, resource security, and biodiversity conservation. Only by steering our technological prowess with deliberate ambidexterity and fueling it with collective effort will we accelerate toward a truly sustainable industrial future.

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Industry 4.0 and the circular economy: digitalization for sustainable transformation

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17.1 Introduction

Rapid industrialization and urbanization have led to unprecedented environmental challenges, including resource depletion, waste accumulation (Kanwal et al., 2024), and environmental degradation. Global GDP has doubled since 1970, and global resource extraction is projected to reach 190 billion tons by 2060 (Oberle, 2019). The traditional linear “take-make-dispose” economic model has proven unsustainable, necessitating a fundamental transformation in how we produce and consume resources (Geissdoerfer et al., 2017). In response, the circular economy has emerged as a promising paradigm that aims to decouple economic growth from resource consumption by maintaining the value of products, materials, and resources in the economy for as long as possible while minimizing waste generation. Simultaneously, Industry 4.0 technologies—including the Internet of Things (IoT), artificial intelligence (AI), blockchain, and cyber-physical systems—are reshaping industrial operations (Khan et al., 2025; Liao et al., 2017). This digital transformation accelerates the shift to a circular economy by enhancing resource efficiency, enabling real-time product tracking, and supporting new business models such as sharing and servitization (Pagoropoulos et al., 2017). Recent studies have demonstrated how digital technologies enhance circular manufacturing through intelligent monitoring, automated control, and optimized resource flows (Kristoffersen et al., 2020). The integration of smart technologies in circular economy initiatives is therefore seen as a promising frontier for

achieving Sustainable Development Goals (SDGs) through improved resource efficiency and digitalized waste management systems (Frank et al., 2019).

The evolution of circular economy principles has been shaped by multiple disciplines, including industrial ecology, cradle-to-cradle design principles, and the performance economy (Ghisellini et al., 2016). Research has increasingly focused on developing scalable frameworks for implementing circular economy strategies across products, industries, and cities (Kirchherr et al., 2017), highlighting their role in enhancing resource efficiency and driving sustainable economic transformation (Bai et al., 2020; Frank et al., 2019; Zhou et al., 2020). The convergence of circular economy principles with Industry 4.0 technologies represents a promising frontier for sustainable development. The combination of the circular economy and Industry 4.0 can contribute to achieving multiple SDGs through enhanced resource efficiency and innovative business models (Dantas et al., 2021). However, significant gaps remain in understanding how specific digital technologies can support different circular economy strategies and in identifying the barriers that might impede their integration (Rajput & Singh, 2019).

While progress has been made, critical gaps remain in understanding the role of Industry 4.0 in circular economy strategies, particularly in scalability, cost-effectiveness, and regulatory adaptation. The scalability, cost-effectiveness, and regulatory challenges of digital circular solutions are still underexplored (Rajput & Singh, 2019). This chapter provides a systematic examination of the mechanisms through which IoT, AI, blockchain, and digital twins enable circular economy transformation, with a particular focus on enhancing life cycle assessment (LCA) accuracy and efficiency. Additionally, it identifies the technical, economic, and policy barriers that may hinder seamless integration while exploring future directions for digital circular economy adoption. By bridging theoretical framework with practical implementation insights, this chapter contributes to a deeper understanding of how Industry 4.0 technologies can drive sustainable industrial transformation.

17.2 Principles and technological enablers of the circular economy

Before exploring the integration of the circular economy with Industry 4.0, it is essential to firstly clarify the fundamental concepts and principles of the circular economy. As a transformative economic paradigm, the circular economy contrasts sharply with the traditional linear model, which follows a “take-make-dispose” approach. Instead, it seeks to maximize resource efficiency and minimize waste by implementing closed-loop systems (Kanwal et al., 2023; Kanwal et al., 2024). A systematic understanding of its evolution and key principles provides the foundation for examining how digital technologies can enhance circular economy implementation. Several scholars have analyzed the circular economy from different perspectives, highlighting its role in waste reduction, sustainable manufacturing, global competitiveness, and ecosystem sustainability (Table 17.1).

The circular economy is based on several core principles that drive resource efficiency, sustainability, and industrial innovation. A key principle is green design, which integrates sustainability from the outset of product and process development. By incorporating eco-friendly materials, optimizing energy consumption, and ensuring durability, industries can

TABLE 17.1 Key thematic perspectives on the circular economy

Circular economy focus areas	Scholarly viewpoints
Waste reduction and recycling policies	Circular economy, aimed at creating eco-friendly cities, reduces waste generation and encourages producers and consumers to take proactive measures for waste sorting and recycling through taxation and other means, thus achieving the goals of a circular economy (Kanwal et al., 2024; Van Berkel et al., 2009).
Economic growth and industrial transformation	Implementing the circular economy development model not only provides a pathway for European society to address environmental degradation but also presents an opportunity for reindustrialization, achieving effective and sustainable long-term economic growth (Bonciu, 2014).
Closed-loop systems and sustainable manufacturing	The circular economy (closed-loop system) is an advancement over the linear economy (open-loop system), and according to the 6 R principles, it requires green manufacturing or recycling solutions to enable materials to be reused (Dolinsky & Maier, 2015).
Global recycling networks and resource conversion	The circular economy is primarily facilitated through a global recycling network, which serves as the main means for waste-to-resource conversion (Gregson et al., 2015).
Sustainable economic growth and competitiveness	It is itself a new model distinct from traditional economic development, with the aim of achieving sustainable growth, enhancing global competitiveness, and creating new employment opportunities (Antikainen & Valkokari, 2016).
Closed-loop material cycles and industrial systems	The circular economy is the concept of a closed-loop material cycle to protect products, components, and materials within industrial systems and extract their maximum utility (Zink & Geyer, 2017).
Ecosystem sustainability and product transformation	The circular economy promotes the feasible relationship between ecosystems and economic growth, emphasizing the concept of product transformation, thereby driving the development of environmental sustainability (Genovese et al., 2017).

significantly reduce waste and emissions across the entire product life cycle—from manufacturing to reuse or recycling. Industry 4.0 technologies such as AI-driven design optimization and digital twins can further enhance green design by enabling predictive simulations and real-time performance assessments.

Another fundamental aspect is the improvement of energy efficiency and the transition toward cleaner fuel sources. The reliance on fossil fuels has long been a driver of environmental degradation, and circular economy strategies advocate for a shift toward low-carbon or carbon-free energy alternatives such as wind, solar, and hydrogen. By leveraging IoT-enabled energy monitoring systems and AI-based energy optimization techniques, industries can minimize carbon footprints (Yu et al., 2024) while maintaining operational efficiency. Additionally, resource recovery and raw material substitution play a crucial role in closing circular economy loops. Industrial waste and by-products, which are often treated as discarded remnants, can be reintegrated into production processes through

blockchain-enabled material traceability and AI-driven waste sorting systems. This shift ensures that secondary materials can serve as viable alternatives to virgin resources, mitigating supply chain vulnerabilities.

Beyond materials and energy, the circular economy extends to innovation in product-service systems, emphasizing the extension of product lifespans and the maximization of resource utilization. Practices such as remanufacturing, refurbishment, and predictive maintenance ensure that resources remain in circulation for as long as possible (Fig. 17.1). IoT-enabled asset tracking and AI-based failure predictions further enhance these processes, facilitating efficient reuse and reducing unnecessary waste. Additionally, resource recovery and raw material substitution play a crucial role in closing circular economy loops. Industrial waste and by-products, which are often treated as discarded remnants, can be reintegrated into production processes through blockchain-enabled material traceability and AI-driven waste sorting systems. This shift ensures that secondary materials can serve as viable alternatives to virgin resources, mitigating supply chain vulnerabilities. Through this integrated approach, industries—empowered by Industry 4.0 technologies—can transition from the traditional linear model to a sustainable, circular economy framework, where data-driven decision-making, automation, and digital intelligence enable continuous resource optimization, reuse, and regeneration (Bjørnbet et al., 2021; Ness, 2008). This transformation ensures that economic growth and environmental responsibility remain aligned, fostering long-term sustainability and industrial efficiency.

17.2.1 Role of digital technologies in enabling the circular economy

In the context of Industry 4.0, digital technologies have become a central force in driving the circular economy. By enabling real-time data collection, process optimization, and

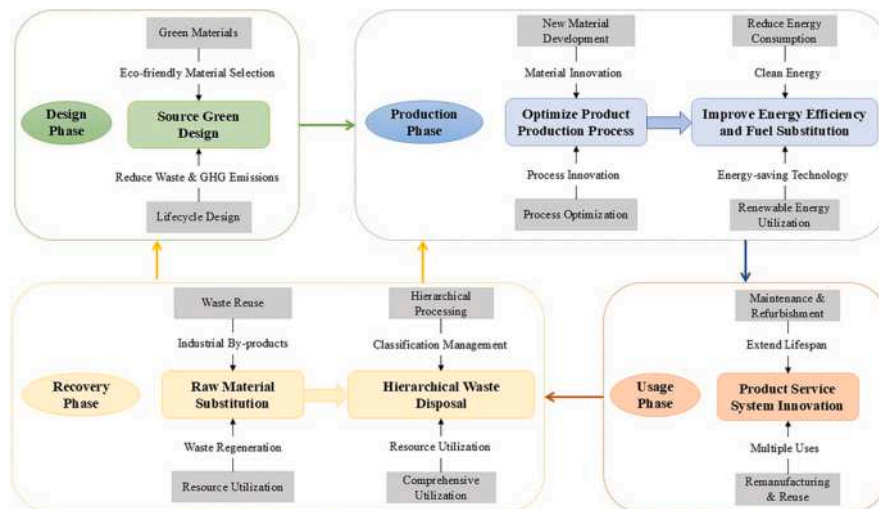


FIGURE 17.1 Schematic diagram of circular economy principles and their interconnected implementation framework. GHG, Greenhouse gas.

intelligent automation, these technologies facilitate resource efficiency and waste minimization. Key enabling technologies include the IoT, big data analytics, cloud computing, AI, and machine learning. These tools support circular economy objectives by improving material tracking, predictive maintenance, and intelligent decision-making.

A substantial body of research validates the transformative role of digital technologies in the circular economy. Case studies define digital technologies as both enablers and triggers in the circular economy, with key enabling technologies such as big data, AI, blockchain, cloud computing, and the IoT driving breakthrough innovations in industries and society (Kumar & Vidhyalakshmi, 2012). In the metallurgical industry, big data analytics enhances material recovery by analyzing production data in real time, enabling dynamic adjustments to recycling processes, increasing resource efficiency, and reducing material waste (Reuter, 2020). In the energy sector, AI has been identified as the most valuable digital technology, providing the highest wage premium to adopting energy companies and the local labor market while significantly contributing to enterprise performance (Lyu & Liu, 2021). Additionally, IoT has been shown to support service-based business models in the LED lighting sector by improving tracking, monitoring, conducting predictive maintenance, and assessing the remaining life of used products. More broadly, digital technologies play a crucial role in improving resource recovery and utilization, particularly through effective data management for material tracking (Ingemarsdotter et al., 2020; Lewandowski, 2016).

Beyond optimizing resource efficiency, digital technologies are reshaping the socio-economic landscape by enabling new business models, improving industrial monitoring, and enhancing policy-driven governance (Kristoffersen et al., 2020). First, digital technologies facilitate data embodiment, enabling seamless information exchange across various sectors. Cloud computing platforms have been leveraged to support data sharing among stakeholders, fostering innovative solutions in water resource and waste management, as well as enabling real-time monitoring of air quality, particularly carbon dioxide and greenhouse gas emissions (O'Donovan et al., 2015). The integration of the digital and circular economies digitizes information in all aspects, including resources, production processes, and waste streams, treating data as the foundation for resource utilization and management, realizing precise distribution and monitoring of resources, and providing data support for the circular economy. Second, digital technologies contribute to the development of intelligent facilities and governance methods. Real-time tracking sensors on public and private buildings can identify potential losses or malfunctions, enhancing maintenance efficiency (Chui et al., 2018). Similarly, real-time quality monitoring systems in sewage pipes, rivers, lakes, and oceans improve reuse capabilities by ensuring water quality control (Chow et al., 2018). Additionally, smart grid systems play a crucial role in transforming the energy dimension of urban metabolism, enabling efficient demand management and rapid response to power outages, peak load shifts, and system faults (Mbungu et al., 2020).

Despite their potential, digital technologies introduce challenges in circular economy implementation. Data privacy and cybersecurity risks emerge as critical concerns, particularly with IoT-enabled monitoring systems that rely on large-scale data collection. Additionally, the substantial costs of AI-driven process optimization may limit adoption among small- and medium-sized enterprises (SMEs), creating disparities in digital transition readiness. Addressing these challenges requires policy frameworks, financial incentives, and global standardization efforts to ensure equitable and secure digital adoption in circular

economy applications. Through these advancements, Industry 4.0 technologies are revolutionizing the circular economy, enabling industries to shift from traditional linear models to smart, data-driven, and resource-efficient systems.

17.3 Life cycle assessment in Industry 4.0

Integrating Industry 4.0 with the circular economy requires systematic methods to assess environmental performance and sustainability outcomes. LCA is a crucial tool in this context, bridging digital transformation and sustainability goals. As the circular economy emphasizes optimizing resource utilization throughout product lifecycles, LCA provides quantitative metrics and standardized methods to assess environmental impacts at each stage (Kanwal et al., 2025). The relationship between Industry 4.0 and LCA is significant, as digital technologies enhance the accuracy and efficiency of LCAs, while LCA, in turn, validates and optimizes the environmental benefits of Industry 4.0-enabled circular economy practices. This synergy makes LCA indispensable for understanding and implementing Industry 4.0 in circular economy practices.

17.3.1 Industry 4.0 enhances life cycle assessment data accuracy

LCA is a tool to assess the potential environmental impacts and resources used throughout a product's life cycle, that is, from raw material acquisition through production and use phases, to waste management (Standardization, 2006). Its purpose is to evaluate all environmental impacts within the entire supply chain, identify the most effective improvement strategies, and avoid burden shifting from one environmental impact to another (Azapagic & Clift, 1999; Hellweg & Canals, 2014). In many cases, the environmental impact assessments within LCA depend on established Life Cycle Inventory (LCI) databases. The data and information in these databases are often compiled from limited sources that merely represent an average of industry practices, leading to potential inadequacies when applied to complex and dynamic LCAs (Browne & Allen, 2004; Xing et al., 2016). Recognizing these limitations, scholars are developing collaborative data-sharing frameworks to improve LCI data accuracy. Notable models include the Supply Chain Collaboration Model (Nakano & Hirao, 2011) and a web-based Decision Support System, which enhances transparency and integration across supply chains (Tsoulfas et al., no date).

Industry 4.0 has driven production digitalization, providing enterprises with real-time environmental data that enhances LCA adoption (Favi et al., 2022), thereby enabling companies with higher degrees of digitalization to adopt LCA methods. This is due to the simplification of data collection, which enables automation and dynamic assessment (Ferrari et al., 2019). Against this backdrop, researchers are developing and applying innovative solutions in information and communication technology, particularly using cloud computing and web-based technologies, to improve computational power and the accuracy of data within LCAs. Cloud-based service frameworks have been developed to enhance data analytics, reducing CO₂ emissions and fuel consumption in intelligent transportation systems. Multimodal, multilevel cloud platforms facilitate dynamic data collection and

exchange for supply chain footprint assessments, supporting life cycle information sharing and collaborative LCA (Hsu et al., 2015). Additionally, digital twin-LCA frameworks enable real-time virtual simulations of production systems, allowing continuous impact assessment and dynamic optimization of resource use and emissions (Xing et al., 2016). Blockchain technology further strengthens LCA by ensuring tamper-proof traceability of material flows through decentralized ledgers, enhancing data integrity for accurate environmental impact assessments. Moreover, IoT technologies within the Industry 4.0 framework leverage vast sensor-collected data to automate LCI analyses and improve efficiency in production facilities (Ferrari et al., 2021; Ghita et al., 2021; Zhang et al., 2020).

17.3.2 Industry 4.0 boosts efficiency and accuracy in life cycle assessment processing and analysis

Industry 4.0 has revolutionized LCA, enhancing both data precision and analytical accuracy. The emergence of AI methods, such as Artificial Neural Networks (ANNs), has enabled LCA practitioners to transcend traditional assessment models, adopting predictive analytics to forecast environmental impacts and thereby allowing organizations to make more informed decisions. ANNs have been utilized to estimate energy consumption for biodiesel production and assess greenhouse gas emissions associated with energy use (Antanasijević et al., 2015). Additionally, AI approaches, including ANN and adaptive neuro-fuzzy inference systems, have been applied to predict life cycle environmental impacts and the energy output of sugarcane production on both planted and ratoon farms (Najafi et al., 2018).

Beyond predictive analytics, Industry 4.0 is also driving advancements in organizational LCA (O-LCA), offering a comprehensive assessment of an organization's environmental footprint (Cucchi et al., 2023). A case study of Italian tile manufacturers demonstrates that Industry 4.0 not only facilitates the adoption of green technologies but also significantly advances organizational LCA (O-LCA), a crucial component in fostering a sustainable manufacturing environment (Cucchi et al., 2023). Additionally, Industry 4.0 enables dynamic LCA, which, unlike traditional static LCA, continuously updates environmental impact assessments based on real-time operational changes. This approach enhances accuracy, particularly in industries where production conditions, energy consumption, and emissions fluctuate over time (Ferrari et al., 2021).

Industry 4.0 has thus not only solidified the foundational data accuracy of LCA but has also propelled the methodology into a new era of sophistication with predictive, organizational, and dynamic applications, thereby reinforcing the role of LCA as an indispensable component of sustainable development and environmental stewardship. Furthermore, there exists a close and complex reciprocal relationship between LCA and Industry 4.0 technologies. The development of Industry 4.0 technologies not only improves the implementation efficiency and accuracy of LCA, but LCA also provides direction and standards for the sustainable development of Industry 4.0 (Cucchi et al., 2023; Ferrari et al., 2021; Raihanian Mashhadi & Behdad, 2018). As Industry 4.0 technologies evolve, their integration with LCA will drive greater automation, predictive accuracy, and real-time decision-making, reinforcing LCA's role as a cornerstone of sustainable industrial development.

17.4 Challenges and barriers in integrating Industry 4.0 with the circular economy

The integration of Industry 4.0 technologies with the circular economy presents complex challenges across technical, economic, and regulatory domains. While Industry 4.0 offers unprecedented opportunities for resource optimization, waste reduction, and process automation, its adoption within circular economy models is hindered by interoperability issues, high implementation costs, and regulatory constraints. Addressing these obstacles is essential for organizations seeking to align digital transformation with sustainable industrial practices. Overcoming these barriers requires collaborative efforts among industries, policymakers, and researchers to ensure that digital technologies support circular economy principles without creating unintended economic or environmental trade-offs.

17.4.1 Technical challenges

The digitization inherent in Industry 4.0 implementation introduces significant cybersecurity vulnerabilities and data privacy concerns that must be carefully addressed. Industrial IoT devices, essential for comprehensive product life cycle monitoring, frequently exhibit inadequate security measures (Xu et al., 2018). This security challenge becomes particularly critical in circular economy models that rely heavily on shared data platforms, such as product-as-a-service systems. A complex tension exists between maintaining operational transparency and ensuring robust privacy protection, especially within the regulatory framework of the EU's General Data Protection Regulation (Brennan et al., 2015; De Angelis et al., 2018). The authors emphasize that strict data localization requirements can create significant operational conflicts within global circular supply chains, potentially compromising the effectiveness of circular economy initiatives.

The technological complexity and associated implementation costs present another substantial barrier, particularly affecting SMEs. The adoption of advanced technologies such as digital twins faces significant obstacles, primarily due to financial constraints and a shortage of specialized technical expertise (Müller et al., 2018). These challenges are especially pronounced in developing economies, where limited access to digital infrastructure further complicates implementation (Ghobakhloo, 2020; Zheng et al., 2021). The combination of high initial investment requirements and the need for specialized technical knowledge creates a significant barrier to entry for many organizations attempting to integrate Industry 4.0 technologies with circular economy practices. As Industry 4.0 technologies continue to evolve, overcoming these technical challenges will be crucial to ensuring seamless digital integration into circular economy frameworks. Addressing data standardization, cybersecurity resilience, and SME accessibility will determine the scalability and long-term success of this transformation.

17.4.2 Economic and market barriers

Integrating Industry 4.0 with the circular economy presents significant economic and market challenges that hinder widespread adoption. These challenges stem from high capital requirements, uncertain returns on investment (ROI), and entrenched consumer

behaviors favoring linear economic models. A fundamental barrier lies in the substantial capital requirements for infrastructure upgrades and digital transformation. A comprehensive analysis has shown that circular production systems require 20%–30% higher initial investments compared to traditional linear models. This financial burden is particularly significant in the implementation of IoT technologies (Lieder & Rashid, 2016), where the deployment of essential infrastructure, including sensor networks and data analytics platforms, entails substantial upfront costs (Tukker, 2015). However, the absence of compelling short-term financial returns often leads to organizational hesitancy in commitment.

The uncertainty surrounding ROI presents another critical challenge. Companies demonstrate reluctance in adopting IoT-driven circular solutions, particularly in sectors with low material recovery rates, such as construction and textiles (Kristoffersen et al., 2020). This hesitation is further reinforced by analyses of circular economy business models, which indicate that industries managing complex waste streams, such as electronic waste, encounter extended investment recovery periods and heightened risks due to technical complexities and high recovery costs (Rosa et al., 2019). Market dynamics and consumer behavior patterns pose additional significant barriers to the successful integration of Industry 4.0 with circular economy principles. Consumer skepticism toward refurbished products and inherent distrust in digital platforms significantly impede the adoption rates of circular business models. This challenge is compounded by deeply entrenched market structures that favor linear consumption patterns. These established market paradigms create substantial inertia against circular alternatives, even in cases where Industry 4.0 technologies enable innovative solutions such as on-demand manufacturing (Antikainen et al., 2018). These entrenched market structures further hinder the adoption of circular economy models, even as Industry 4.0 enables innovative solutions such as on-demand manufacturing.

17.4.3 Regulatory and policy gaps

Regulatory and policy inadequacies present significant barriers to integrating Industry 4.0 with the circular economy. These challenges stem from fragmented global standards, intellectual property conflicts, liability concerns, and digital infrastructure disparities, creating complex legal and operational uncertainties for businesses and policymakers. A fundamental issue lies in the significant lag between technological advancement and regulatory frameworks. The global absence of harmonized standards for digital circular economy practices presents a significant challenge, particularly in emerging technologies such as blockchain-based material traceability systems (Kirchherr et al., 2018). This regulatory vacuum leads to operational uncertainties and implementation barriers across international supply chains. Additionally, inconsistent regulations on electronic waste management and data ownership further complicate cross-border circular supply chains that rely on Industry 4.0 technologies. These complexities are especially pronounced when blockchain-based traceability systems face jurisdictional conflicts arising from differing data sovereignty laws (Govindan & Hasanagic, 2018).

The intersection of intellectual property rights and liability considerations presents another significant regulatory challenge. A fundamental tension exists between traditional

intellectual property frameworks, which were designed for linear economic models, and the emerging requirements of open-source circular economy innovations (Ranta et al., 2018). This conflict becomes particularly evident in collaborative product repair platforms, where the sharing of technical information and repair methodologies may conflict with established IP protection mechanisms. Additionally, closed-loop systems present critical liability concerns, particularly regarding the potential failures of AI-driven predictive maintenance systems, raising questions about accountability and risk management (Pagoropoulos et al., 2017). These scenarios raise complex questions about accountability distribution between manufacturers and service providers, highlighting the need for more sophisticated liability frameworks that can accommodate the complexities of integrated Industry 4.0 and circular economy systems.

Global disparities in digital infrastructure further complicate the adoption of Industry 4.0 in circular economy frameworks. Ghobakhloo and Fathi (2021) highlight a stark divide: while 60% of European manufacturers leverage IoT for resource efficiency, only 15% of African manufacturers have achieved similar adoption, primarily due to limited high-speed internet and cloud computing access. Because these technical, economic, and regulatory barriers are interconnected, addressing them requires coordinated efforts from policy-makers, industries, and researchers. Addressing these challenges is essential for scaling Industry 4.0 technologies in circular economy applications and for fostering sustainable industrial systems.

17.5 Future directions and opportunities

The future of Industry 4.0 and circular economy integration presents key opportunities for innovation and practical implementation. Advancements in digital twins, AI, and blockchain offer transformative potential for resource optimization, waste reduction, and circular supply chains. However, realizing these benefits will require technological advancements, investment incentives, and regulatory evolution to support Industry 4.0-enabled circular economy solutions. Digital twins present a particularly promising frontier for circular economy applications. Advanced simulation capabilities can significantly improve resource efficiency and waste reduction in complex supply chains (Belaud et al., 2019). Studies on agri-food systems show how digital twins can optimize by-product management and reduce food waste through real-time monitoring and predictive analytics. This suggests broader applications across other industrial sectors where resource optimization is crucial. The integration of AI with circular economy principles offers transformative potential for waste reduction and resource optimization. AI plays a crucial role in enhancing circular economy practices through several key applications, including predictive maintenance to extend product lifespans, automated sorting systems to improve recycling efficiency, and demand forecasting to minimize overproduction. These capabilities contribute to optimizing resource use, reducing waste, and increasing the overall sustainability of industrial processes (Awan et al., 2021). Research highlights the need to develop more sophisticated AI algorithms specifically designed for circular economy applications. Blockchain technology continues to emerge as a crucial enabler for transparent and secure

circular supply chains. Blockchain can enhance product traceability, verify sustainability claims, and facilitate the implementation of circular business models. Findings suggest that blockchain could be particularly valuable in establishing trust and transparency in secondary material markets, a critical component of circular economy implementation (Upadhyay et al., 2021).

To realize these technological opportunities, future development requires coordinated efforts across multiple dimensions. For successful implementation of digital circular economy, key priorities include: establishing standardized protocols for data sharing and interoperability in sustainable supply chains (Bag et al., 2020), developing incentive mechanisms to encourage industry investment, particularly for small and medium enterprises (Bressanelli et al., 2020), and creating evolving regulatory frameworks that balance innovation with environmental protection (Kamble et al., 2021). These advancements are particularly crucial for emerging economies, where robust digital infrastructure will be fundamental for Industry 4.0 technology adoption (Cezarino et al., 2019). Looking ahead, the successful integration of Industry 4.0 and the circular economy will require a balanced approach that combines technological innovation with systemic transformation. This includes not only advancing technical capabilities but also developing appropriate governance mechanisms, business models, and collaborative frameworks that can support the transition to a digital circular economy.

17.6 Conclusion

This chapter examined the integration of Industry 4.0 technologies with circular economy principles, highlighting key technological advancements, challenges, and future opportunities. Digital technologies are key enablers of circular economy implementation, revolutionizing resource tracking, management, and optimization. The integration of IoT, AI, blockchain, and digital twins has unlocked new possibilities for sustainable industrial practices. Beyond resource optimization, Industry 4.0 has transformed LCA methodologies, enhancing data precision and real-time environmental assessments through dynamic LCA and O-LCA. These innovations provide more accurate environmental impact measurements, enabling industries to make data-driven sustainability decisions. However, the widespread adoption of Industry 4.0 in circular economy applications still faces significant barriers. Technical challenges include data interoperability and cybersecurity risks, while economic hurdles involve high initial investments and uncertain ROI, particularly for SMEs. Additionally, regulatory gaps in standardization, intellectual property rights, and data governance further complicate implementation efforts. To successfully integrate Industry 4.0 with circular economy models, advancing technical capabilities must go hand in hand with regulatory innovation and business model adaptation. Addressing these challenges will require standardized protocols, investment incentives for SMEs, and evolving regulatory frameworks that balance technological innovation with sustainability goals. Despite significant progress, unlocking the full potential of Industry 4.0 in circular economy frameworks requires ongoing R&D, investment in scalable technologies, and supportive policy frameworks. Cross-sector collaboration among governments, industries, and research

institutions will be key to overcoming existing barriers and accelerating the transition toward a sustainable, data-driven industrial future.

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Leadership of organizations and workforce development

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18.1 Introduction

Caiado et al. (2023) point out that while many companies are moving towards Industry 4.0 and sustainability development, they often do not have a clear idea of what this goal entails and how to approach it. For businesses that have decided to fully adopt Industry 4.0, it is essential to start with an analysis of their current level of maturity. Akdil et al. (2018) describe readiness and maturity models as a systematic approach to evaluating organizations in different business areas, dividing maturity into different levels. Maturity frameworks are key to assessing organizations because they provide a structured approach that helps define the optimal steps to achieve the necessary changes at different levels. The models enable effective assessment of organizations from different perspectives and allow audits, benchmarking of results, and monitoring of progress towards the desired level of maturity. The process involves gradual transitions between levels, starting at the basic level and ending at the advanced level.

The main pillars of the maturity model evaluation are:

- **Strategy:** Plan for implementing Industry 4.0, use of available resources for digitization, and adaptation of business models.
- **Customers:** Use of customer data, digitization of sales and services, digital competence of customers.
- **Products:** Product personalization, product digitization, integration of products into other systems.
- **Leadership:** Willingness of management to undergo a transformation, digital competence management, and existence of a central strategy for Industry 4.0.
- **Operations:** Decentralization of processes, modeling and simulation, interdisciplinary collaboration.
- **Employees:** ICT competence, openness to new technologies, and independence.
- **Culture:** Knowledge sharing, open innovation, and the value of ICT in society.

- **Governance:** Technology standards, Industry 4.0 labor regulations, intellectual property protection.
- **Technology:** Modern ICT, use of mobile devices, machine-to-machine (M2M) communication.

This approach, as outlined in a study by [Schumacher et al. \(2016\)](#), provides a framework for organizations to assess their readiness and progress on the path to Industry 4.0. [Facchini et al. \(2022\)](#) discuss specific models, such as Accenture's Digital Capabilities Assessment (DCA), that focus on the digital competencies necessary to compete in current and future markets. The tool assesses five main areas: strategy and leadership, people and culture, products and services, customer experience, and business support. It provides a framework for diagnosing digital maturity, comprising seven core competencies and 41 subcapabilities. Another example is the Smart Grid Maturity Model (SGMM) ([Kapustina et al., 2020](#)), which describes five phases (exploration and initiation, functional investment, cross-functional integration, optimization, and innovation) applied to eight areas such as strategy, technology, organization, and more. The Digital Maturity Model developed by Deloitte focuses on assessing digital capabilities among businesses and uses five dimensions, including customer, strategy, and technology. This model is pioneering in the field of intercompany digital maturity assessment. Concluding their analysis of preparedness models, [Hizam-Hanafiah et al. \(2020\)](#) identified six key assessment dimensions, which include technology, employees, strategy, processes, leadership, and innovation. This research shows that SMEs that do not have sufficient resources to implement large-scale changes can use models with six basic dimensions to effectively assess their readiness for Industry 4.0. This simple and versatile structure offers the advantage of lower implementation costs and flexible adaptation to different industries.

Organizational leadership and workforce development are key to successfully adapting to the challenges of Industry 4.0, as shown in the overview of readiness and maturity models. Leadership includes management's ability to drive change and develop digital skills and the implementation of a central strategy that facilitates the transition to the new industrial model. Transformation is always linked to employee competencies, and it is their development (nowadays mainly in the field of ICT) that is key. These tasks must be fulfilled by the strategy defined for the HR department, in terms of lifelong and regular training, so that employees are able to respond adequately to the development of new products and the pace of their introduction. This development also promotes interdisciplinary cooperation and adaptation to new work roles. Organizational leadership and workforce development are interlinked and form the basis for implementing changes to increase the organization's maturity in digital competencies. Each step in the readiness model is linked to these factors, supporting achieving effective and sustainable organizational growth.

18.2 Leadership of organizations

Leadership in an organization focuses on leadership's ability to create a vision, direction, and environment that supports achieving organizational goals. Leaders set the strategy and

cultivate an environment where employees have the motivation and resources to succeed. Successful leadership requires communicating with different levels of the organization, providing feedback, and creating an atmosphere of trust that fosters collaboration. Leaders must adapt to change and manage the organization in a rapid technological and market change environment. Flexibility in decision-making and the ability to respond to new challenges are essential to maintain the long-term stability and competitiveness of the organization (Erhan et al., 2022). Leaders who constantly innovate and adapt to new conditions can lead organizations to success. Another important part of leadership is the ability to develop and support talent in the company. Through training, mentoring, and effective delegation of responsibilities to subordinates, management should focus more on supporting employees' professional development, creating opportunities for growth, and helping them adapt to new challenges (Sivathanu et al., 2018).

Leaders in organizations should also be mindful of cultivating values and ethical standards that promote a healthy and productive work culture. Transparency, integrity, and fairness maintain a positive working atmosphere and long-term employee loyalty. When management clearly shows what values are important in an organization, employees follow them and integrate them into their daily work. Communication is another essential leadership skill (Alnuaimi et al., 2022).

Leadership in an organization is a balance between strategic management, a human approach, and the ability to adapt to change. Strong leaders motivate the team, set a clear direction, and create space for innovation, which is essential for the long-term success of the organization. (Eagly & Johnson, 1990)

18.3 Leadership in the implementation of Industry 4.0

From the perspective of leadership in the implementation of Industry 4.0 in the company, there are several key limitations and obstacles that the management of the company should address. Effective leadership is essential for a successful organizational transformation, but it can face various challenges that can slow down the process or even jeopardize its success. Below are the main challenges associated with the introduction of new technologies in connection with the leader (Attar & Abdul-Kareem, 2020; Jung et al., 2003; Shamim et al., 2016; Sivathanu et al., 2018).

- **Lack of leadership support for change**
Lack of support for change from top management can be a major problem. A direct influence on employee motivation for change is the personal commitment and energy that leaders devote to the transformation. Successful leadership should clearly communicate strategy and actively encourage innovation as well as adaptation to new technologies at all levels of the organization.
- **Management's reluctance to delegate responsibility**
Another challenge may be the tendency of some managers to concentrate all decision-making at the top level. When implementing Industry 4.0, the emphasis is on an agile and

flexible approach, which includes delegating responsibility to lower levels of the organization. When leadership does not allow junior managers and specialists to participate in decision-making processes or in adapting new technologies to the organization's specific needs, it can slow down reaction times and reduce the effectiveness of implementation.

- **Insufficient investment in employee development**

Leadership not recognizing the importance of developing employees' skills can face serious obstacles to implementing Industry 4.0. Successful transformation depends on how quickly and effectively an organization can adapt its workforce to new technologies and processes. If management does not invest enough in training and education, employees cannot use new technologies effectively, leading to implementation failure. Leadership must ensure that the organization has the necessary competencies at all levels and that the adaptation process to new technologies runs smoothly.

- **Inability to communicate change and vision**

Another key limit is the ability of management to communicate change and a vision of transformation. If leadership fails to communicate clearly and effectively the reasons and benefits of implementing Industry 4.0, it can lead to misunderstanding, resistance, and frustration among employees. Clear communication about specific steps the organization will take, what changes will take place, and how it will benefit all employees is essential to create support and engagement across the organization.

- **Risk aversion and innovation**

Some executives may be overly cautious and reluctant to invest in unproven technologies or processes that may pose some risk. A certain amount of risk is always associated with transformation, but the people responsible for these transformations no longer feel the need to take risks and see risk not as an opportunity but often as a potential loss of the current ideal state from a personal perspective.

- **Unclear vision and strategy for implementation**

Unclear vision and inconsistent goals often lead to inconsistent leadership and command. A clearly defined strategy and authority in this sense are essential. Leadership needs to set specific goals, deadlines, and metrics to measure progress so that all steps are toward a single goal and the organization has a clear picture of its digital transformation journey.

- **Organizational culture and mindset change**

The implementation of Industry 4.0 requires a change in mindset, both at the individual level and at the level of the entire organization. Leadership must create a culture of openness where employees are not afraid of new technologies and innovations but actively seek them out. If leadership does not foster a culture of innovation and flexibility, the organization may encounter adaptability issues, slowing down the entire transformation process.

18.4 Workforce and Industry 4.0

Human resource management is a concept that builds on the personnel management used until then. As a difference between these concepts and especially as elements

characteristic of human resource management, [Koubek and Josef \(2007\)](#) mention the following key areas:

- A strategic approach to personnel work and all personnel activities (when making decisions in the organization, a long-term perspective is taken into account and the impact of decisions affects not only the near future).
- Focus on external factors of the formation and functioning of the organization's workforce
- Personnel work ceases to be a matter for professional HR professionals and becomes part of the daily work of all managers.

The concept of human resource management perceives people who work in an organization as one of the important resources in addition to, for example, financial, material, or informational resources that the company can have. The logical interest of every organization is to achieve organizational goals as effectively as possible and to ensure sufficient, preferably continuously increasing performance. Human resources management and development assumes that the people in the organization can ensure this performance with the right leadership and development. [Armstrong et al. \(2014\)](#) state that human resource management is oriented towards achieving goals in the following defined areas:

- Organizational efficiency
- Human Capital Management
- Knowledge management
- Compensation management
- Employment relations
- Meeting different needs
- Bridging the gap between rhetoric and reality (practical application of theory)

Human resource management can be divided into hard and soft management. A certain depersonalization is characteristic of the tough management of human resources. People are seen as a resource comparable to other resources (such as material resources) and are treated as such by management. [Armstrong et al. \(2014\)](#) emphasizes the rational management style typical of a hard approach. The organization focuses on its interests, or the interests of management, in connection with the corporate strategy, and gaining added value from people. Although this approach recognizes the importance of human resources, it tends to approach them mechanically, takes less into account the individual assumptions of individuals, and rational rules govern everything. Instead of the uniqueness of individuals, emphasis is placed on fulfilling strategies and adhering to rules. Less attention is paid to communication or motivation, for example.

On the other hand, soft human resource management is based on the abovementioned aspects. If we call the hard procedure of human resource management typical management, then the soft procedure is more leadership-oriented. It works more with the concept of human capital, and people in the organization are not objects but means to achieve goals. Emphasis is placed more on relationships (compared to rationality in hard management methods). Leaders are aware of the importance of people and value them highly. With the help of leadership, motivation, education, and appropriately selected communication techniques, managers develop employees, increase their loyalty to the organization, and involvement in decision-making. The organization helps to improve the qualities of individuals because it is aware that quality, satisfied, and engaged employees will pay off for the organization.

In practice, however, we do not usually encounter a purely defined approach to human resource management. A suitable combination of soft and hard management, their blending and adaptation to individual situations, interests, and needs of the organization and its employees appears to be more advantageous and frequent. Combining these techniques makes it possible to reduce the individual disadvantages of each of them, or to compensate for them in certain situations with the advantages of the other type of management.

With the increasing complexity of Industry 4.0 systems, especially due to automation and the interconnection of individual components, worker demands are also changing. The ability to understand organizational and process structures becomes a key qualification for employees in this environment. It is important to be able to identify the individual elements of the production system, to understand the boundaries of these systems, and to understand their functions and patterns of mutual relations. This capability, which includes predicting the behavior of systems, becomes the basis for functioning effectively in a highly digitized work environment.

18.5 Skills requirements for workers in Industry 4.0

Future workers must have different skills, which are divided into the categories of “must have,” “should have,” and “can have.” This classification system applies to personal and technical skills, including specific technological knowledge and soft skills such as teamwork or communication. The table below shows specific examples of these skills (Table 18.1).

TABLE 18.1 Classification of necessary skills and abilities for Industry 4.0.

	A must have	Should have	May have
Technical	IT capabilities	Knowledge management	Programming
	Ability to work and analyze data	Interdisciplinary general knowledge of technology	Specialized knowledge of technology
	Statistical knowledge	Data protection and IT security awareness	Knowledge on ergonometry
	Organizational and process awareness	Specialized production and process knowledge	Legislative awareness
	Ability to use the latest equipment		
Personality	Self-time management	Faith in new technologies	
	Adaptability to change	Lifelong learning	
	Teamwork		
	Social skills		
	Communication skills		

18.6 Transform manufacturing processes

In the smart factory environment, where people, machines, and resources communicate with each other as naturally as in social networks, production becomes a highly connected and dynamic process. Smart products can autonomously collect data about the production process, thus directly contributing to its improvement and optimization. This approach shows that the successful implementation of Industry 4.0 requires collaboration between experts from different technological fields and interdisciplinary cooperation. Key technology areas include (Vrchota, 2019):

- Big data
- Autonomous robots
- Digital simulation of twins
- Universal system integration
- Industrial Internet of Things (IoT)
- Cybersecurity
- Cloud Computing
- Flexible production
- Augmented reality

18.7 The role of education and professional development

Training and continuous professional development are key factors in achieving the goals of Industry 4.0 and in adapting employees' work skills to new technological requirements. In this context, the growing importance of partnerships between industry and academic institutions to provide access to the latest scientific and technical studies is highlighted. For the future, there will be an increasing emphasis on developing transferable skills and competency assessment. Initiatives such as the "Academy Cube" and the European Commission's "eSkills for Jobs 2016" program are already working to improve cooperation between the academic and industrial sectors, thereby facilitating the transfer of new knowledge between the two areas.

18.8 Academic skills and their application in Industry 4.0

For workers in Industry 4.0, the emphasis is not only on technical and scientific skills, which are easily measurable and defined, but also on soft skills. Some of the hard skills that are essential for mechanical engineers in this environment include, for example, numerical skills, analytical thinking, programming, and knowledge of specific software tools. On the other hand, soft skills such as teamwork, communication, and analytical thinking are also very important for successful work in modern production conditions.

An important category of skills is also newly emerging, namely digital skills. These skills include not only basic digital literacy, which are skills necessary to work with digital tools

and applications, but also specialized digital skills that are needed for specific professional areas, such as working with IT or digital tools for specific industrial applications.

To succeed in the Fourth Industrial Revolution, manufacturing companies need to prepare their employees for new competencies that are key to successfully adapting to Industry 4.0. Given the growing erudition and specialization of professions, companies need to establish stronger cooperation with educational institutions. There is often a need to define key learning objectives for workers to participate in this new production environment. These objectives include:

- **The use of new methods and technologies** that will become key elements of work in Industry 4.0.
- **Improving new forms of organizational structures** that relate not only to processes, but also to personnel matters.
- **Enabling new human roles in production processes**, which means adapting jobs to new technological and organizational changes.

The table below describes the qualifications and skills required for Industry 4.0 IT roles. These roles encompass a wide range of skills, and all IT job roles require a deep understanding of the processes involved in efficient data processing (Tables 18.2 and 18.3).

As Benešová (2017) states, the development of these skills will be key to the successful transformation of jobs and to ensure safety, efficiency, and competitiveness in the industrial environment of Industry 4.0.

18.9 Barriers and risks of implementation

The implementation of Industry 4.0 is of interest not only among scientists but also among companies that are directly focused on this industrial revolution. As reported by Chauhan et al. (2021), digitalization, decentralized systems, service orientation, and modular production are key principles that can significantly improve business performance. However, the changes associated with Industry 4.0 are accompanied by uncertainty, which challenges businesses. The main barriers to implementing Industry 4.0 include the following:

1. **Need for organizational and process adjustments:** The introduction of digital technologies requires fundamental changes in companies' organizational and process structures. The emergence of decentralized organizations, the adoption of autonomous robotics, and the implementation of the Internet of Things are challenges that require the comprehensive integration of new technologies (Fantini et al., 2020; Karadayi-Usta, 2020).
2. **Lack of skilled workforce:** Employee skills and requirements for higher education and specialized qualifications are key to working effectively with Industry 4.0 technologies. A multidisciplinary workforce with highly developed soft and hard skills is necessary for fully integrating these technologies (Stentoft & Rajkumar, 2020).

TABLE 18.2 Qualifications and skills required for a job in IT in Industry 4.0.

Necessary IT professions for Industry 4.0	Qualification	Skills
Computer Science Specialist	Secondary/Postgraduate IT Education	Language skills—English, German, etc.
	Experience in a similar position	
	Advanced knowledge of large-scale domain and network management	Autonomy, responsibility, and flexibility
	Basic knowledge of working with databases, virtualization, and cloud services	“Communicative reliability” - ability - planning, leading a small team, organizational skills; Troubleshooting
PLC Programmer	Secondary education focused on electrical engineering	Language skills—English, German, etc.
	Practice	Knowledge of working with Beckhoff TwinCAT
	Proven experience with machine programming	Responsibility; Flexibility; Communicative reliability;
	PLC programming and knowledge	Ability and willingness to learn new things
Robotic Programmer	Knowledge of offline and online robot programming	Language skills—English, German, etc. Analytical, logical thinking
	Experience with basic parameterization and calibration of a robot	
	Project management, coordination of robot programmer teams, and coordination with PLC programmers	Responsibility
	Secondary/postgraduate education focused on automation technology	Flexibility “Communicative reliability” Knowledge of the simulation process; Troubleshooting
Software Engineer	Secondary postgraduate education in IT;	Language skills – English, German, etc.
	Knowledge of C/C++ programming;	Autonomy;
	Knowledge of C#/.NET”;	Creativity;
	Practice;	Flexibility
	Basic knowledge of working with databases (SQL)	Analytical/logical thinking; Troubleshooting;

(Continued)

TABLE 18.2 (Continued)

Necessary IT professions for Industry 4.0	Qualification	Skills
Data Analyst	Secondary/postgraduate education in a technical or mathematical/statistical field PL / SQL—advanced UML—advanced	Language skills—English, German, etc.; Autonomy; Creativity; Flexibility; Analytical, logical thinking Knowledge of working with a table (Excel), Basic knowledge of statistics, and troubleshooting
Cybersecurity	Secondary/Postgraduate IT Education Knowledge of security standards and communication standards Knowledge of servers (level—administrator)	Language skills—English, autonomy, responsibility Creativity; cooperation Ability and willingness to learn new things Analytical/logical thinking

From Benešová, A., & Tupa, J. (2017). Requirements for education and qualification of people in Industry 4.0. *Procedia Manufacturing*, 11, 2195–2202.

TABLE 18.3 High-tech and medium high-tech industry types.

High-tech	Medium high-tech
• Manufacture of basic pharmaceutical products and pharmaceutical preparations; • Manufacture of computers, electronic and optical devices, and equipment; • Manufacture of aircraft and spacecraft, and related equipment.	• Production of weapons and ammunition, • Production of chemicals and chemical preparations, • Production of machinery and equipment n.e.c., • Electrical equipment manufacturing, • Manufacture of motor vehicles, trailers, and semitrailers, • Manufacture of other means of transport and equipment except (ships, aircraft) • Production of medical and dental instruments and supplies.

3. **Lack of knowledge and data management systems:** Existing systems are not ready for real-time data processing, which requires the implementation of robust knowledge management systems that will be able to efficiently store, retrieve, and leverage data to improve processes and integrate with the Internet of Things (Stentoft & Rajkumar, 2020).

4. **Lack of understanding of the benefits of IoT:** While the Internet of Things can deliver significant gains to businesses, many organizations still do not fully understand its full potential. This ignorance can lead to financial losses (Fantini et al., 2020).
5. **Inadequate communication and IT infrastructure:** A robust IT and communication infrastructure is essential for implementing Industry 4.0 technologies to enable efficient real-time data collection, analysis, and distribution (Karadayi-Usta, 2020; Kiraz et al., 2020).
6. **Security and privacy issues:** Cyberattacks pose an increasing threat, especially given the amount of data that is generated and disseminated to businesses through cyberphysical systems and the Internet of Things. Security issues related to identity verification, authorization procedures, and data privacy will be major challenges (Dalmarco et al., 2019).
7. **Insufficient standardization efforts:** For SMEs, which face higher costs for smart technology integration and modernization, without standardised standards, this problem is particularly acute. The introduction of harmonized standards is essential for the efficient production and implementation of components supporting Industry 4.0. Therefore the lack of such standards represents a significant barrier for companies trying to adapt to modern trends (Schroeder et al., 2019; Stentoft & Rajkumar, 2020).
8. **Lack of a digital strategy:** Organizations still face challenges in creating and implementing digital strategies that should integrate both vertical and horizontal aspects of the value chain. The compatibility and interoperability of different IT systems are key elements of this integration (Ghadge et al., 2020).
9. **Missing ready-made solutions:** Today's digital technologies still need further development for full deployment as ready-to-use solutions. To fully implement these technologies, it is necessary to integrate them with legacy systems and enable real-time information management and full interoperability with analytical systems (Barros et al., 2017).
10. **Need for a high volume of investment:** Implementing Industry 4.0 requires high capital investment, which is a challenge, especially for small- and medium-sized enterprises. New technologies increase the risk of financial losses and unrealized ROI (Kamble et al., 2018).
11. **Need for adaptive modernization:** Implementing Industry 4.0 entails upgrading existing systems to machines that support cyber-physical systems (CPS). This process involves connecting new technologies with existing production, logistics, and organizational structures, which requires high investments and complex changes that can hinder a complete digital transformation (Stock & Seliger, 2016).

However, the obstacles to implementing Industry 4.0 are much broader. For example, Attiany et al. (2023) highlight employees' resistance to new technologies, which may be due to their low level of technological maturity or lack of competencies. Elhusseiny and Crispim (2022) add that fear of change, lack of research activities, and lack of experience also pose significant obstacles.

Türkeş et al. (2019) warn of human factors such as loss of intimacy caused by excessive dependence on robots, which can lead to worker apathy and introversion. Another challenge is the demographic situation, where population ageing may slow adaptation to new technologies.

Further, as reported by [Sima et al. \(2020\)](#), automation will lead to the demise of some traditional professions, and new positions will emerge that will require new digital skills. Businesses and governments must promote lifelong learning that enables employees to adapt to the new requirements of Industry 4.0. Education 4.0 is becoming essential for the future, and it must cover four dimensions: vocational, entrepreneurial, financial, and digital education. Creating flexible and accessible educational programs that meet the needs of the future economy is key to the successful implementation of Industry 4.0.

18.10 Selected factors influencing the implementation of Industry 4.0 from the perspective of human capital within the EU

The chapter points out the barriers to the implementation of Industry 4.0. The common denominator for these barriers is the assumption that human capital is ready for the upcoming industrial revolution. In their contribution, Vrchota et al. (2020) state the main assumptions of human resources for Industry 4.0:

- Population structure by level of education
- Level of computer skills
- Internet availability and use
- Flexibility and adaptability of the population
- Share of technical staff employed
- Lifelong learning
- Student mobility in tertiary education
- Education Expenditure
- Number of graduates of technical and natural sciences
- Number of ICT employees
- Employment in high-tech, medium-high-tech, and knowledge-intensive industries
- Student use of computers

Selected indicators are further compared in this chapter within the EU with a focus on the Czech Republic.

18.11 Level of education

Within the indicator, the level of educational attainment of the population from 24 to 64 years of age (MEYS, OECD, ISCED) is recorded here. The data are divided according to the ISCED methodology (0–8), where level 0–2 represents the population with no education, with primary education, and lower secondary education (in the Czech Republic, most often with primary education). ISCED levels 3–4 represent secondary and postsecondary education, where we can imagine a school-leaving certificate, a VET certificate, or a completed practical school. The last group consists of residents with ISCED 5–8 education.

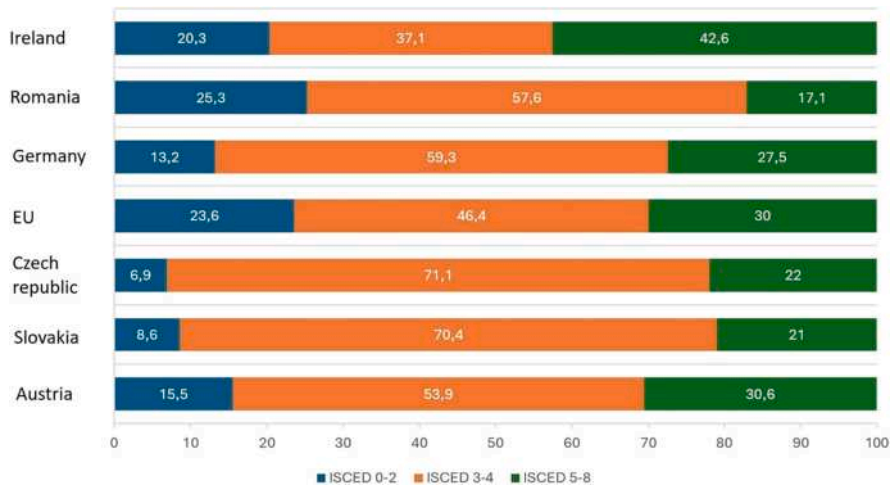


FIGURE 18.1 Educational attainment rate for the population aged 25–64 in selected countries. Sources: From EUROSTAT, MINISTRY OF EDUCATION, YOUTH AND SPORTS, OECD, ISCED.

This group is represented by tertiary education, tertiary professional schools, bachelor's and master's forms of study, and higher completed education.

The EU population's educational attainment share is very diverse, as shown in the following figure. From the point of view of the European average, the Czech Republic has approximately 25% more employees with a high school diploma. Compared to other EU countries, the Czech Republic has a smaller share of low-skilled employees, at 6.9% compared to the European average of 23.6%, and the Slovak Republic is in a similar situation. The Czech Republic also achieves a lower level in higher education, 8% below the EU average (Fig. 18.1).

In terms of countries with the highest share of employees at ISCED level 5–8, Ireland is 42.6%, and on the opposite side is Romania with 17.1%. Austria and Germany have this level higher than the Czech Republic. In order to increase competitiveness in the upcoming stage of Industry 4.0, which will prioritize mainly knowledge-based employees, priority will be given to increasing levels 5 to 8 according to ISCED. Although the Czech Republic has long been the leader in terms of secondary education and at the same time remains below the European average for tertiary education, one of the priorities is not to increase the capacity of universities, but rather to focus on improving the quality and field structure.

18.12 Level of computer skills

From the point of view of Industry 4.0, information technology will play a crucial role in the employability of individuals in the labor market. Computer skills are now indispensable in terms of personal and professional life. The level of computer skills itself primarily depends on the person's age, the state's economic level, which is often associated with

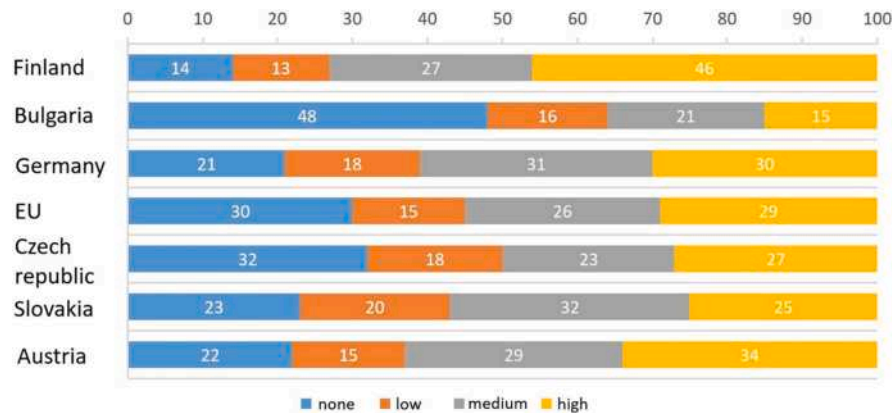


FIGURE 18.2 Share of computer skills in the population in selected countries. Sources: From EUROS-TAT, CZSO.

household equipment (income, education), and access to the Internet. Household equipment is often enough to substitute for sufficient ICT in public spaces (libraries, municipal offices, schools). These skills are surveyed among the population aged 16–74 and represent a series of tasks associated with computer use. Overall, the level is divided into three categories. The Czech Republic still does not reach the European average by 2% in terms of computer illiteracy, and in terms of high level, it lags behind other countries, led by Finland (46%). Bulgaria is among the countries with the lowest level, as shown in the figure below, where almost half of the population does not have computer skills (Fig. 18.2).

From the point of view of these statistics, the difference between the Czech Republic and, for example, Austria or Germany is not so marked, and at the same time, in terms of the development trend, it can be expected that in the coming years we will achieve a literacy level similar to that of these countries at the low and medium levels. However, in terms of competence and competitiveness in the labor market, workers with a high level of computer skills will be preferred in the coming period.

18.13 Education expenditure

Education plays a primary role in terms of competitiveness in the labor market and the readiness of the population for Industry 4.0. It can also be argued that there is a direct correlation between education expenditures and the population's education. The indicator of total expenditure per pupil is expressed based on data representing expenditure on educational institutions (public, private, foreign funds), as well as the sum of current and investment expenditures. All volume is then converted through purchasing power parity to a purchasing power standard (PPS) to eliminate differences in the purchasing power of national currencies. The number of students includes all forms of study. From the point of view of individual EU Member States, the Czech Republic still does not reach the level of the European average and ranks in the lower half. Among the countries with the lowest share of

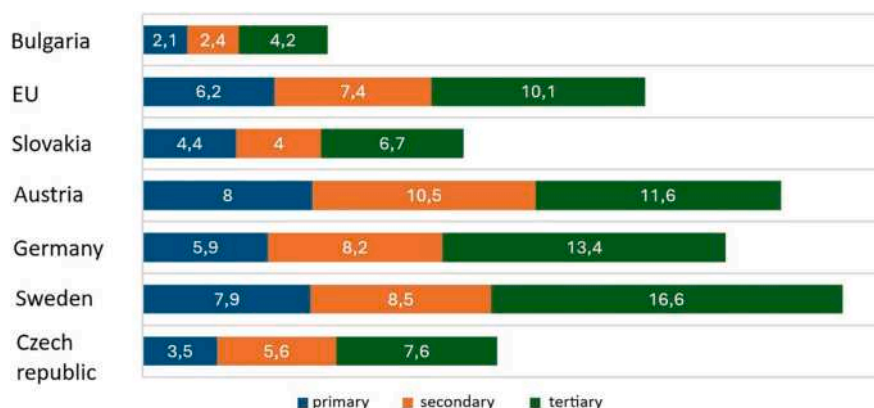


FIGURE 18.3 Total education expenditure per student in 1000 PPS by education class in the EU. Sources: From EUROSTAT, OECD, MINISTRY OF EDUCATION, YOUTH AND SPORTS.

expenditure in education are Bulgaria and Romania, where the total expenditure is only about 8700 PPS, where there is a marked difference between these countries and the Nordic countries of Europe, where the expenditure reaches up to 33000 PPS (Denmark, Sweden) (Fig. 18.3).

The Czech Republic, like Slovakia, with expenditures below 17,000 PPS, ranks among the countries of the eastern region. Here, it is necessary to place greater emphasis on expenditure on education, as its development and topicality can play a crucial role in the preparedness of graduates for the new requirements of the labor market associated with Industry 4.0, where the Czech Republic should measure itself and be competitive with work in Austria or Germany, where it is currently losing about 13400 PPS and 10800 PPS, respectively.

18.14 Employment in high-tech, medium-high-tech, and knowledge-intensive sectors

From the point of view of the future development of the country's economy, human activities in high- and medium-technology-intensive sectors in manufacturing, as well as in services in knowledge-intensive sectors, play an increasingly important role. These activities are usually tracked in individual countries as a share of value added, exports, or total employment, as in the graphs below.

Methodologically, areas according to the European Economic Area NACE are included in the comparison, these are:

On the other hand, countries such as Greece, Cyprus, Latvia, and Lithuania are in the worst situation. None of the abovementioned countries reaches a share of even 2% of total employment. In terms of trend, it is necessary to mention the gradual growth in the Czech Republic in these sectors, which is mainly due to the development of the medium-high-tech industry.

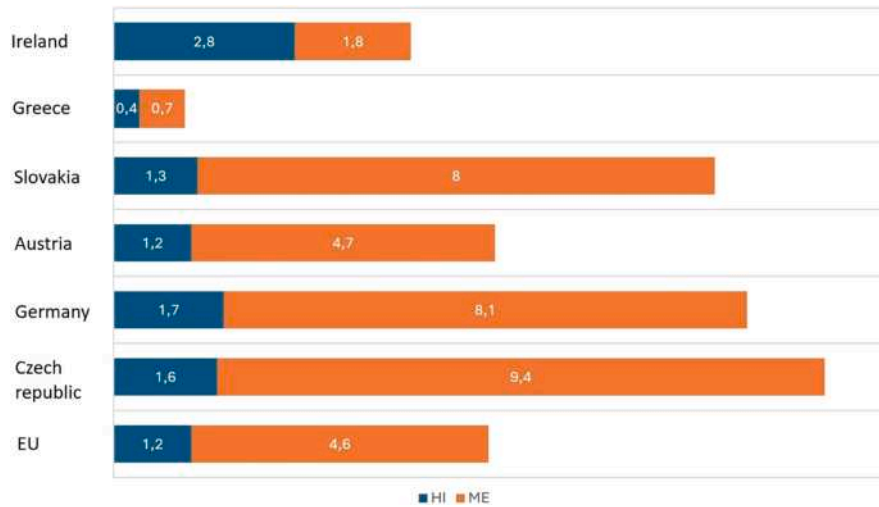


FIGURE 18.4 Employment in the high-tech and medium-high-tech sectors in selected EU countries. Sources: From EUROSTAT, UNU-MERIT.

Fig. 18.4 shows the representation of high-tech and medium-high-tech sectors, where we see the leading position of the Czech Republic with an employment share of 1.6% in high-tech and 9.4% in medium-high-tech. Ireland has the largest share of High-tech over Medium-High-tech among the European Union countries, where High-tech is approximately twice the level of most EU countries. In addition to Ireland, Malta, Denmark, and Hungary, for example, have a high share of employment in the high-tech sector.

As the two graphs above show, the Czech Republic is very appropriately oriented towards key areas of industry in terms of Industry 4.0. Therefore, it is necessary to take advantage of this traditional advantage, to support it by developing knowledge in ICT and a sufficient number of suitable, technically proficient graduates.

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Managing organizational change and transformation for Industry 4.0 integration

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19.1 Introduction

The advent of Industry 4.0 has been recognized as a pivotal factor in enhancing the operational efficiency of supply chain systems. While numerous enterprises adopt Industry 4.0 to promote deeper organizational integration through data-driven strategies, others leverage cyber-physical systems (CPS) to reshape the interrelations among leadership, organizational structures, and customer engagement. Conceptually, Industry 4.0 constitutes a socio-technical system that warrants investigation through the lens of management practices, employee feedback mechanisms, and the causal interdependencies. The foundational elements of Industry 4.0—encompassing data analytics, CPS, Internet of Things (IoT), smart technologies, cloud computing, big data analytics, sustainable production, and intelligent machinery—are central to the development of smart factories. This evolution entails the convergence of information systems and manufacturing processes, fostering a production environment characterized by heightened intelligence and responsiveness to market fluctuations. Through such integration, Industry 4.0 not only enhances manufacturing flexibility but also enables mass customization, quality improvement, and productivity growth. Consequently, it empowers enterprises to address the increasing demand for highly customized products, achieving reduced time-to-market and elevated quality standards in a competitive global market. Advancing industrial technological development fundamentally relies on enhancing efficiency, fostering innovation, and promoting the digital transformation of enterprises. In response to global market expansion, the rise of mass customization, and increasing product complexity, it is essential to reformulate design methodologies and business process development approaches. These processes must evolve toward data-driven, AI-assisted, intelligent, and service-oriented paradigms to effectively

meet the demands of contemporary industrial environments (Salierno et al., 2021). In the context of Industry 4.0, the Intelligent Manufacturing System (IMS) adopts a service-oriented architecture (SOA) framework via Internet-based platforms to deliver collaborative, customizable, flexible, and reconfigurable services to end-users. This approach facilitates a high degree of integration between human and machine interactions, supporting dynamic adaptability and responsiveness within manufacturing processes. The outcome is the formation of a highly integrated human-machine manufacturing system. For instance, the implementation of adaptive automation assembly systems or collaborative assembly systems (CAS) minimizes operators' physical movements while leveraging the flexibility and adaptability of human labor alongside the precision and repeatability of robotic systems. This synergy effectively shortens assembly cycle times and enhances overall productivity within the manufacturing process (Faccio, Minto, Rosati & Bottin, 2020) (Horvath & Szabo, 2019). Industry 4.0 heralds a new technological era by integrating embedded production system technologies with intelligent manufacturing processes, complemented by tools such as RFID to facilitate process automation and enhance system operations and management. This integration fundamentally transforms not only the industrial and production value chains but also the underlying business models. Nevertheless, these advancements introduce new managerial and service-related challenges, particularly regarding interorganizational collaboration and the mechanisms through which firms create, deliver, and capture value. Such challenges extend to the strategic implications of service management within evolving business models. To maintain competitiveness and ensure long-term corporate sustainability in this context, the quality of products, services, and processes becomes a critical priority. From a strategic perspective, the implementation of Industry 4.0 enables organizations to gain deeper insight into their internal strengths and weaknesses, thereby facilitating the optimization of business models. This includes the strategic utilization of key resources such as information technology and software systems to enhance product customization, increase customer engagement, and develop value-driven product designs and data-informed service recommendations. Additionally, Industry 4.0 fosters stronger collaboration within supply chains. It serves as a strategic enabler, not only improving the efficiency of supply chain operations but also leveraging advanced technologies to establish interconnected networks of partners, thereby delivering tailored products and services to customers with greater precision and responsiveness.

The adoption of Industry 4.0 technologies—encompassing the IoT, additive manufacturing, big data analytics, cloud manufacturing, digital twins, and blockchain—enables organizations to effectively address unique and complex requirements. These technologies collectively facilitate enhanced customization, real-time monitoring, and secure data management, thereby supporting sophisticated and adaptive production and service processes.

For instance, Ahleroff et al. (2021) proposed that personalized protective equipment can be developed under a Mass Personalization as a Service (MPaaS) model, which not only delivers optimal solutions for both service providers and customers but also encompasses service planning, scheduling, and execution processes. Consequently, as products and services become increasingly diversified, the collaborative framework within Industry 4.0 has evolved into a service-oriented network composed of enterprises, wherein local production systems, industrial clusters, or outsourced partners operate around product or

service supply chains. To ensure long-term sustainability, services in the Industry 4.0 era must exhibit a high degree of flexibility, balancing productivity with customization needs while fostering extensive integration among customers, enterprises, and suppliers. Leveraging the principles and technologies of Industry 4.0, enterprises are actively employing digital innovations to transform supply chain operations, thereby enhancing the overall value delivered through service management to their customers. This digital transformation enables organizations to optimize processes, improve responsiveness, and provide more customized and efficient services within increasingly complex and dynamic market environments.

K Company is a manufacturer of retractable protective covers (safeguarding armor) with 38 years of experience. Due to the nature of Taiwan's industry, which is characterized by small batches and diverse product types, the majority of orders have unique specifications. The company previously relied on manual design processes, including physical measurement, reference to design specifications, and CAD-based 3D modeling, which required a lead time (L/T) of 480 minutes and a production cycle of 3 days. K Company has systematized design rules and standards and implemented a newly developed CPS system. The information processing module within the CPS system integrates with digital manufacturing systems (e.g., CAD/CAM/CAE) and manufacturing execution systems (MES) to access design and manufacturing information related to equipment, workpieces, products, processes, and personnel. Simultaneously, it captures real-time data from the manufacturing system, environment, and personnel, and then combines these two types of data to calculate and process optimized production process control procedures. Therefore, K Company's CPS possesses adaptability, resilience, fault tolerance, and the ability to make decisions based on predictions. In smart manufacturing applications, the same cyber model is used throughout all stages of the production process. Customers input the necessary values for their machines, and the CPS system automatically calculates and verifies the design, producing 3D models, 3D exploded views, 2D engineering drawings, 2D unfolded drawings, and BOM tables in just 8 minutes. In addition to the 8-minute design calculation time, the input parameter and verification/editing times each take 20 minutes, resulting in a total time (L/T) of only 48 minutes. After implementing CPS in production, the time from material input to output for retractable covers is now less than 10 minutes. The entire production process has been reduced from 3 days to 4 hours, and the production area has been reduced from 1980 to 990 m², while output has doubled. Rather than being influenced by the original production model, employees across the entire organization focused on process reengineering. They abandoned the use of standardized drawings from the design department for each production unit, instead modifying the corresponding cyber models and producing drawings independently. Customer orders are now manufactured in batches according to the required delivery dates. In the Taiwanese manufacturing industry, inventory typically accounts for 15%–45% of annual revenue, but K Company's work-in-progress and finished goods costs account for less than 1% of total revenue. K Company believes that the key to successfully implementing Industry 4.0 lies in establishing rules, processes, and objectives, then delegating authority to vice presidents, assistant managers from the General Manager's Office, Manufacturing Department, Technical Department, Marketing Department, and Management Department to execute operations through decentralized management. This approach allows employees to have room for initiative

while encouraging outstanding employees to pursue internal entrepreneurship, thereby enhancing employee satisfaction and expanding new customer bases.

The socio-technical system concept clearly states that digital technology connects people, technical systems, and organizations. This connection empowers people to make autonomous and well-informed decisions in a networked environment. Industry 4.0's objective is clear: to minimize human influence and ensure consistent production quality. However, it is crucial to recognize the unquantifiable factors that still play a pivotal role. These include the leadership of business leaders, organizational culture, incentive systems, and the organizational commitment of employees (Fan et al., 2021). Employees' identification with the organization, openness, and willingness to learn are critical to the adoption of Industry 4.0 (Veile et al., 2019; Horvath & Szabo, 2019). Recent studies have demonstrated that the advent of Industry 4.0 will precipitate a transition in the workforce toward higher value-added services, a diminution in standardized low-skill activities, and a transformation in organizational culture and service management patterns before and after the change. This phenomenon is pertinent to the current and future outlook of the industrial sector.

19.2 The changing essence of leadership in Industry 4.0

Leadership is defined as the ability to influence others, forge a path for oneself and others, and motivate others to take effective action to accomplish mutually agreed-upon organizational goals (Gardner et al., 2018). Leaders have the capacity to influence, mold, and preserve the organizational culture that is desired, which can potentially impact innovative work behaviors by establishing novel shared values (Naqshbandi & Tabche, 2018). The behaviors and competencies exhibited by managers and leaders have been demonstrated to exert a positive or negative influence on employee engagement. The presence of effective leadership has been demonstrated to foster an environment conducive to innovation within an organization (Khan et al., 2018) and can help to improve, shape, and preserve the desired organizational culture, which may influence innovative work behaviors by generating new shared values (Naqshbandi & Tabche, 2018). Leadership plays a pivotal role in shaping and regulating organizational culture, as well as fostering Organizational Citizenship Behavior (OCB). This, in turn, exerts a substantial positive influence on employees' work behaviors (Khan et al., 2020).

The three primary components of the Industrial IoT (IIoT) in Industry 4.0 are smart devices, smart systems, and smart decisions. The implementation of the Industry 4.0 concept, which is the future direction of the enterprise, also requires the contribution of top management to encourage comprehensive change management activities and processes. Furthermore, organizational and production structures must be adjusted to align with the need to create associated value (Ziaei Nafchi & Mohelská, 2020). For companies, the promotion of Industry 4.0 falls under the umbrella of socio-technical systems, as it entails intricate interactions between human actors and technological elements within the industrial milieu. Compared to the past, Schulze and Pinkow (2020) argued in the context of organizational leadership, the ability to directly influence the members of the organization to achieve specific tasks was once a sufficient measure of leadership efficacy. However, in

the contemporary business environment, leaders must also promote diversity within the organization to facilitate its adaptation to changing external conditions. Furthermore, leaders must actively participate in organizational processes to compel change and ensure the organization's ability to respond effectively to external demands. It is imperative that they play an active role in encouraging the organization to innovate, leveraging the networked infrastructure of Industry 4.0 technologies to expand innovative activities. Consequently, emerging leaders exhibit a maker instinct, characterized by their capacity to construct and cultivate solutions, in addition to their aptitude for engaging with others in the decision-making process. As their roles and responsibilities increase, and they are burdened with additional obligations such as managing relationships, coordinating stakeholders, and administration, they will have different organizational interactions than those of traditional businesses as they face conflicts in organizational culture.

The prevailing academic focus on industrial digital transformation is predominantly centered on the role of CPS solutions as agents of change. Conventionally, data processing activities in operations management were typically organized in accordance with prevailing business structures within and between companies. In the context of the digital transformation, the increasing importance of Industry 4.0 Big Data is a key factor in the evolution of business structures, which will be shaped by the solutions offered by new data processing methods. The digital transformation of Industry 4.0 is poised to redirect the focus from the pursuit of efficiency and effectiveness in physical production processes to the realm of data management and its influence on decision-making processes. The fourth industrial revolution necessitates an organizational design characterized by flexible rules and policies, wherein leaders can delegate authority to employees as data structures transform, thereby fostering teamwork and horizontal communication.

A prominent illustration of an enterprise within the semiconductor industry that exemplifies the adaptable regulations and methodologies of Industry 4.0 is TSMC, the global leader in semiconductor manufacturing. TSMC has exhibited a flexible organizational structure and decentralized leadership in its pursuit of Industry 4.0, underscoring the adaptability of its operational model. TSMC's data-driven smart manufacturing technology has been demonstrated to enhance production processes, while also fostering effective teamwork and horizontal communication. The advent of Industry 4.0 has endowed TSMC with the capacity to expeditiously address fluctuations in market demand, particularly with regard to the fabrication of high-precision, defect-free wafers. The company employs sophisticated analytical methods, including big data analysis, artificial intelligence (AI), and machine learning (ML), to enhance production efficiency and ensure the optimal functioning of equipment. In the process, TSMC's management designed a flexible organizational structure that allows leaders to delegate decision-making authority to frontline employees. Due to the generation and processing of a substantial volume of data and information in real time during the production process, the conventional hierarchical management model is no longer adequate to respond promptly to market fluctuations. TSMC enables engineers and technicians to make autonomous decisions using data, adjust the production line based on equipment operation data, and optimize product quality, thereby significantly enhancing the efficiency of the entire team. Furthermore, TSMC places significant emphasis on fostering horizontal communication across various departments, exemplified by the close collaboration between the IT and production

divisions. The utilization of a data-sharing platform and a unified data structure serves to dismantle the barriers between departments, thereby fostering collaboration and innovation. Consequently, this fosters the realization of a more flexible and efficient manufacturing process.

The comprehensive utilization of historical data, manifested in the form of models and rules, constitutes an additional characteristic of Industry 4.0. This phenomenon is poised to transform the nature of leadership, deviating from the conventional model of a limited number of management levels to the adoption of more intricate organizational structures. In light of the evolving nature of data quality and quantity during processing, operations management is compelled to recalibrate its decision-making processes. The data provide direct insight into the actual state of resources and the progress of the value creation process in the industrial environment. Operations management is capable of reacting to events in the plant and elsewhere without significant delay. This facilitates a continuous feedback loop between decision-making and the subsequent monitoring of consequences. Decisions can be made using comprehensive models developed from historical data and adapted to the entire system using existing knowledge. Furthermore, the decision-making process can be distributed across different organizations without constant reference to a central control entity. Additionally, evaluations during the decision-making process can better reflect the overall requirements of the entire organization.

19.2.1 Organizational change and organizational culture transformation in Industry 4.0 integration

An organization's culture can be conceptualized as a set of shared norms, values, and worldviews that are established within the organization as its members interact with their environment. Organizational culture is defined as the shared beliefs, principles, standards, and assumptions that shape behavior by creating commitment, giving guidance, and generating a consolidated identity. When an organizational culture is aligned with the organization's environment, resources, values, and goals, it can function effectively. Consequently, organizational culture is a pivotal factor in determining the quality of work life and professional performance, while also exerting a significant influence on organizational change and transformation. The prevailing organizational culture is shaped by the foundational beliefs of its originators, the collective experiences of its constituents, and the novel values espoused by its leaders. Consequently, this culture manifests in diverse orientations, including bureaucratic, innovative, and supportive. As organizations expand in scale, they tend to adopt a more bureaucratic and less supportive culture, which is typically characterized by reliance on interpersonal relationships. These relationships are known to be highly dependent on mutual trust, encouragement, and cooperation, which become increasingly challenging to cultivate as organizations mature. However, a notable exception to this trend is observed in the context of innovation culture. In this regard, there is no substantial discrepancy between organizations of varying sizes. Innovation cultures in smaller organizations are predominantly driven by the pursuit of innovation, while larger organizations prioritize the development of innovative solutions (Ziaei Nafchi & Mohelská, 2020). In the context of Industry 4.0, organizations of varying sizes are subject to an increase

in information, concurrent with a shift in organizational culture from a supportive to an innovative one, precipitated by result-oriented and intelligent organizational adjustments.

Chonsawat and Sopadang (2020) posit that the preparation of companies is crucial for the implementation of Industry 4.0. The implementation of Industry 4.0 is expected to be supported by open mindedness and a flexible culture (Veile et al., 2019). The implementation of smart concepts is contingent upon the presence of adequate resources, skilled and competent employees, and a favorable organizational culture (Odwaz'ny et al., 2018). The concept of socio-technical systems serves as the theoretical foundation for Industry 4.0, which integrates digital technology with three constituent elements: people, technological systems, and organizations. Digital technologies have the capacity to render individuals, technologies (i.e., "things" such as machines and products), and organizations "smart," thereby enabling autonomous, fully informed decision-making in a networked environment. Consequently, intelligent organizations employ analogous digital technologies to enable horizontal and vertical integration, thereby connecting autonomous entities to extended value networks (Xu et al., 2018). Accordingly, the concept of Industry 4.0 delineates the organizational structure of the firm, while the production process is predicated on interactive technologies and devices, thereby characterizing a "smart" factory. In this paradigm, physical processes are governed by computer-driven systems with decentralized decision-making processes, which are meticulously orchestrated to rely on the self-control mechanisms of the self-organizing members.

As a result, the transformations precipitated by Industry 4.0 cannot disregard the paradigm of organizational transformation. The implementation of organizational innovation is imperative to facilitate the seamless operation of the IIoT. The concept of Industry 4.0 as "socio-technical systems" necessitates a reevaluation and redesign of people, machines, the surrounding environment, and all levels of organization to develop new technologies. The foundational tenets of Industry 4.0 encompass the IoT and the concept of smart manufacturing. In this paradigm, products, components, and production machinery are equipped with the capacity to collect and disseminate data in real time. This evolution signifies a transition from centralized factory control systems to a decentralized model of intelligence. Accordingly, the organization will function on networked platforms, both real and virtual, sharing and participating in services provided by other enterprises, professionals, and productive communities through online platforms. The advent of Industry 4.0 is poised to catalyze the dissemination and utilization of services, characterized by the convergence of advanced technologies and the seamless integration of human capital and systems. The crux of this paradigm shift lies in the pivotal role of organizational governance in propelling enterprises towards the Industry 4.0 paradigm. To achieve this objective, it is imperative to consider the impact of cultural barriers during the redesign process of the organization and the company. Furthermore, the culture must demonstrate a willingness to embrace the adoption of Industry 4.0 (Müller et al., 2021). Empirical evidence suggests that, however, is that organizations often encounter significant challenges in implementing smart factory technologies due to a variety of factors. These include resistance to change, emotional reactions, and a general reluctance to adopt new technologies (Sung, 2018). Consequently, organizational objectives must encompass a digital strategy, organizational culture, employee perceptions, and leadership to facilitate adaptation to the Industry 4.0 transformation.

19.2.2 The impact of incentives on organizational culture in Industry 4.0 integration

Organizational culture is defined as a pattern of values, norms, beliefs, attitudes, and assumptions that determine how individuals behave and how tasks are completed within an organization. This cultural pattern is typically shaped through the actions of organizational management. The provision of team support has been demonstrated to exert a positive and direct influence on the organization. Employees frequently require the exchange of information with other employees and the support of the organization's team to accomplish their tasks. Conversely, when middle management departments are subject to budgetary constraints or a lack of autonomy, they are often regarded as impediments to effective organizational transformation. Thus, the successful transformation of organizations is of paramount importance and must be executed meticulously, while also considering the personal interests of multiple stakeholders within the prevailing organizational structure (Birkel et al., 2019). In addition to receiving support from their peers and teams, employees also require guidance and motivation from their supervisors. Supervisors fulfill a guidance role, offering contextual support to employees as they strive towards a variety of objectives. The establishment of adequate communication within the company is imperative, particularly from the perspectives of management and leadership. The acceptance of the necessity for change by employees is contingent upon the existence of both requirements and a clearly delineated strategy. Conversely, the presence of internal resistance can be attributed to the presence of unclear or dishonest communication between management and employees (Birkel et al., 2019).

Motivation is defined as the methods adopted by managers to address the needs and goals of their employees, to create an appropriate working environment to induce and stimulate the strong will to work, so that the employees will automatically and spontaneously realize their potential to contribute to the organization, so that the organization's goals can be successfully achieved. Social Exchange Theory posits that leaders and followers establish a reciprocal relationship, wherein one party acquires something of value from the other in return, and the other party is obligated to respond in kind. Therefore, when employees perceive that the organization has provided substantial support, it is more probable that they will exhibit optimal performance (Rahman et al., 2018). The positive impact of trust, communication, reward systems, and organizational structure on organizational culture has been demonstrated. Incentives are a method of motivating employees to carry out their professional duties. From a business perspective, the various methods employed by a company to achieve organizational goals or increase employee productivity can be referred to as incentives. The role of organizational culture is twofold: it can impede or facilitate the effectiveness of the network of relationships and interactions available within the organization. Accordingly, this improves the performance of personnel by improving or increasing productivity. Consequently, organizational culture ought to embody consistency, adaptability, engagement, and a sense of purpose. In essence, the efficacy of an organization is contingent upon its ability to foster engagement and steadfastness among its constituents. Consequently, an organization's compensation system exerts a substantial influence on both the organization's culture and the employees' behavior.

The potential consequences of an organization's reluctance to embrace transparency and innovation, leading to its inability to adapt to new developments, are significant. The implementation of Industry 4.0 necessitates comprehensive preparations on the part of companies, including training and incentives (Birkel et al., 2019). Once a new technology has been accepted, leaders can provide support to achieve the desired results. The occurrence of this phenomenon is contingent upon the facilitation of cooperation and technological learning among members of the organization by senior management (Villena-Manzanares et al., 2021).

19.2.3 The relationship between organizational commitment and organizational culture in Industry 4.0 integration

Organizational commitment is defined as "the relative strength of an individual's identification with and involvement in a particular organization" (Al-Jabari & Ghazzawi, 2019). Organizational culture has the capacity to influence the attitudes and behaviors of members, aligning them with the values and expectations of the organization. This cultural influence can also foster a sense of commitment among individuals toward the corporate values. Organizational commitment is defined as the psychological state in which employees identify with a particular organization in the hope of retaining their membership. Employees who align with and believe in the organization's goals and values tend to exhibit higher levels of dedication and satisfaction in their work, often viewing the benefits offered by the organization with greater enthusiasm. Employees who demonstrate a strong sense of commitment to the organization are more likely to exhibit superior performance compared to those who exhibit a weaker commitment. This is because committed employees allocate more effort towards the organization's success, working diligently to accomplish its objectives and fulfill its responsibilities. Effective employee performance is also the result of commitment to the organization. The results of employee performance can be expressed in terms of commitment to stay on task and achieve organizational goals, quality of service, acceptance of change, and taking on additional work assignments. Therefore, it is also referred to as the intensity of employee participation and identification with the organization. Organizational commitment plays a pivotal role in fostering bonds between individuals and organizations, thereby cultivating a shared aspiration for optimal organizational performance. A considerable body of research has been dedicated to the examination of the positive implications of organizational commitment and its repercussions on factors such as productivity, motivation, turnover intention, and absenteeism. This research has identified organizational commitment as a potent instrument for both employees and organizations, facilitating the enhancement of productivity and efficiency.

Organizational commitment is defined as the degree to which an employee is emotionally connected to and engaged with their organization. The term "organizational loyalty" refers to an employee's alignment with the organization's objectives and principles, as well as their strong desire to remain with the organization and their perception of retention as a significant event. Employees' actions also affect the culture of the organization, and the organization will strive to increase employees' commitment to the organization. The concept of a "cluster" can be utilized to describe an organization, whether it be a nation or a family, thereby fostering a collaborative environment.

In the context of Microsoft's ongoing digital transformation, the company has placed a significant emphasis on cultivating organizational commitment as a means of driving cultural change. The company initiated a professional development program to foster a stronger identification with organizational goals among employees and encourage the adoption of new technologies through learning and application. These initiatives resulted in a more proactive involvement of employees in the technology transition, which ultimately contributed to Microsoft's successful transformation from a traditional software company to a leading cloud-based service provider.

Toyota Motor Corporation highlighted the pivotal role of employee engagement in aligning with the organization's mission when implementing smart manufacturing technologies. Toyota has cultivated employee acceptance of Industry 4.0 technologies through personnel training and the concept of continuous improvement (Kaizen), thereby achieving substantial productivity gains by elevating the level of employee commitment. This process has enabled Toyota to maintain its competitive standing in the global market.

In order for Industry 4.0 to achieve success in the business realm, a comprehensive transformation must be implemented across various domains. This transformation encompasses business processes, technological infrastructure, organizational operations, and cultural shifts. Additionally, it involves the enhancement of employee skills, particularly in areas such as governance, information technology, business and partner relationships, data-driven communication and analytics, and the optimization of business and IT data quality. However, with the advent of Industry 4.0, the increased complexity of the layers involved has led to a concomitant decline in the effectiveness of organizational culture as a support system. A supportive culture is often characterized by its reliance on relationships, which in turn necessitates mutual trust, encouragement, and cooperation. As organizations grow in size, the maintenance of such a culture becomes increasingly challenging (Ziaei Nafchi & Mohelská, 2020). A collaborative, exploratory, and entrepreneurial mindset is imperative for business success and must be integrated into the company's workforce, recognized as its most valuable asset. It is incumbent upon managers to persuade their staff of the merits of Industry 4.0 and to proactively address their concerns. In light of this, employee training and development initiatives should prioritize specific competencies and skills pertinent to Industry 4.0, including data analysis, information technology, software, and human-machine interaction technologies. These competencies will facilitate enhanced cooperation and trust among employees, thereby contributing to the stability and success of the company (Sokolová & Mohelská, 2018).

19.2.4 Organizational change and service management models in Industry 4.0 integration

To facilitate the exchange of product expectations and expertise, it is essential to cultivate closer relationships among company employees, customers, and suppliers. Digital technologies play a pivotal role in enabling companies to openly share core information with suppliers and vice versa. In the contemporary business landscape, the ability to comprehend, acknowledge, and attentively engage with customers has become paramount. The contemporary business landscape is characterized by intensified

competition and waning customer loyalty. This phenomenon has given rise to business models that prioritize the cultivation of relationships with customers. It has been demonstrated that customers exhibit greater satisfaction when services are customer-centric, as this approach prioritizes elements such as fair pricing, quality service, and customization. This shift in focus away from profit maximization and towards customer satisfaction is indicative of a more holistic and customer-oriented business model. In addition to pursuing optimal service management, it is imperative for businesses to nurture robust patronage relationships with consumers. However, it is crucial to consider the evolving demands of customers and their resistance to Industry 4.0-related technologies. While customers may be expressing increasing concerns regarding novel product and service capabilities, they appear to be hesitant to incur the financial costs associated with emerging technologies. This phenomenon has the potential to adversely impact the entire supply chain. At present, a considerable number of companies continue to prioritize the promotion of their products. In the future, the company's strategic emphasis will be on the delivery of solutions and the resolution of customer issues. Consequently, there is a risk that service management models will not be able to adapt quickly enough to these future requirements. Concurrently, the implementation of the new model will necessitate a radical restructuring of the company's organizational structure, which itself poses a significant challenge to the company (Birkel et al., 2019).

Accordingly, the confluence of production technology and various process relationships, in conjunction with e-commerce services and logistics, and the delivery of products through the Internet, has given rise to a novel business model of "design to consumer" (D2C). In the context of Industry 4.0, the distinction between the customer and the end-user becomes increasingly blurred, as companies collaborate with one another in a manner akin to their interactions with customers. In such a collaborative scenario, the business and the customer guide the process by building a relationship of mutual trust. Salespeople who prioritize service management are better equipped to discern customer needs with greater precision, thereby ensuring the delivery of superior service. A company's service management strategy should encompass the following elements: active listening, provision of service, fulfillment of commitments, and customer satisfaction. Moreover, a core focus of the strategy should be the continual enhancement of customer satisfaction. The innovation network engendered by Industry 4.0 has the potential to yield novel service value by integrating suppliers and customers into horizontal alliances. Companies leverage this by meticulously organizing their networks with other companies and coordinating with them to ensure compliance with the principles of service management.

Lak and Rezaeenour (2018) posit that Industry 4.0 has the potential to leverage CPS to facilitate communication and interaction between humans and smart factories. This, in turn, would enable smart factories to deliver service-oriented products through virtualization, decentralized production, and the capacity to collect and analyze data. The advent of Industry 4.0 has precipitated a paradigm shift in the realm of service management, with companies leveraging digital technologies to transform their service delivery models and enhance customer value. The implementation of Industry 4.0 technology can serve as a strategic instrument to enhance the efficiency of internal service management operations. Companies can leverage a network of partners interconnected by Industry 4.0 technology to offer customized product bundles to their customers. In the context of the Industry 4.0

paradigm, characterized by the integration of advanced technologies, the concept of a “smart factory” emerges. Within this paradigm, the utilization of computer-integrated manufacturing (CIMS) processes is of paramount importance, and these processes are subject to close monitoring through the implementation of virtual mapping methodologies. The decentralization of real-time decision-making within the Industry 4.0 framework is a distinguishing feature, contributing to the agile and efficient operation of the manufacturing system. Real-time communication and collaboration can occur among people, between machines, or between people and machines. The IoT domain facilitates the provision of services from within or outside the enterprise by both internal and external organizations (Kozma et al., 2021). The smart technologies employed in Industry 4.0 facilitate the dissemination of information between providers and customers, thereby enabling connections within the value chain and enhancing the system’s agility in responding to environmental changes (Ooi et al., 2018). To capitalize on this, companies must meticulously organize their networks with other companies and coordinate with each other to ensure that the appropriate information is accessible to target users. The advent of service-oriented architecture (SOA) has been instrumental in addressing the interoperability challenges inherent to large-scale automation systems. This paradigm facilitates the exchange of information through the provision and consumption of services by designated systems (Kozma et al., 2021).

Given the networked, collaborative nature of Industry 4.0, where decision-making processes are dispersed among people and machines through the flow of data and information between enterprise modules, the influence of organizational culture will become paramount. Consequently, the motivation of employees and their engagement with the system at the management level will continue to be an influential factor in service management.

19.3 Conclusion

A considerable number of companies have placed a strong emphasis on the implementation of novel technologies while neglecting to consider the repercussions of non-technical factors in the context of Industry 4.0. The advent of Industry 4.0, with its attendant implications for leadership, organizational culture, and employee response to new technologies, is poised to transform the manner in which companies manage their customer base. This transformation will, in turn, exert a significant influence on the sustainability of these enterprises. Numerous enterprises that have initiated the adoption of Industry 4.0 have endeavored to enhance the integration of their organizations with data. However, a significant proportion of these endeavors have met with failure. The underlying causes of these failures have been attributed to the relationship between leaders and the organization, as well as to the demands of the customer. The latter can be attributed to the manner in which the company manages its customer service. A case study of Company K in this article demonstrates that the key to promoting Industry 4.0 lies in transforming the organization’s culture. The transition from a top-down leadership structure in Company K to the employees’ autonomous transformation of the production process through the integration

of Industry 4.0 technologies underscores the pivotal role of organizational culture in fostering the adoption of Industry 4.0 practices. Moreover, the employees of the organization exhibit reluctance to adopt Industry 4.0, and the leadership of the managers, in conjunction with the incentives, will foster enhanced cooperation among the employees. Through the integration of Industry 4.0 technology, the value of service management can be augmented.

The advent of Industry 4.0 has been shown to be associated with an increase in the amount of data collected within large enterprises. This increase in data has been demonstrated to be accompanied by a shift in organizational culture, precipitated by result-oriented and intelligent organizational adjustments. In the context of Industry 4.0, where employees are confronted with an overwhelming volume of data and information, there is a likelihood of resistance to the collaborative relationship between humans and machines. This resistance can result in changes to organizational culture. Leadership has been demonstrated to exert a significant influence on the organizational culture, and the presence of adequate incentives for employees has been shown to yield positive outcomes, particularly in the context of service management. The degree to which employees self-commit to the organization exerts a significant influence on its organizational culture. Employees who exhibit a high degree of self-discipline and the capacity to commit to completing their assigned tasks and achieving organizational objectives can effect substantial changes within the organization, thereby impacting the management of services. While the evolution of a company is contingent on its leadership, who bear the responsibility of cultivating an organizational culture conducive to openness, it is imperative for companies to fortify the synergy between humans and machines within the data-centric infrastructure of Industry 4.0. In contrast to the past, when companies frequently relied on the charisma of leaders, the advent of Industry 4.0 underscores the significance of the organization's role in decision-making. This paradigm shift has given rise to the emergence of decentralized organizational concepts, thereby reducing the incidence of decision-making errors.

Despite the capacity of companies to outsource and engage in other specializations to enhance service management effectiveness, the establishment of an organizational culture remains a critical imperative. Operators can proactively cultivate human-machine collaboration through the implementation of Industry 4.0 technologies; however, they must remain under the oversight of service management. Enterprises must meticulously organize their networks and collaborate with other units to ensure that the appropriate information is accessible to their target users. The advent of Industry 4.0 has ushered in a paradigm shift in the realm of manufacturing, marked by the integration of data analytics and CPSs. This integration has profound implications for decision-making, facilitating the exchange of information between humans, machines, and machines themselves. The IoT and the proliferation of smart technologies have played a pivotal role in fostering interconnectedness within the value chain, thereby enhancing the agility of the industrial sector in responding to external environmental changes. The exchange of information is facilitated by systems that embody a Service-Oriented Architecture (SOA), thereby ensuring the seamless integration of operational processes and technological infrastructures. Ultimately, the core of any enterprise is its people. Despite the potential of Industry 4.0 to foster enhanced collaboration between humans and machines, boost operational efficiency, and refine

customer services, employees may exhibit resistance to the implementation of novel technologies due to the potential division of labor. Consequently, enterprises must establish effective incentives to obtain robust organizational commitment from employees to ensure the effective and sustainable promotion of Industry 4.0.

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Critical social perspectives on automation and job impacts

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20.1 Introduction

The emergence of the Fourth Industrial Revolution and advancements in digital transformation have necessitated that organizations integrate Industry 4.0 technologies into their operations. Industry 4.0 represents a new era of digital industrial technology that integrates data, machines, processes, materials, IT systems, and people throughout the value chain. Technologies under Industry 4.0 encompass autonomous robots, big data and analytics, additive manufacturing, cybersecurity, cloud computing, the Internet of Things (IoT), artificial intelligence (AI), as well as integrated systems, and machine learning. These technologies enable the gathering and examination of data across interconnected systems, resulting in more efficient processes, higher quality products, and cost reductions (Rüßmann et al., 2015; World Economic Forum, 2019). Furthermore, these technologies can enable organizations to enhance their innovation, competitiveness, and sustainability (Bai et al., 2020; Mastos et al., 2020).

In the contemporary business landscape, sustainability is becoming increasingly vital for organizations. Beyond economic concerns, organizations must also adopt measures to protect environmental and social resources. Economic sustainability focuses on long-term economic growth that does not harm environmental and social systems. Environmental sustainability focuses on safeguarding the ecological balance and managing the use of natural resources. Social sustainability, on the other hand, is about maintaining human well-being, addressing fairness and equality within society, and respecting fundamental human rights like security and healthcare (Dempsey et al., 2011; Ghobakhloo, 2020; Stock et al., 2018). To achieve overall sustainability, these three dimensions must be considered together. This increased consciousness has also influenced customer purchasing behaviors, leading to a demand for more sustainable products and services. Ultimately, a more sustainable organization is anticipated to be more competitive (Bai et al., 2020).

While the economic (Ghobakhloo, 2020; Kagermann et al., 2013; Kamble et al., 2018; Müller & Voigt, 2018; Sanders et al., 2016) and environmental benefits (Beier et al., 2017; Ford & Despeisse, 2016; Müller et al., 2018; Sarkis & Zhu, 2018; Stock et al., 2018) of Industry 4.0 are widely recognized, its social impacts remain a critical area of investigation. Social sustainability, which encompasses the well-being of individuals and communities, equity, social inclusion, and cohesion, is increasingly relevant in the context of rapid technological advancements. As Industry 4.0 technologies become more pervasive, understanding their effects on social sustainability becomes essential for ensuring that advancements in technology lead to the broader goals of sustainable development.

This chapter aims to explore the multifaceted impacts of Industry 4.0 technologies on social sustainability. It delves into both the positive and negative impacts, examining how these technologies can enhance or hinder social well-being at both micro (individual and organizational) and macro (broader societal) levels. By drawing on existing literature and empirical data collected through surveys, this chapter seeks to provide a comprehensive understanding of the social dimensions of Industry 4.0 and offer insights into how these technologies can be employed to promote a fairer and more inclusive future. For this purpose, a research model is developed, hypotheses are formulated, and a questionnaire is created based on specific measurement items. Then, data collected from 231 industry professionals are analyzed using structural equation modeling (SEM). Additionally, the survey includes five open-ended questions designed to provide richer insights and enable further analysis of key areas, such as integration processes, examples of successful implementation of Industry 4.0 technologies, employee adaptation, skill development, and social impacts.

The rest of this chapter is structured as follows. The following section reviews the literature on the effects of Industry 4.0 technologies on social sustainability. Building on this review and expert insights, Section 20.3 presents a conceptual research model and associated hypotheses. Section 20.4 outlines the research methodology. Section 20.5 reports the data analysis and hypothesis testing results using SEM. Section 20.6 discusses the findings and research implications, integrating quantitative results with qualitative insights derived from open-ended survey responses to provide a comprehensive perspective on the impacts of Industry 4.0 technologies. Finally, the last section summarizes the conclusions.

20.2 Literature review

In this section, we examine the literature on the social impacts of Industry 4.0 technologies. Comprehensive literature reviews on the sustainable Industry 4.0 framework are provided by Beier et al. (2020), Grybauskas et al. (2022), Kamble et al. (2018), Machado et al. (2020), and Santos and Sant'Anna (2024). The key findings from our literature review are summarized as follows.

A significant portion of the literature has focused on the impact of Industry 4.0 technologies on employment, with a considerable debate over whether these advancements will result in job losses or the creation of new employment opportunities. Researchers such as Freddi (2018), Zemtsov (2020), and Nara et al. (2021) express concerns that automation

could lead to a substantial reduction in the workforce. Bowles (2014) estimates that between 40% and 60% of jobs in Europe are at risk due to technological progress. Similarly, Frey and Osborne (2017) predict that 47% of jobs in the United States are vulnerable to computerization, meaning they could be automated in the near future, possibly within the next two decades. Graetz and Michaels (2018) find that while robots do not drastically decrease overall employment, they lead to a decline in the proportion of jobs held by low-skilled workers. Beier et al. (2022) conduct a comparative survey among professionals from Brazil, China, and Germany, revealing that the manufacturing and assembly sectors, particularly those with a higher concentration of low-skilled labor, are more likely to experience job losses. This trend is especially noticeable in larger companies.

On the other hand, some researchers challenge the idea of full human automation, proposing that although certain jobs might be eliminated, new and potentially more fulfilling employment opportunities will arise. Bonekamp and Sure (2015) and Stock and Seliger (2016) foresee the creation of roles in areas like strategic planning, process control, decision-making support, and information technology. Additionally, Shet and Pereira (2021) argue that new opportunities will develop within the Science, Technology, Engineering, and Mathematics (STEM) fields. These emerging roles may include engineers in systems control and automation, data and robotics specialists, IT architects, and project managers overseeing drone operations (Flores et al., 2020).

In addition to examining job losses and the creation of new employment opportunities, the literature also explores the connection between job skill levels and the evolving landscape of work in the Industry 4.0 age. There are two primary perspectives on this issue. One suggests that to effectively utilize Industry 4.0 technologies, workers will need to develop new competencies, leading to the eventual disappearance of unskilled labor altogether (Brynjolfsson & McAfee, 2014; Shet & Pereira, 2021). On the other hand, another view argues that these technologies will fragment jobs into smaller, less skill-intensive tasks, thereby reducing the overall skill requirements for many positions (Acemoglu, 2002; Freddi, 2018). Additionally, some researchers contend that AI will eventually reach a level of cognitive ability similar to humans, posing a threat to even highly skilled jobs (Alibasic et al., 2022; Brynjolfsson & McAfee, 2014).

The evolution of the labor market in response to Industry 4.0 technologies is complex and multifaceted. While there are legitimate concerns about job losses, particularly in low-skill sectors, the potential for new job creation in high-skill areas presents an optimistic counterbalance. Policymakers, educators, and businesses must work together to ensure that the workforce is prepared for the transition, with a focus on upskilling and reskilling to meet the demands of the new digital economy. Consequently, learning and training environments gain increased significance in the Industry 4.0 context (Herrmann et al., 2014), with technologies like augmented and virtual reality (AR/VR) providing efficient solutions for industrial training (Gavish et al., 2015). AI and data analytics solutions provide managers to monitor employee information and design personalized career development strategies or training programs tailored to individual employees (Ghobakhloo, 2020). The shift to Industry 4.0 also calls for a new approach to education, known as Education 4.0, emphasizing hands-on technical training, online platforms, and advanced learning tools to meet the growing demand for skilled workers (Moraes et al., 2023). Continuous learning is essential, with workers needing to regularly update their skills to stay relevant in a rapidly

evolving job market. Independent learning and self-improvement are expected to become core aspects of modern education, promoting lifelong development (Abulibdeh et al., 2024). Furthermore, innovative educational technologies such as digital simulations, interactive learning tools, and mobile applications are vital for preparing individuals for Industry 4.0 challenges (Grybauskas et al., 2022; Pacheco-Velazquez et al., 2024). With many future job roles still uncertain, educational systems must focus on building flexible programs that allow for quick adaptation to changing technological needs, ensuring that the workforce remains equipped to success in a dynamic, technology-driven environment (Miranda et al., 2021).

The evolving relationship between work and employees in the Industry 4.0 context is a key topic of discussion in the literature. In this environment, the integration of advanced technologies and new economic models is transforming traditional employment structures. The growth of the gig economy, characterized by temporary contracts and freelance employment, offers employees greater flexibility in how and when they work (Dirik, 2022; Starr-Glass, 2019). This shift enables workers to better balance their professional and private lives, as remote work and flexible hours become increasingly common (Fasuludeen Kunju et al., 2022). However, it also obscures the lines between professional responsibilities and personal life, which may result in increased stress and difficulty disconnecting from work (Eichhorst et al., 2017). While the gig economy provides opportunities for independence, it often lacks the stability, benefits, and protections found in traditional employment, leaving some workers more vulnerable (Qiao & Cheng, 2023). Additionally, Industry 4.0 technologies such as AI and automation are enabling new methods of monitoring employee performance, which can enhance productivity but also raise concerns about privacy and excessive surveillance (Wolniak et al., 2024). As this landscape continues to evolve, the challenge for employers will be to leverage technological advancements for efficiency while ensuring employee well-being and maintaining healthy work–life boundaries.

In terms of employee health, Industry 4.0 offers both opportunities and challenges. Robots and automated systems can now perform dangerous or physically demanding tasks, reducing workplace injuries and improving long-term safety for workers (Müller & Voigt, 2018). This shift enables employees to focus on less hazardous, more cognitive tasks, contributing to better health outcomes (Ullah, 2020). However, continuous monitoring can lead to stress, as workers may feel constantly under observation (Heinold et al., 2023). Additionally, remote work and the emphasis on lifelong learning can extend work hours, making it difficult for employees to disengage from work and recover (Ghislieri et al., 2018; Piątkowski, 2020). This extension of work time, combined with the pressure to constantly upskill, may negatively affect employee mental and physical well-being. Therefore it is crucial that organizations find ways to balance technological progress with strategies that promote employee health and maintain clear boundaries between work and personal life.

Alongside the key microlevel effects previously mentioned, the literature identifies additional impacts of Industry 4.0 technologies on social sustainability. These include the ability to conduct fair wage assessments (Kiel et al., 2017), achieve a more balanced distribution of income and wealth (Branger & Pang, 2015), and enhance employee inclusion, interaction, and involvement (Ghobakhloo, 2020; Stock et al., 2018). Blockchain technologies provide the means to monitor sustainability metrics, including issues like child labor (Stock et al., 2018), while innovative input/output devices contribute to increased data security.

Furthermore, Industry 4.0 promotes the development of smarter work environments and the production of innovative products that enhance quality of life (Grybauskas et al., 2022).

A smaller segment of the literature focuses on the broader macro and regional impacts on social sustainability (Grybauskas et al., 2022). Digitally driven regional growth under Industry 4.0 is intricately tied to the economic structure and job market of a region. Regions with a strong presence in digital industries, such as technology, software development, and data services, tend to experience job growth as the demand for high-skilled workers increases. Conversely, regions reliant on automation-prone industries, such as manufacturing or agriculture, may see a decline in jobs as automation and AI replace manual labor (Ciffolilli & Muscio, 2018). This creates an uneven regional advancement, where digital and service-based economies thrive, while more traditional sectors face job losses (Du et al., 2024). Disadvantaged and rural areas are at risk of falling behind because they lack access to important infrastructure, such as high-speed Internet. Without proper digital connectivity, these areas struggle to attract investment in Industry 4.0 technologies, intensifying economic disparities. However, with the right investment in Internet connectivity and digital skills, rural and disadvantaged regions have the potential to tap into new opportunities, revitalizing their job markets and reducing urban overcrowding by encouraging decentralized production. Regional development policies that focus on digital infrastructure and education are critical for ensuring balanced growth and preventing further economic polarization (Salemink et al., 2017).

In the Industry 4.0 environment, a lack of digital proficiency is increasingly becoming a major barrier to employment, particularly as the demand for technologically skilled workers continues to rise. Individuals who lack these essential skills face significant challenges in securing stable and well-paying jobs, which in turn contributes to growing income inequality (Cserhati & Pirisi, 2020; Syuntyurenko, 2020). Beyond the job market, this deficiency also leads to social exclusion, as those without digital know-how struggle with bureaucratic tasks such as completing forms online or accessing essential services (Adamczyk & Betlej, 2021). This often results in them being viewed and treated as outsiders, further deepening their marginalization in an increasingly digital world (Amaral & Daniel, 2016).

Furthermore, with respect to the macro and regional impacts on social sustainability, the literature has highlighted the transformative potential of remote working in reshaping population distribution and regional development. Remote working has the potential to significantly impact society, particularly by encouraging a shift towards rural areas. As more people take advantage of remote work opportunities, they may choose to relocate away from crowded urban centers in favor of quieter, more affordable rural regions (Graziano, 2021). This migration can play a crucial role in renewing these areas, bringing new economic activity and growth to regions that may have struggled with economic slowdown or population decline (Kiss & Nedelka, 2020). Increased demand for housing, local services, and infrastructure in rural areas can stimulate development, while reducing urban congestion and overpopulation. Furthermore, remote work can help bridge the urban-rural divide by creating a more balanced distribution of job opportunities, leading to greater regional equality and economic sustainability (Georgieva, 2022). However, for this shift to be successful, rural regions must also be equipped with the necessary digital infrastructure to support a growing remote workforce (Choudhuri et al., 2021).

Finally, beyond the key macrolevel effects previously discussed, the literature highlights several other ways in which Industry 4.0 technologies impact social sustainability. These include shifts in work organization that promote cooperation both within and across companies (Bonekamp & Sure, 2015), enhanced collaboration between nations to foster business relationships and share technological advancements, as well as political concerns stemming from the potential negative social consequences (Grybauskas et al., 2022).

20.3 Research model and hypotheses

In this study, the research model presented in Fig. 20.1 investigates the social sustainability impacts of Industry 4.0 technologies, considering both positive and negative effects at micro- and macrolevels. The implementation of Industry 4.0 technologies serves as the independent variable, with hypothesized outcomes across different social dimensions. Recognizing that *firm size* and *sector* may influence how Industry 4.0 technologies are adopted (Oliveira et al., 2014), these variables are included as control variables to provide a more detailed understanding.

At the microlevel, Industry 4.0 technologies are anticipated to bring both positive and negative social effects:

- **H1.** Industry 4.0 technologies have significant positive social effects on a microscale.
- **H2.** Industry 4.0 technologies have significant negative social effects on a microscale.

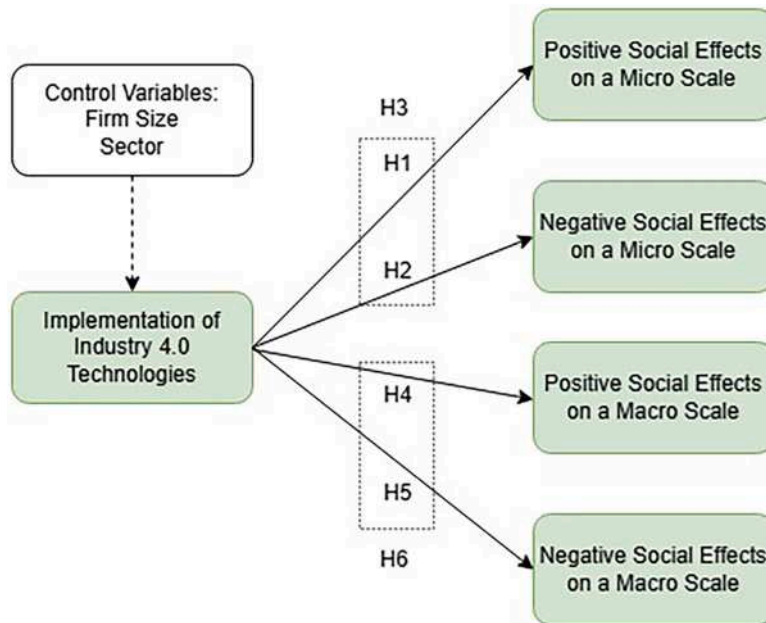


FIGURE 20.1 The research model.

The positive social effects on a microscale (H1) may include improved working conditions, enhanced employee safety, and a better work–life balance due to increased automation and technological support. However, negative effects (H2) might arise, such as job insecurity due to automation, potential privacy concerns from increased monitoring, and challenges related to work–life boundaries. To balance these views, H3 posits that

- **H3.** The positive social effects of Industry 4.0 technologies on a microscale outweigh their negative effects.

This hypothesis (H3) implies that the overall effect on employees and small groups within organizations is expected to be positive on balance, with the advantages outweighing any challenges posed by these technologies.

On a macrolevel, the model considers how Industry 4.0 technologies influence broader societal and organizational outcomes, with both positive and negative effects hypothesized:

- **H4.** Industry 4.0 technologies have significant positive social effects on a macroscale.
- **H5.** Industry 4.0 technologies have significant negative social effects on a macroscale.

The anticipated positive macrolevel effects (H4) may include enhanced collaboration between organizations and countries, contributions to regional economic development through remote work, and strengthened societal resilience as advanced technologies help reduce risks, making communities better equipped to handle challenges. Conversely, negative effects (H5) might involve increased income disparities, regional inequalities in technology adoption, and ethical issues related to AI-driven decisions. Hypothesis 6 (H6) further proposes:

- **H6.** The positive social effects of Industry 4.0 technologies on a macro scale outweigh their negative effects.

This final hypothesis (H6) suggests that the broader societal and organizational benefits of Industry 4.0, such as improved collaboration and economic resilience, will ultimately outweigh any negative impacts, leading to a net positive effect on social sustainability at the macrolevel.

By structuring the hypotheses in this way, the model allows for a comprehensive analysis of the dual impact of Industry 4.0 technologies on social sustainability. It considers both micro- and macroperspectives, examining whether the adoption of these technologies supports social well-being or introduces new societal risks. This dual-level analysis provides a balanced view of Industry 4.0's role in advancing social sustainability, offering insights into how organizations and society can maximize the benefits while mitigating potential challenges.

20.4 Research methodology

20.4.1 Measurement

The objective of this study is to examine the social sustainability impacts of Industry 4.0 technologies. An online survey is conducted to evaluate the hypothesized relationships,

with responses gathered from participants across five sectors: manufacturing and industry, services, technology and innovation, retail and consumer services, and finance and energy. The majority of respondents are from Türkiye (152 responses), with additional participants from countries such as Germany, the United States, and the United Kingdom, totaling 231 responses. A carefully crafted questionnaire, developed by a panel of knowledgeable researchers in the field, serves as the primary data collection tool. The questionnaire design follows a multistep process, beginning with an initial draft in English, followed by translation into Turkish, and a subsequent back-translation to ensure consistency and clarity in the items (Lii & Kuo, 2016). The finalized questionnaire is presented to respondents in both English and Turkish, allowing participants to choose their preferred language for accurate and comprehensive responses. The measurement items used in the questionnaire are provided in [Appendix A](#).

Following established literature, the constructs excluding *implementation of Industry 4.0 technologies* are evaluated using a five-point Likert scale, spanning from “strongly disagree” to “strongly agree.” The extent of Industry 4.0 adoption is assessed by asking respondents about their organization’s implementation of various technologies (e.g., IoT, AI, and robotics) and the number of years these technologies have been in use. Additionally, three control variables are included to enhance the analysis: two related to firm size and one to sector. Firm size is evaluated based on the number of employees in the organization (FS1), categorized as 0–50, 51–250, and 250+ employees, and the organization’s annual revenue (FS2), with categories of 0–50, 51–250, and 250+ million USD. The sector (SEC) is grouped into the five categories mentioned above. To further enrich the analysis, the survey also incorporates five open-ended questions aimed at exploring how organizations integrate Industry 4.0 technologies, examples of successful implementation, their effects on employee morale and job satisfaction, skill development efforts, and social sustainability.

20.4.2 Sampling and data collection

The sampling framework for this study involves distributing an online questionnaire through LinkedIn and direct outreach to select companies implementing Industry 4.0 technologies. The survey targets individuals in relevant roles who are either in managerial positions or have direct experience with Industry 4.0 applications. Data collection takes place from July to October 2024. To ensure content validity, a detailed description of Industry 4.0 technologies is provided to respondents, emphasizing the importance of having knowledgeable participants complete the survey. A total of 231 responses are received, with no missing values, as the online form requires all fields to be completed before submission. Although a few outliers are identified in the data, they are retained to avoid manipulating the dataset. This decision is made to preserve the integrity and representativeness of the data. The respondent demographic profiles are presented in [Table 20.1](#).

To assess nonresponse bias, a Kolmogorov–Smirnov test is conducted, comparing early and late respondents. The analysis reveals no significant differences in the sample distributions, indicating that nonresponse bias appears to be minimal (Ryans, 1974). Additionally, Harman’s one-factor test is employed to evaluate common method bias (Podsakoff et al., 2003). The test indicates that the first factor accounts for less than half of the

TABLE 20.1 Respondent demographic profiles.

Category	Frequency	Percentage (%)
Country		
Türkiye	152	65.80
Global	39	16.88
Europe	23	9.96
North America	7	3.03
Asia	4	1.73
Middle East	3	1.30
Africa	2	0.87
South America	1	0.43
Sector		
Manufacturing and industry	84	36.36
Services	74	32.03
Technology and innovation	45	19.48
Retail and consumer services	18	7.79
Finance and energy	10	4.33
Firm's number of employees		
250+	188	81.39
51–250	23	9.96
0–50	20	8.66
Firm's annual revenue (in million USD)		
250+	142	61.47
51–250	45	19.48
0–50	44	19.05
Department		
Operations and logistics	79	34.20
Technology and innovation	62	26.84
Sales and marketing	32	13.85
Management and administration	24	10.39
Planning and procurement	10	4.33
Sustainability and special projects	8	3.46
Quality and compliance	6	2.60
Human resources and development	5	2.16
Consulting	3	1.30

(Continued)

TABLE 20.1 (Continued)

Category	Frequency	Percentage (%)
Finance and legal	2	0.87
Position		
Technical and specialist roles	78	33.77
Mid-level management	53	22.94
Senior management	20	8.66
Top management	18	7.79
Engineering and technical leadership	15	6.49
Administrative roles	14	6.06
Consulting and advisory	10	4.33
Analyst	7	3.03
Owner/partner	6	2.60
Other (e.g., data scientist, SAP specialist, and functional leader)	10	4.33

total variance (i.e., 17.68%), supporting the conclusion that common method bias is not present in the dataset.

20.5 Data analysis and results

This research employs structural equation modeling (SEM) to empirically test the proposed framework. SEM is an advanced multivariate analysis technique that enables the simultaneous investigation of a complex network of dependencies between observed variables and latent constructs, as well as the interactions among latent constructs themselves (Hair et al., 2019). The study follows a two-step approach as recommended by Anderson and Gerbing (1988), beginning with the measurement model estimation, followed by the structural model analysis. The analyses are conducted using AMOS 23.0 software, applying the maximum likelihood estimation method to evaluate the fit of both the measurement and structural models.

20.5.1 The measurement model

The initial measurement model in this study includes five constructs with a total of 42 measurement items. Although the data does not exhibit a perfect normal distribution (multivariate kurtosis: 133.69; critical ratio: 16.33), previous studies (e.g., Hu et al., 1992; Olsson et al., 2000) demonstrate that maximum likelihood estimation is robust under nonnormality, often outperforming alternative methods like generalized least squares or

asymptotically distribution-free methods (Schermelleh-Engel et al., 2003). Therefore maximum likelihood estimation is used in the analysis.

Following the approach suggested by Hair et al. (2019), the measurement model is evaluated using confirmatory factor analysis (CFA). In line with their recommendations, the model's goodness-of-fit is assessed by considering the chi-square value and degrees of freedom, along with the root mean square error of approximation (RMSEA) and standardized root mean residual (SRMR) as absolute fit indices, and the comparative fit index (CFI) as an incremental fit index. While various cut-off values for these indices exist in the literature, the evaluation in this study is based on widely accepted thresholds: a chi-square to degrees of freedom ratio (χ^2/df) below 3.00, an RMSEA below 0.08, an SRMR below 0.08, and a CFI of 0.90 or higher (Byrne, 2013; Hair et al., 2019; Jöreskog & Sörbom, 1993; Malhotra, 2020).

As the initial measurement model does not achieve an acceptable fit, indicators with factor loadings below 0.50 are removed to improve model fit (Hair et al., 2019). The excluded items are TECH8, PMI9, PMA6, NMA3, NMA4, and NMA6 (refer to Appendix A). Additionally, modification indices are applied to refine the model, as values around 4.00 or above suggest that model fit could be significantly improved by allowing the specified path to be estimated (Hair et al., 2019). Accordingly, the final measurement model consists of five constructs encompassing a total of 36 measurement items. This model yields a chi-square value of 778.75 with 569 degrees of freedom, significant at the 0.001 level. All goodness-of-fit indices fall within the recommended thresholds, indicating a good fit for the measurement model: χ^2/df of 1.37, RMSEA of 0.04, SRMR of 0.06, and CFI of 0.93.

After assessing the fit of the measurement model, it is essential to evaluate construct validity, encompassing both convergent and discriminant validity. To establish convergent validity, three key criteria are examined: factor loadings, average variance extracted (AVE), and construct reliability (CR) (Hair et al., 2019). First, we assess factor loadings, with all loadings being significant at the 0.001 level. Most factor loadings exceed the preferred threshold of 0.70, with some slightly lower but still above the acceptable threshold of 0.50 (Hair et al., 2019). Second, the AVE is calculated for each latent construct to further assess convergent validity. Although some AVE values fall below the recommended threshold of 0.50 (Hair et al., 2019, Fornell and Larcker (1981) suggest that convergent validity can still be considered sufficient if the CR is high. Third, CR is calculated for each construct, with all CR values exceeding the 0.70 threshold, indicating acceptable levels of reliability (Hair et al., 2019), further supporting convergent validity. The results of the measurement model are summarized in Table 20.2.

To assess discriminant validity, we compare the AVE values for each construct pair with the squared correlation estimates between them (Fornell & Larcker, 1981). Although discriminant validity is not achieved between PMI and PMA and between NMI and NMA, this result is reasonable given the conceptual similarity of these constructs. As Malhotra (2020) notes, some intercorrelation is expected when constructs measure different facets of a broader concept. Here, PMI and PMA both capture positive impacts, and NMI and NMA measure negative impacts, each at micro- and macrolevels. Thus the observed intercorrelations are contextually explained by the conceptual overlap between these constructs, with the overall model remaining reliable and valid.

TABLE 20.2 Results of the measurement model.

Construct	Measurement item	Factor loading ^a	AVE	CR
TECH			0.4133	0.8210
	TECH1	0.6941		
	TECH2	0.7349		
	TECH3	0.6714		
	TECH4	0.6461		
	TECH5	0.6297		
	TECH6	0.5698		
	TECH7	0.6089		
	TECH9	0.5183		
	TECH10	0.6547		
	TECH11	0.6512		
	TECHYEAR	0.6655		
PMI			0.4147	0.9093
	PMI1	0.5340		
	PMI2	0.5602		
	PMI3	0.6822		
	PMI4	0.6628		
	PMI5	0.7584		
	PMI6	0.6775		
	PMI7	0.6933		
	PMI8	0.6221		
	PMI10	0.5719		
NMI			0.3206	0.7458
	NMI1	0.6060		
	NMI2	0.5490		
	NMI3	0.5772		
	NMI4	0.5496		
	NMI5	0.5576		
	NMI6	0.5642		
	NMI7	0.5908		
	NMI8	0.5315		
PMA			0.4304	0.7800
	PMA1	0.5088		

(Continued)

TABLE 20.2 (Continued)

Construct	Measurement item	Factor loading ^a	AVE	CR
NMA	PMA2	0.6022	0.5654	0.7719
	PMA3	0.8087		
	PMA4	0.7913		
	PMA5	0.5003		
	NMA1	0.7765		
	NMA2	0.8201		
	NMA5	0.6486		

AVE, Average variance extracted; CR, construct reliability.

^a All factor loadings are significant at the 0.001 level (two-tailed).

Following the assessment of convergent and discriminant validities, we proceed to analyze standardized residual covariances and modification indices to identify any potential issues in the measurement model. The analysis shows that all standardized residual covariances are below |4.00|, consistent with the recommendations of [Hair et al. \(2019\)](#), indicating no inherent problems with the model. Additionally, we assess the modification indices, where higher values suggest opportunities to improve model fit by allowing the relevant paths to be estimated. The modification indices observed in the measurement model fall within acceptable ranges, further supporting the model's validity.

20.5.2 The structural model

After validating the measurement model, we proceed to assess the structural model, focusing on testing the hypothesized relationships. The structural model examines how the adoption of Industry 4.0 technologies (TECH) influences both positive and negative social impacts at the micro (PMI and NMI) and macro (PMA and NMA) levels. These latent variables capture the range of social effects associated with Industry 4.0 adoption.

To evaluate the goodness-of-fit of the structural model, we use the same metrics applied to the measurement model. The model achieves a chi-square value of 942.98 with 678 degrees of freedom, significant at the 0.001 level. The fit indices, including a normed chi-square (χ^2/df) of 1.39, RMSEA of 0.04, SRMR of 0.07, and CFI of 0.92, all meet the recommended thresholds. These results confirm that the structural model aligns well with the data, indicating that the overall model is an appropriate representation of the relationships between Industry 4.0 technologies and social sustainability outcomes.

Once the goodness-of-fit measures for the structural model are evaluated, the focus shifts to examining the loading estimates. A comparison between loading estimates from the measurement and structural models shows minimal variation, with a maximum difference of only 0.0177. This consistency among the indicator variables suggests stability, confirming the validity of the measurement model ([Hair et al., 2019](#)). [Table 20.3](#) presents the results of

TABLE 20.3 Results of hypotheses testing.

Hypothesis	Relationship	Path coefficient	<i>t</i> -value	<i>p</i> -value	Decision
H1	TECH - > PMI	0.2826	3.4499	0.0000	Supported ^a
H2	TECH - > NMI	-0.0228	-0.2861	0.7748	Not supported
H3	Positive vs negative (micro)	Pos: 0.2826 Neg: -0.0228	4.9210	0.0000	Supported ^a
H4	TECH - > PMA	0.2658	3.1728	0.0015	Supported ^b
H5	TECH - > NMA	0.1292	1.7056	0.0881	Not supported
H6	Positive vs negative (macro)	Pos: 0.2658 Neg: 0.1292	2.0034	0.0457	Supported ^c

^a Significant at the 0.001 level (two-tailed).

^b Significant at the 0.01 level (two-tailed).

^c Significant at the 0.05 level (two-tailed).

the structural model, summarizing hypothesis testing outcomes. To evaluate H3 and H6, which hypothesize that the positive social effects of Industry 4.0 technologies outweigh the negative effects at both micro- and macrolevels, we compare the positive and negative path coefficients. We calculate the *t*-values for these comparisons by assessing the difference between the coefficients relative to their standard errors. The resulting *t*-values are then used to determine two-tailed *p*-values, allowing us to assess whether the positive effects significantly exceed the negative effects, thus supporting the hypotheses.

The findings indicate strong support for the positive effects of Industry 4.0 technologies on social sustainability at both micro (H1) and macro (H4) levels. This suggests that these technologies make substantial contributions to social sustainability, benefiting individuals, organizations, and society as a whole. Conversely, the analysis shows that the negative effects of Industry 4.0 on social sustainability, both at the micro (H2) and macro (H5) levels, are statistically insignificant. Moreover, comparisons between positive and negative impacts at the micro (H3) and macro (H6) levels reveal that the positive effects significantly outweigh the negative ones. Together, these findings reinforce the idea that the benefits of Industry 4.0 for individuals, workplaces, and broader society are far more pronounced than any potential drawbacks.

An analysis of factor loadings presented in Fig. 20.2 highlights the distinct contributions of positive macrolevel (PMA) and microlevel (PMI) indicators to the model. Among the PMA indicators, the highest contributions are observed for enhancing collaboration between countries (PMA3) and companies (PMA4) to develop business relationships and share technologies. These findings underscore the strong emphasis on fostering global and organizational partnerships, which play a vital role in fostering innovation and supporting economic growth. At the microlevel, PMI indicators such as the creation of smart work environments (PMI5), the production of innovative products that improve quality of life (PMI7), increased data security through innovative devices (PMI3), and the growing importance of innovative vocational training methods to keep up with technological advancements (PMI6) emerge as the most impactful. These results highlight the importance of workplace improvements, enhanced productivity, and innovation as core benefits of

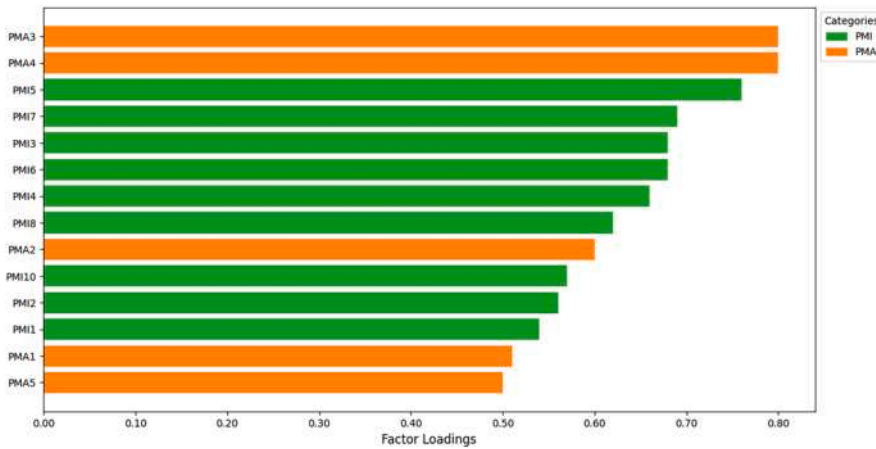


FIGURE 20.2 Factor loadings for positive social effects.

Industry 4.0 technologies. While other indicators in both PMA and PMI categories exhibit relatively lower contributions, they remain meaningful in capturing the broader dimensions of social sustainability.

The analysis of negative social effects reveals that these indicators are statistically insignificant. Nevertheless, factor loadings shed light on potential areas of concern that organizations and policymakers should monitor closely. At the macrolevel, high-loading indicators include income disparities arising from digital skill requirements (NMA2), uneven regional development due to sectoral differences in technology adoption (NMA1), and biases in AI decision-making processes (NMA5). At the microlevel, challenges such as employees struggling to adapt to technological advancements (NMI7) and work disruptions caused by insufficient skills (NMI1) stand out. Although these issues do not pose immediate risks, they signal areas where Industry 4.0 technologies could create challenges if not proactively managed.

Beyond the impacts on social sustainability, we analyze the influence of control variables on the adoption of Industry 4.0 technologies. The results are presented in Table 20.4. The analysis reveals that both employee size (FS1) and annual revenue (FS2) significantly influence the adoption of Industry 4.0 technologies. Organizations with a larger workforce and higher revenue are better positioned to implement these technologies, reflecting their access to resources, robust infrastructure, and workforce capacity required for advanced system integration. However, exceptions are observed for IoT (TECH1) and AR/VR (TECH5), where firms with lower revenue exhibit higher adoption rates than medium-revenue firms.

Sectoral differences (SEC) also play a key role in determining adoption patterns. Significant variations are observed in the implementation of six technologies across sectors, including IoT (TECH1), big data and analytics (TECH2), AI (TECH3), AR/VR (TECH5), cloud computing (TECH7), and blockchain (TECH9), as presented in Fig. 20.3. The technology and innovation sector records the highest adoption rates for IoT, big data and analytics, AI, and cloud computing, while AR/VR experiences the highest adoption in the

TABLE 20.4 Effects of control variables.

Relationship	Path coefficient	<i>t</i> -value	<i>p</i> -value
FS1 - > TECH	0.1817	2.2247	0.0261 ^b
FS2 - > TECH	0.2252	2.7382	0.0062 ^a
SEC - > TECH	0.1704	2.5523	0.0107 ^b

^a Significant at the 0.01 level (two-tailed).

^b Significant at the 0.05 level (two-tailed).

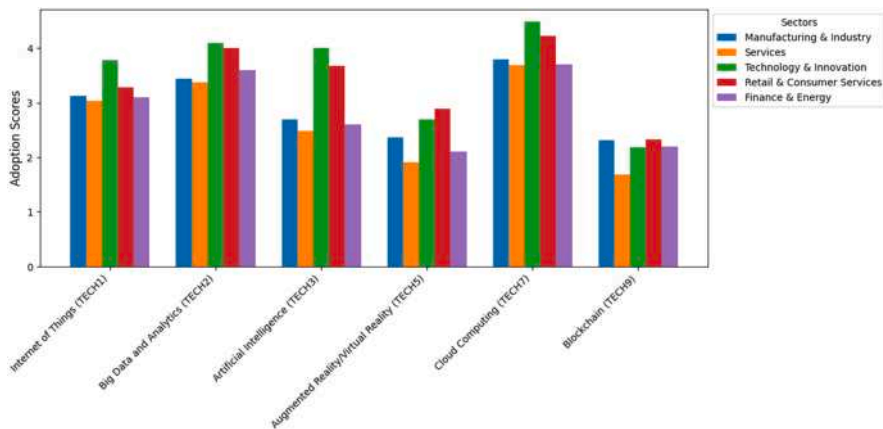


FIGURE 20.3 Technology adoption across sectors.

retail and consumer services sector. Blockchain adoption is highest in the manufacturing and industry sector, as well as in retail and consumer services. Other sectors demonstrate distinct adoption patterns that align with their specific needs. The services sector prioritizes cybersecurity and cloud computing, whereas the finance and energy sector focuses on cybersecurity and high-speed infrastructure.

Finally, it is important to note that Industry 4.0 technologies explain 15.72% of the variance in overall adoption, 7.98% in PMI, and 7.07% in PMA. For negative impacts, the explained variances are notably smaller, with 0.05% for NMI and 1.67% for NMA, which are also statistically insignificant. This suggests that Industry 4.0 technologies have minimal influence on negative social impacts, aligning more strongly with positive outcomes. These modest values reflect the study's focus on the direct effects of Industry 4.0 technologies, excluding broader contextual factors that may also play a role.

20.6 Discussion

This section explores the implications of Industry 4.0 technologies on social sustainability, adoption patterns, and sectoral differences, integrating insights from both significant and

nuanced findings. In addition to the quantitative results, qualitative insights gathered from survey responses provide valuable context, shedding light on how organizations adopt Industry 4.0 technologies, showcasing successful implementation examples, and highlighting their impact on employee morale, job satisfaction, and skill development initiatives. These responses also offer perspectives on the perceived social sustainability impacts of these technologies, including both opportunities and challenges. By analyzing the positive and negative social impacts, organizational characteristics, and sector-specific dynamics, while incorporating these qualitative insights, this section highlights the broader implications for managers, organizations, and policymakers aiming to maximize the benefits of Industry 4.0 while mitigating potential drawbacks.

20.6.1 Main findings and managerial implications

20.6.1.1 *Positive social effects of Industry 4.0*

The results highlight the distinct roles of positive macrolevel (PMA) and microlevel (PMI) indicators in reflecting the impacts of Industry 4.0 technologies. At the macrolevel, the highest loading indicators PMA3 and PMA4 highlight the importance of collaboration and shared technologies, aligning with the findings of [Grybauskas et al. \(2022\)](#) and [Bonekamp and Sure \(2015\)](#). These findings suggest that Industry 4.0 fosters global and interorganizational partnerships, enabling the exchange of knowledge and resources across boundaries. Such collaborations can accelerate innovation and create competitive advantages, particularly for industries that rely heavily on international supply chains or joint technological ventures.

At the microlevel, the highest-loading indicators PMI5, PMI7, PMI3, and PMI6 emphasize the benefits of Industry 4.0 within workplaces, aligning with the findings of [Grybauskas et al. \(2022\)](#) and [Herrmann et al. \(2014\)](#). The creation of smart work environments (PMI5) illustrates how advanced technologies can enhance operational efficiency and employee satisfaction. Similarly, the development of innovative products (PMI7) aligns with Industry 4.0 potential to improve individual quality of life through cutting-edge advancements. The emphasis on data security (PMI3) reflects the growing need for robust cybersecurity measures in increasingly interconnected systems. Additionally, the importance of innovative vocational training methods (PMI6) highlights the necessity of equipping employees with the skills required to adapt to rapid technological advancements.

Macrolevel benefits focus on external factors such as collaboration and partnerships, while microlevel benefits center around internal improvements, such as workplace efficiency and employee well-being. This dichotomy suggests that while Industry 4.0 provides broad societal benefits, organizations must also address internal processes to maximize its value.

Despite these strong contributions, the lower loadings observed for certain indicators imply that not all aspects of Industry 4.0 are equally impactful. For instance, the indicators related to fostering employment opportunities in less developed regions through remote work (PMA1) and promoting socially responsible decision-making by managers (PMA5) show comparatively lower contributions. This indicates that while Industry 4.0 has the potential to address regional and managerial challenges, its impact in these areas may be

less pronounced, possibly due to insufficient focus or practical challenges in implementation.

These findings have significant implications for both organizations and policymakers. Organizations should focus on fostering collaboration and workplace innovation to maximize the benefits of Industry 4.0, with investments in technologies that enhance operational efficiency, employee satisfaction, and well-being. Prioritizing the creation of supportive and secure workspaces, alongside promoting skill development through innovation, can further strengthen workplace outcomes. Cybersecurity and smart work environments should be central to these efforts. On the policy side, governments can play a crucial role by facilitating international partnerships and providing training programs to address workforce challenges, ensuring that the benefits of Industry 4.0 are widespread and equitable.

By integrating these efforts, stakeholders can address both the broader societal impacts and the internal organizational improvements driven by Industry 4.0 technologies. This approach enables the creation of well-rounded strategies that capitalize on global opportunities like collaboration and innovation, while also focusing on specific needs such as enhancing workplaces and supporting employees. Such a balance ensures that the advantages of Industry 4.0 are effectively realized at both global and local levels.

20.6.1.2 Negative social effects of Industry 4.0

Although the negative social effects of Industry 4.0 technologies are found to be statistically insignificant, the factor loadings provide valuable insights into potential areas of concern. At the macrolevel, indicators such as income disparities due to digital skill gaps (NMA2) and uneven development between regions (NMA1) suggest that technological advancements could worsen existing inequalities if access to digital skills and resources remains uneven. Concerns regarding digital skill gaps have been emphasized by [Cserhati and Pirisi \(2020\)](#), [Salemink et al. \(2017\)](#), and [Syuntyurenko \(2020\)](#), whereas uneven regional development has been noted in the observations of [Du et al. \(2024\)](#). These findings underline the need for policies promoting equitable access to technology and training to ensure that the benefits of Industry 4.0 are inclusive and widely shared. Similarly, the risk of bias in AI decision-making processes (NMA5) highlighted by [Grybauskas et al. \(2022\)](#) underscores the importance of developing and following ethical AI practices to ensure fairness in decision-making and inclusivity.

At the microlevel, the challenges associated with adapting to new technologies (NMI7) and skill gaps leading to work disruptions (NMI1) highlight the need for continuous investment in employee training and reskilling programs. Managers should actively foster an environment of lifelong learning and offer tailored support during technology transitions to reduce productivity losses and address employee dissatisfaction. While large firms can capitalize on their resources to drive these initiatives, smaller firms may need external assistance or collaborations to achieve comparable results. Other concerns, such as insufficient employee skills for high-skill roles (NMI3), job security fears (NMI6), and privacy risks from monitoring tools (NMI5), further emphasize the importance of fostering a balanced approach to adoption.

While the statistical insignificance of these effects suggests that they do not currently pose substantial risks, their presence as high-loading indicators highlights areas that require attention to ensure that Industry 4.0 adoption is both equitable and sustainable. Policymakers should proactively address these issues by funding and supporting inclusive training programs, promoting ethical AI practices, and implementing policies to safeguard employee rights. Additionally, they should prioritize initiatives that reduce disparities in digital skill access and address regional inequalities, ensuring that the benefits of Industry 4.0 are distributed more evenly across different regions and demographics. These efforts can help mitigate systemic imbalances while maximizing the long-term positive impacts of Industry 4.0 technologies.

20.6.1.3 Effects of firm size

The findings highlight the significant influence of firm size on Industry 4.0 adoption. Larger organizations, with their superior financial resources, infrastructure, and workforce capacity, are generally better positioned to integrate these technologies comprehensively. However, exceptions for technologies such as IoT and AR/VR suggest that smaller organizations may find unique opportunities where these solutions align more closely with their operational needs and financial capacity. For instance, the accessibility and utility of IoT in streamlining basic operations make it an attractive option for lower revenue firms. Similarly, AR/VR may appeal to smaller firms through its suitability for niche applications that require lower upfront investments but deliver high returns in specific contexts.

To utilize these opportunities, managers in smaller firms can focus on niche technologies that maximize value with relatively minimal costs. For example, adopting IoT can streamline processes effectively, while leveraging AR/VR in targeted applications can enhance operations without overextending resources. Meanwhile, larger firms should continue to prioritize comprehensive technology adoption strategies that take advantage of their financial and infrastructural strengths. Managers in these organizations should focus on integrating advanced systems like AI and robotics across their operations to maximize efficiency and innovation.

Supporting these efforts, policymakers can provide targeted subsidies or grants for small and medium-sized enterprises (SMEs) to enable Industry 4.0 adoption with demonstrated potential for operational efficiency and customer engagement. Establishing innovation hubs and offering tailored training programs can further equip SMEs with the necessary skills and resources to adopt and implement these technologies successfully. Additionally, policymakers can encourage cross-sector collaboration and facilitate knowledge sharing between large and small firms. Such initiatives can help ensure that the benefits of Industry 4.0 technologies extend across the entire business ecosystem, fostering inclusive and sustainable growth.

20.6.1.4 Sector-specific adoption patterns

Sectoral differences provide further insight into the dynamics of Industry 4.0 adoption. The technology and innovation sector's leadership in data-driven technologies such as IoT, big data and analytics, AI, and cloud computing highlights its inherent focus on innovation and process optimization. These technologies are critical for maintaining competitiveness in

a rapidly evolving technological landscape. Meanwhile, AR/VR adoption in the retail and consumer services sector aligns with its potential to enhance customer experience and marketing strategies, making it a natural fit for industries that prioritize consumer engagement.

The dual dominance of blockchain in the manufacturing and retail sectors reflects its versatility. In manufacturing, blockchain likely enhances supply chain transparency and efficiency, while in retail, it supports secure transactions and builds consumer trust. Similarly, the prioritization of cybersecurity and cloud computing in the services sector is driven by the need to protect sensitive data and ensure operational scalability, aligning with the sector's reliance on digital services. The finance and energy sector's preference for cybersecurity and high-speed infrastructure further reflects its emphasis on secure systems and robust networks to meet regulatory requirements and operational demands.

These findings indicate that specific technologies are adopted in ways that closely align with sector-specific priorities and operational contexts. Organizations should prioritize aligning their technology adoption strategies with sector-specific demands. For instance, retail firms should emphasize customer-centric technologies like AR/VR, while manufacturing organizations can maximize efficiency gains through blockchain and IoT. By tailoring strategies to align with sector priorities, organizations can better integrate Industry 4.0 technologies into their operational frameworks, ensuring both relevance and sustainability.

Policymakers, meanwhile, can play a pivotal role by creating targeted incentives for sectors to adopt technologies that address their unique challenges, such as grants for blockchain applications in supply chain optimization or AR/VR adoption in retail. Establishing sector-specific innovation hubs and fostering cross-sector collaboration can further accelerate the adoption of tailored technologies. Fig. 20.4 presents a detailed strategy map tailored for Industry 4.0 stakeholders, including managers, organizations, and governments.

20.6.1.5 Insights from open-ended survey responses

The open-ended survey responses provide rich insights into how organizations across different sectors and firm sizes are integrating Industry 4.0 technologies, highlighting both

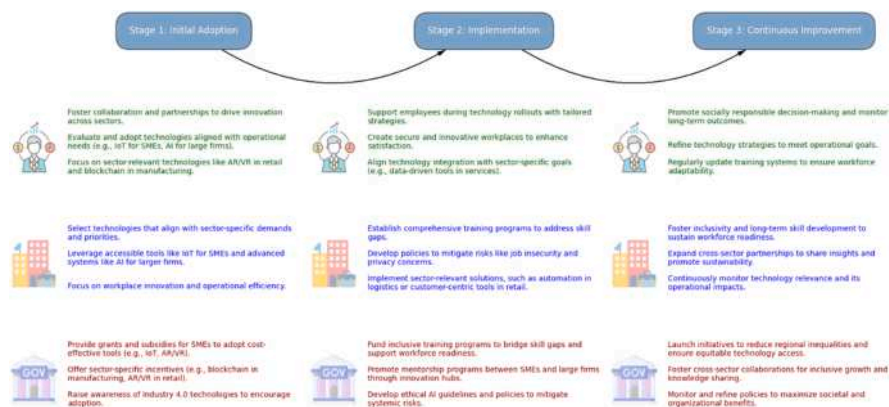


FIGURE 20.4 Comprehensive strategy map for Industry 4.0 stakeholders.

the opportunities and challenges these advancements bring to various processes and social dynamics. This subsection outlines the questions and key insights derived from these responses.

- *How did your organization integrate Industry 4.0 technologies into which processes and in what way?*

A variety of integration strategies have emerged across sectors. In manufacturing, companies focus on automation and production optimization, leveraging technologies like automated warehouses, production lines, and data-driven decision-making processes to enhance efficiency and product quality. Similarly, logistics firms emphasize automation in warehousing and transportation systems while employing real-time data analytics and cybersecurity measures to ensure smooth operations. Technology firms stand out with their advanced use of AI and big data, and analytics for operational optimization and decision-making. In contrast, education-focused organizations often experience slower adoption of Industry 4.0 technologies, prioritizing employee training and preparation for future integration rather than implementing comprehensive systems.

Across sectors, a common challenge is the lack of full integration due to gaps in resources, expertise, or organizational readiness. Training to upskill employees is recognized as critical, though many firms have yet to fully address this need. Larger firms lead in adoption, leveraging AI, robotics, and cloud computing to streamline operations. Medium-sized firms exhibit moderate adoption, focusing on cloud computing and cybersecurity, while smaller firms are cautious, often limiting adoption to basic automation and data storage solutions.

- *Can you share examples of successful implementation of Industry 4.0 technologies in your organization?*

The responses reveal numerous examples of successful Industry 4.0 technology implementations across sectors. Companies frequently utilize AI, robotics, and automation systems to enhance efficiency and productivity, with specific technologies like robotic picking systems, cloud computing, and robotic process automation (RPA) highlighted. Notable improvements include enhanced production efficiency, with reported gains reaching up to 32%, as well as personalized customer services driven by data analytics.

In manufacturing, respondents emphasize factory automation, AI-based production processes, and systems like manufacturing execution systems (MES) for improved production control. Technology firms focus on advancements in big data, cybersecurity, and AI, such as semantic AI for pharmaceutical applications. Logistics firms highlight AI and data analytics for optimizing routes and predicting customer needs, enhancing both operational efficiency and customer experience. Service firms report on the use of RPA for automating tasks like account management and cloud-based systems for data management.

Overall, successful implementations span a range of innovations, from automation in manufacturing to AI-driven customer engagement in logistics and services. While larger firms lead with advanced technologies like robotic systems and MES, medium-sized firms report gains in production quality through AI and automation, and smaller firms often focus on basic automation and cloud solutions, though some remain in the early stages of adoption.

- *How did the implementation of Industry 4.0 technologies affect employee morale and job satisfaction in your organization?*

The implementation of Industry 4.0 technologies has shown a mixed impact on employee morale and job satisfaction, varying by sector and firm size. Many respondents highlight positive effects, such as reduced repetitive tasks and improved efficiency, allowing employees to concentrate on more meaningful work. However, challenges like job displacement, increased workloads, and adaptation difficulties negatively impact morale for some employees.

In manufacturing, automation improves job satisfaction by streamlining tasks, though job losses in certain roles raise concerns. Technology firms report predominantly positive responses, with teams such as R&D benefiting from increased efficiency and support. In logistics, some employees feel empowered by automation, while others experience short-term stress during the adaptation phase. Similarly, service firms achieve better workload management but also face transitional challenges.

The effects also vary by firm size. Larger firms generally report higher satisfaction levels, as their structured training programs and resources facilitate smoother transitions. However, even large firms encounter adaptation-related stress in some areas, particularly where roles are automated. Medium-sized firms show a balance of positive and negative impacts, with temporary dissatisfaction linked to increased workloads during the transition. Smaller firms report more pronounced concerns about job security and adaptation challenges, reflecting their limited resources for workforce support.

- *How did your organization address the need for skill development for employees to adapt to Industry 4.0 technologies?*

Many organizations address skill development through training programs and upskilling initiatives, utilizing both internal and external resources. Adaptive learning platforms and regular workshops are frequently mentioned, with customized training tailored to departmental needs. Manufacturing focuses on internal programs and external consultants, while technology firms emphasize continuous learning through online platforms. Logistics combines external consultants and periodic training sessions, and service firms prioritize sector-specific training and informational sessions.

Most companies actively work to bridge skill gaps, though some are still in the early stages of implementation. Larger firms implement structured programs with specialized teams and external consultants, ensuring that employees are well-equipped for technological shifts. Medium-sized firms rely on regular workshops and sector-specific training but face ongoing challenges in expanding their efforts. Smaller firms often manage in-house training but struggle with limited resources, leaving some without formal programs.

- *Do you have any other comments or opinions on the effects of Industry 4.0 technologies on social sustainability?*

Respondents generally convey a predominantly positive outlook regarding the social sustainability impacts of Industry 4.0 technologies. Automation and robotics are frequently acknowledged for reducing repetitive and hazardous tasks, leading to safer work environments and improved operational efficiency. In logistics, automation enhances safety by minimizing human involvement in dangerous tasks, while manufacturing respondents emphasize its role in optimizing production processes and

critical role in shaping the adoption and social outcomes of Industry 4.0 technologies, necessitating further investigation.

Second, while this study highlights firm size and sector-based differences, it does not fully account for the unique challenges faced by small firms with limited resources or specific industries. Sector-specific studies could delve deeper into the distinct adoption patterns, barriers, opportunities, and social impacts of Industry 4.0 technologies within industries, offering tailored recommendations for these contexts.

Finally, while the open-ended survey responses complement and enrich the quantitative findings, they also highlight areas that require further exploration, such as employee well-being, skill development, and the long-term effectiveness of training programs. These insights reveal dimensions that were not fully captured or emphasized in the statistical analysis. Future research could employ mixed-method approaches to provide a more inclusive understanding, combining in-depth qualitative studies with large-scale quantitative analyses to explore these dimensions comprehensively.

20.7 Conclusion

This study investigates the social sustainability impacts of Industry 4.0 technologies, using SEM complemented by qualitative insights derived from open-ended survey responses. It explores both positive and negative effects at micro- and macrolevels, offering critical perspectives on how these technologies influence individuals, organizations, and society. The findings also shed light on adoption patterns across different firm sizes and sectors.

The findings indicate that Industry 4.0 technologies make significant positive contributions to social sustainability, while their negative effects remain statistically insignificant. This observation aligns with qualitative feedback from survey participants, who largely conveyed positive perceptions. Key benefits include strengthening collaboration between countries and companies to foster business relationships and share technologies, creating smart work environments, improving quality of life through innovative products, enhancing data security, and emphasizing advanced vocational training methods to keep pace with technological advancements.

While the negative impacts are not statistically significant, certain challenges merit thoughtful consideration. These include potential disparities arising from digital skill gaps, uneven regional development, biases in AI decision-making, employee adaptation struggles, and work disruptions due to inadequate skills. Addressing these areas through targeted training initiatives, equitable access to technology, and ethical AI practices can ensure that the benefits of Industry 4.0 are maximized, while potential drawbacks are effectively mitigated.

The analysis also highlights the significant influence of firm size and sectoral needs on Industry 4.0 adoption. Larger firms with higher revenue tend to lead in integrating advanced systems due to their robust resources and infrastructure. In contrast, smaller firms often focus on accessible technologies such as IoT and AR/VR, aligning with cost-effective and scalable solutions. Sectoral differences further shape technology adoption, with

each sector prioritizing tools tailored to its specific demands. For instance, the technology and innovation sector emphasize IoT, big data and analytics, AI, and cloud computing, while AR/VR sees its highest adoption in retail and consumer services. Manufacturing and retail sectors lead in blockchain adoption, whereas the finance and energy sector prioritizes cybersecurity and high-speed infrastructure. These findings underline the importance of customizing Industry 4.0 strategies to the unique capacities and needs of different firms and industries.

Survey responses enrich the analysis by providing practical insights into the implementation strategies, workforce impacts, and skill development efforts across different sectors. Notably, the emphasis on training and workforce support, highlighted both in quantitative findings and the word cloud analysis, reinforces the critical importance of upskilling initiatives in ensuring the successful integration of Industry 4.0 technologies.

Furthermore, this study provides actionable insights for stakeholders, including managers, organizations, and policymakers, highlighting the social benefits and adoption dynamics of Industry 4.0 technologies. By addressing identified challenges and leveraging sector-specific opportunities, stakeholders can design inclusive strategies that maximize the societal and organizational benefits of these transformative technologies.

In conclusion, Industry 4.0 technologies hold immense potential to transform industries and enhance social sustainability. However, realizing these benefits requires a balanced approach that addresses key challenges like digital skill gaps, uneven regional development, and employee adaptation struggles. By prioritizing targeted training programs, promoting equitable access to technology, and implementing ethical AI practices, stakeholders can ensure that Industry 4.0 technologies deliver widespread societal benefits while minimizing potential drawbacks. This collective effort will help cultivate a more equitable and sustainable future, maximizing the potential of these innovations for all.

AI disclosure

During the preparation of this work, the author(s) used ChatGPT 4o to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Appendix A

Measurement items used in the questionnaire.

Constructs	Measurement items
Implementation of Industry 4.0 technologies (TECH)	<i>To what extent have the following Industry 4.0 technologies been implemented in your organization?</i> Internet of Things (TECH1) Big data and analytics (TECH2) Artificial intelligence (TECH3) Robotics (TECH4) Augmented reality/virtual reality (TECH5) Cybersecurity (TECH6) Cloud computing (TECH7) Additive manufacturing (3D Printing) (TECH8) Blockchain (TECH9) High-speed infrastructure (TECH10) Cyber-physical systems (TECH11) <i>How many years have Industry 4.0 technologies been used in your organization?</i> (TECHYEAR) Not yet used 0–1 2–3 4–5 6–10 10+
Positive social effects on a micro-scale (PMI)	New job opportunities arise due to technological advancements (PMI1) Employee safety and welfare increase due to automation and monitoring tools (PMI2) Data security increases due to innovative input/output devices (PMI3) Operational efficiency increases due to advanced technologies (PMI4) A smart work environment is created due to advanced technologies (PMI5) Innovative vocational training methods gain importance to keep up with technological advancements (PMI6) Innovative products that improve the quality of life can be produced due to advanced technologies (PMI7)

Negative social effects on a micro-scale (NMI)	A better work–life balance is offered to employees due to advanced technologies (PMI8)
	Fair wage evaluations are made due to monitoring tools (PMI9)
	Employee integration, communication, and participation become more effective due to advanced technologies (PMI10)
	Work disruptions occur due to employees lagging behind Industry 4.0 skill requirements (NMI1)
	Job losses occur for low-skilled labor due to automation and high-skill jobs (NMI2)
	Current employee skills are generally insufficient for high-skill jobs in an Industry 4.0 environment (NMI3)
	Working hours extend due to flexible working conditions and an increase in the number of jobs, negatively affecting employee health (NMI4)
	Monitoring tools negatively impact employee privacy (NMI5)
	Technological advancements cause job security concerns among employees (NMI6)
	Employees have difficulty adapting to technological advancements (NMI7)
Positive social effects on a macro-scale (PMA)	Employers expect more work from employees (NMI8)
	Remote work opportunities help develop less developed regions by creating employment (PMA1)
	Remote work opportunities reduce population density in urban areas (PMA2)
	Collaboration between countries increases to develop business relationships and share technologies (PMA3)
	Collaboration between companies increases to develop business relationships and share technologies (PMA4)
	Managers adopt a more socially responsible approach when making decisions (PMA5)
Negative social effects on a macro-scale (NMA)	Risks to society decrease due to advanced technologies (PMA6)
	Technology adoption and sectoral differences lead to uneven development between regions (NMA1)
	Income disparities arise between different job types based on digital skill requirements (NMA2)
	Lack of digital skills among employees reduces the effectiveness of Industry 4.0 technologies (NMA3)
	Lack of digital skills leads to social exclusion (e.g., inability to benefit from online public services or banking transactions) (NMA4)
	The use of artificial intelligence in decision-making processes leads to biased decisions (NMA5)
	Politicians slow down the transition to these technologies due to fears of negative social impacts (NMA6)

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Policy pathways to incentivize Industry 4.0 technology adoption

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21.1 Introduction

The Fourth Industrial Revolution, commonly referred to as Industry 4.0/Industrie 4.0 and/Industrial Internet of Things (IIoT), marks a significant evolution from the third industrial revolution that focused on automation. While the definitions are equivocal, Industry 4.0 is characterized by the integration of cyber-physical systems into manufacturing processes, facilitated by the Internet of Things (IoT) with the emergence of cutting-edge technologies such as 3D printing, artificial intelligence (AI), advanced robotics, autonomous systems, and big data analytics.

Despite the gradual and slow adoption of Industry 4.0 technologies, particularly among small- and medium-sized enterprises (SMEs), the European Commission has announced the next evolution, the Fifth Industrial Revolution (Industry 5.0). Industry 5.0 is a transition from the perceived technology-centric approach of Industry 4.0 to a value-driven model, focusing on social and environmental objectives. The European Union defines Industry 5.0 as an initiative that 'provides a vision of an industry that aims beyond efficiency and productivity as the sole goals and reinforces the role and the contribution of industry to society. Despite the conception of newer versions, the benefits of Industry 4.0 technologies are yet to be fully realised by firms, especially SMEs (Li et al., 2019).

Extant research on Industry 4.0 primarily focused on firm-level studies, particularly on the antecedents of technology adoption intentions, the benefits, and the role of Industry 4.0 technologies in performance improvement (Annarelli et al., 2021; Hopkins, 2021; Lee & Lim, 2021; Nakandala et al., 2023; Suleiman et al., 2022). However, there have been limited studies from a policy perspective regarding the enabling, promoting, and nurturing of Industry 4.0 technology adoptions through policy instruments. Hence, this chapter investigates the benefits and challenges of Industry 4.0 technology adoption and presents a capability framework for developing policy design principles. It adopts the neo-Schumpeterian perspective and discusses the utility of both demand-side and supply-side policy

instruments (OECD, 2022a) and develops a number of policy design principles to respond to barriers and capability deficits of SMEs in advanced technology adoption.

The chapter is organized as follows. The next section discusses the benefits of Industry 4.0 technologies, followed by the gaps in technology adoption levels among firms. Then, the barriers to Industry 4.0 technology adoption and capability challenges faced by SMEs are analyzed, identifying the theoretical frameworks of TAM (Davis et al., 1989) and DOI (Rogers et al., 2014). The policy interventions for Industry 4.0 technology adoption are then discussed, leading to the development of policy design principles. Finally, the chapter concludes with limitations and suggestions for future research.

21.2 Benefits of Industry 4.0 technologies

Industry 4.0 technologies offer various benefits to firms, including enhanced operations efficiency, supply chain and operations resilience, and sustainable business practices contributing to the competitive performance and competitive advantage of firms (Kamble et al., 2019; Nakandala et al., 2023). Through the use of Industry 4.0 technologies such as cyber-physical systems, IoT, M2M, robots, and VR/AR, firms are able to exchange data in real time across machines, equipment, products, supply chain actors, and customers to implement intelligent and autonomous manufacturing systems.

The integration of advanced technologies enables mass product customisation, predictive maintenance of machinery and systems, real-time monitoring of operations for increased productivity with minimum plant downtime, and data-driven decision-making, impacting various organizational functions such as manufacturing, marketing, supply chain management, and risk management. The capabilities of Industry 4.0 technologies include real-time responses, process optimisations, proactive maintenance, and thereby enhancing efficiency, agility, resilience, and reliability (Lee & Lim, 2021; Suleiman et al., 2022). Consequently, firms are enabled to meet dynamic market demands more effectively. Moreover, these technologies play a crucial role in promoting circular economy practices, monitoring product life cycles, and optimizing natural resource utilization to improve sustainability performance (Ralston & Blackhurst, 2020; Turner et al., 2013). Hence, these capabilities through Industry 4.0 technologies to yield a competitive edge are significant (Illa & Padhi, 2018).

In manufacturing, the integration of technologies such as robotics, autonomous mobile robots, infrared technology, machine-to-machine communication, and the IIoT has revolutionised operations. The deployment of autonomous guided vehicles (AGVs) and IIoT has led to automated, lean manufacturing processes (Vlachos et al., 2023). Beyond increases in productivity, technology-driven worker well-being, resilience, and sustainability benefits are being realised by firms.

Industry 4.0 technologies are instrumental in responding to challenges confronted by manufacturing organizations, such as the mass personalization of products, making decisions in real-time, as well as monitoring uncertainty around the demand and supply (Oztemel & Gursev, 2020). These technologies also improve sustainability performance by boosting operational efficiency, responsiveness, traceability, and capacity utilization in

addition to reducing costs (Tortorella et al., 2019). This is because Industry 4.0 technologies facilitate data transparency, which reduces errors in product deliveries in distribution and supply orders and enhances environmental performance by eliminating losses and wastages (Chauhan et al., 2021). Moreover, Industry 4.0 is anticipated to extend beyond organizations to unlock the potential of interconnected processes at the industry level (Kiel et al., 2017).

Industry 4.0 implementations involve virtual applications, decentralized systems, real-time capabilities, modular production, service orientation, empowering technologies, and system interoperability (Ghobakhloo et al., 2021). These enhance an organization's operations and performance by improving the process, product, and business models (Tortorella & Fettermann, 2018). For example, IoT is used in decentralized value chain networks, allowing the full benefits to be realized through interconnections using smart information and digital technologies, where data collected from such digitalized systems are used for enhanced production capacity, real-time monitoring of operations, and efficiency improvements (Kerin & Pham, 2019).

The human-centric approach in Industry 5.0 has catalyzed the adoption of technologies that augment human capabilities in the workplace. For example, collaborative robotics (Cobots), wearable technologies, and augmented reality devices are being increasingly used to enhance worker safety, efficiency, and well-being (Papacharalampopoulos et al., 2023). Cobots are relatively more movable, lightweight, easy to program, and safe, as well as are likely to be less costly and usable in an environment with human worker interactions with industrial robots, and are more fitting to and popular with small to medium-scale operations.

The sustainability and resilience benefits of Industry 4.0 technologies are evident in various applications. For instance, 3D printing and IoT solutions contribute to material efficiency and waste reduction. AI and digital twins are employed for predictive analytics and scenario planning, enhancing operations and supply chain resilience (Tao et al., 2018). Empirical studies, such as Nakandala et al. (2023), that investigated Australian manufacturing firms, have validated the positive effects of Industry 4.0 technologies on operational and supply chain resilience.

21.3 Varying levels of technology adoption

Large firms lead industry 4.0 technology adoption relative to SMEs. A study by Buer et al. (2021) investigated 212 Norwegian firms and reported that the company size is a major determinant of digitalisation and IT competence levels. Large firms typically have a higher level of shop floor digitalisation with digital resources and IT infrastructure, as well as digital competences and learning opportunities for their employees. Their processes are more streamlined, and they possess capabilities that enable Industry 4.0 technology adoptions. For example, lean capabilities are known to be a strong enabler of Industry 4.0 technologies, where the majority of large firms have such capabilities well developed through long-term investments and continuous improvements (Raj & Jeyaraj, 2023).

SMEs approach Industry 4.0 technology adoption differently from large firms and the commercial benefit of their investment is uncertain for them. Large firms tend to have digital

infrastructure such as Enterprise Resource Planning systems that provide the technology capabilities for the adoption of cyber-physical systems and management systems such as lean management capacities that make their processes ready for the digitalisation process (Karadayi-Usta, 2019; Müller, 2019). While the leap of the process improvements and investments could be incremental for large firms, SMEs may find that to be significant relative to their small level of operations, even though technology prices are falling.

The process of value creation through Industry 4.0 technologies is multifaceted. Muller (2019) investigated the business model approaches of German SME manufacturers on how they capture the benefits of Industry 4.0 and report that the range of adoption levels from being a craft manufacturer to preliminary stage planner to Industry 4.0 user and then to full-scale adopters. They report that craft manufacturers do not expect their business models to be influenced by Industry 4.0, but have curiosity towards future business model innovations to envision value creation innovations in their production, to finally possess business model innovations through value creation, offer, and capture.

The disparity in the adoption of advanced technologies among manufacturing firms is known. A significant digital readiness gap exists between larger and smaller Australian firms, particularly in the context of Industry 4.0 supply chain technologies (Hopkins, 2021). This discrepancy underscores the challenges faced by smaller firms in embracing digital transformation. In their research study on Australian manufacturing firms, Nakandala et al. (2023) observed varying levels of the implementation of front-end manufacturing technologies among sample firms. Their findings indicate that mature technologies involving product and raw material identification and traceability, sensors, actuators, Programmable Logic Controllers (PLCs), and enterprise resource planning systems are the most widely adopted among the surveyed firms. Conversely, more sophisticated manufacturing front-end technologies, including AI for production planning, virtual commissioning, industrial robots, autonomous guided vehicles, and AI for predictive maintenance and automatic nonconformity identification, are less prevalent in the surveyed firms.

While the specific technological needs may vary depending on a firm's operational context, there is a general lag in the adoption of emerging, advanced technologies by firms. This lag presents a significant challenge for the industry, highlighting the need for policies and strategies that support and accelerate the digital transformation of manufacturing firms, particularly SMEs. Hence, the heterogeneity of Industry 4.0 technologies needs to be recognized, and the industry-specific technology requirements are important to be considered (Frank et al., 2019; Hopkins, 2021). Policy initiatives are essential to ensure a more inclusive and comprehensive adoption of Industry 4.0 technologies across the sector, thereby enhancing overall competitiveness and efficiency.

21.4 Barriers to technology adoption in small- and medium-sized enterprises

The slow adoption of its technologies can be associated with numerous challenges firms face in the implementation of Industry 4.0 technologies. A common understanding is that Industry 4.0 technologies involve high initial investment costs, making the lack of financial resources a significant barrier to advanced technology adoption (Raut et al., 2020) and this is

particularly concerning for SMEs, given their lack of affordability even when technology costs have been decreasing. Moreover, the limited access to credit for SMEs exacerbates the issue (Khanzode et al., 2021). The lack of economies of scale in production and small customer bases often leads SMEs to have low bargaining power with large technology suppliers, financially disadvantaging them (Malekifar et al., 2014).

The lack of management awareness of advanced technologies, their uses, and benefits is a significant issue hindering firms from their potential for digital transformation opportunities. The limited time is available for managers to explore technology options due to operational demands, and not all SME managers have digital technology awareness. As Nakandala et al. (2024) argued, all managers, not only IT and technology managers, are required to develop digital skills to lead the firm in their digital transformation efforts. The challenges with the limited availability of advanced technological skills in the workforce and the shortage of advanced education and training systems for technological capacity development cause difficulties in hiring qualified staff (Karadayi-Usta, 2019). Hence, there are significant concerns about the lack of skilled labor in technology and increasing concerns about data security (Müller, 2019). Further, the lack of advanced digital infrastructure hinders the adoption of Industry 4.0 technologies in organizations. The lack of readiness of existing operations and systems in terms of the presence of nonstandardised processes and systems at low levels of technology in SMEs creates compatibility issues and complexities in technology selection and implementation (Müller, 2019).

The lack of perseverance through concentrating on the result, not the process, and the patience that is required in digital transformation entails is another issue for Industry 4.0 in SMEs, given that they pursue short-term goals (Karadayi-Usta, 2019). The absence of management tools for making informed technology investment decisions or for creating technology roadmaps for the firm complicates the matter. Industry 4.0 success requires integrated approaches with the supply chain partners, where the lack of cooperation with supply chain partners and not having integrated knowledge management systems or standardization across partners becomes a challenge (Núñez-Merino et al., 2020).

Industry 4.0 technologies are characterized by a significant degree of heterogeneity, which in turn influences the diverse factors affecting their adoption. This diversity is replicated in the SME sector, where differences in their strategic goals, operations, technology levels, and resource availability, including in-house skills, are common. Despite this heterogeneity, extant research has reported shared barriers SMEs face in adopting advanced technologies (Fig. 21.1). These challenges are not novel but have persisted over time, impeding the technological advancement of SMEs.

21.5 Capabilities required for Industry 4.0 implementations

Firms are increasingly calling for a greater focus on the successful implementation of Industry 4.0 technologies and enabling organizational capabilities (Annarelli et al., 2021). Established organizational capabilities that function as formal routines to effectively utilize digital resources are important for realising the advantages of Industry 4.0 technology implementations (Li et al., 2019). Organizations that have resources and capabilities are

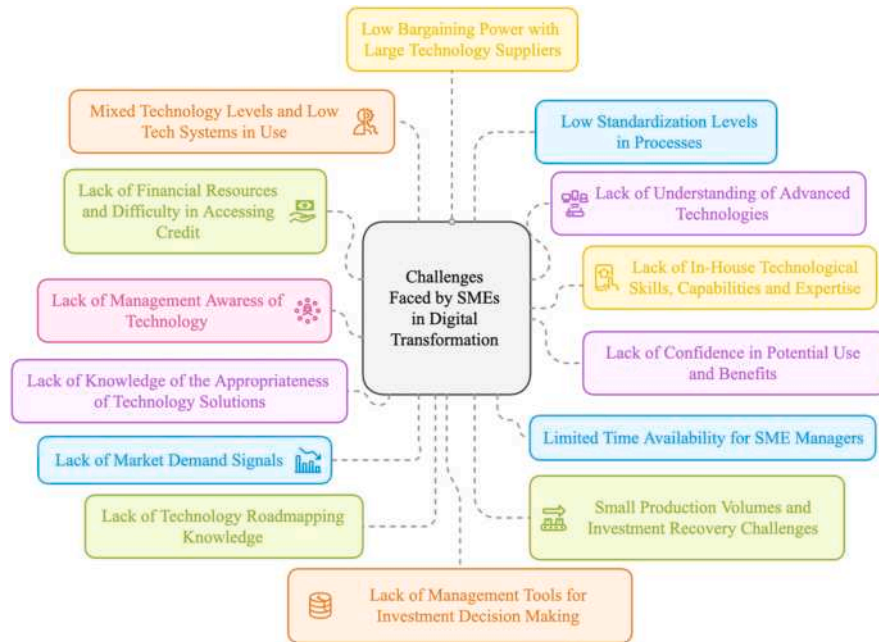


FIGURE 21.1 Common barriers encountered by small- and medium-sized enterprises (SMEs) in advanced technology adoption.

argued to be more successful in managing and gaining competitiveness from Industry 4.0. Hence, Industry 4.0 organizational capabilities are imperative prerequisites for organizations to ensure a sustained competitive advantage.

A critical issue identified in the technology management literature is the lack of absorptive capacity (AC) within SMEs to effectively integrate and leverage new technologies. AC is the ability to recognize the value, assimilate, and apply new knowledge and technologies (Cohen & Levinthal, 1990), whereas its reconceptualisation is two different capabilities of potential AC and realized AC. The potential AC of firms enables the acquisition of relevant external knowledge and assimilation through routing and processes, and the realized AC is the ability to combine new knowledge with existing knowledge through knowledge transformation and then utilize it through knowledge exploitation (Zahra & George, 2002).

Limited AC not only affects the immediate implementation of such technologies but also hinders the benefits that could be derived from technological acquisitions (Hashem, 2024). This challenge recognizes the need for targeted strategies and support mechanisms to respond to the capability constraints of SMEs, particularly in enhancing their capacity to acquire, assimilate, and utilize advanced technologies. A firm's prior knowledge is significantly important for its AC development, where those with R&D capabilities surpass others, disadvantaging SMEs (Afuah & Tucci, 2003).

Industry 4.0 technologies demand a higher level of capabilities and skills compared to conventional manufacturing. They require a reassessment of management capabilities,

organizational structures and leadership, strategic capabilities, stakeholder relationships, innovation capabilities and culture, internal processes and skills. From an organizational capability perspective, a unified framework of organizational capabilities is presented in Fig. 21.2. A range of capabilities, including technological, strategic, innovation, networking, cultural, leadership, financial, and people and skills, are identified with dominant subcapabilities.

21.6 Policy interventions for Industry 4.0 technology adoption

Technology upgrades of the domestic industry are a constant focus of policy, requiring mission-oriented industrial policies. Industrial policy is defined as the “interventions intended to improve structurally the performance of the domestic business sector” (OECD, 2022a, p 4). Targeted policies have been a center of discussion for a considerable time with concerns related to anticompetition effects and opportunity costs of public funds (OECD, 2022a). From the structuralist view, government policies and interventions are required for local industry development. Structuralists argue against neoliberalists on the imperfections of the free market-based approaches and find that the governments have a

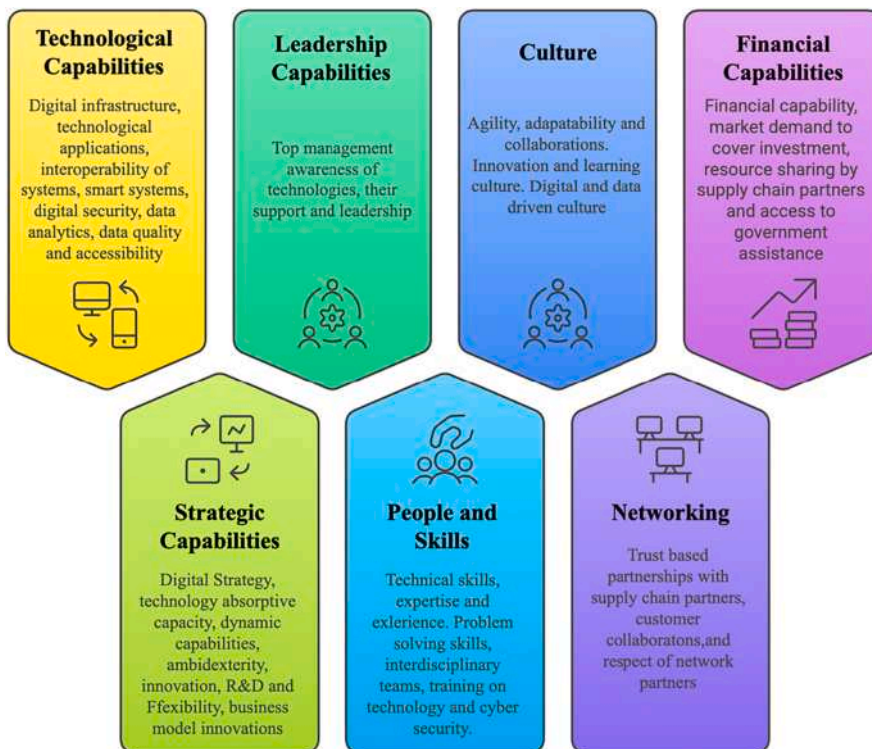


FIGURE 21.2 Unified capability framework for Industry 4.0 technology adoption.

significant role to play with institutions and policies to address market failures in industrial development (Lall, 2003).

Diverse industrial policies are requirement to address multidimensional performance measurements and heterogeneous capabilities of firms. Industrial policies can take various forms, such as those that provide R&D incentives, intellectual property protection, and skill development. The benefit realization by firms varies based on firm characteristics. For example, some argue that large firms are able to navigate the system, accept government subsidies without increasing economic activities (Criscuolo et al., 2019) and others have found evidence for young firms benefiting from innovation and R&D policies compared to mature firms (OECD, 2022b). Some industries, such as the manufacturing industry, primarily comprise SMEs, which require different policies addressing their inherent and specific characteristics, requirements, barriers, and capabilities.

National Innovation Systems research paves the way for recognizing geographical, sectoral, firm-level, and industrial differences from a system perspective. As Kim (1997) showed, the innovation and development paths for catching-up countries are different from those in developed economies. If we consider a local industry level, firms with different levels of technological capabilities and competitiveness coexist (Li et al., 2019; Nakandala et al., 2023). This heterogeneity should be integrated into policy designs. A lack of heterogeneous policies addressing their different requirements is not geared to create an environment conducive to technological upgrading of industries with both technologically advanced firms and those with lower technological capabilities (Nakandala et al., 2015). They propose a pluralistic approach catering to the differences in firm-level capabilities and technology requirements to achieve desired technological change through optimal utilization of existing resources.

From a neo-Schumpeterian perspective, two types of policy instruments have been proposed in recent times: (1) demand-pull instruments that improve firm-level performance and (2) supply-push instruments that affect industry dynamics (OECD, 2022b). Supply-push instruments affect domestic production, and demand-side instruments affect domestic consumption. These two types of policy instruments are complementary, and the mix needs to be carefully considered (ibid) as discussed next.

21.7 Demand-side policy instruments

Demand-side instruments are based on the rationale that creating demand for products (those produced utilizing advanced technologies) incentivises advanced technology adoption by firms. The lack of confidence in firms on their ability to capture commercial value created through their investments in technology arises from the uncertainties in the market behavior, where consumers may not be willing to absorb high prices, resulting in negative effects on firm competitiveness. In response to this issue, increasing consumer demand to incentivise upstream firms in a supply chain has been a commonly adopted approach. Good examples of the trickling effects of demand variation through policy interventions along the supply chain to foster economic activities of the supply end come from the electric vehicle and solar power industries. In the electric vehicle (EV) industry, governments offer rebates

and tax exemptions to consumers with the intention of fostering the EV industry (OECD, 2022b). Similarly, in the renewable energy industry, government rebates for households are designed to increase the use of solar energy (Borenstein, 2017).

These policy interventions are likely to be responded to differently by different firms. Those with advanced technological capabilities are required to invest a little compared to those that lag in technological development. Moreover, location specificity of effects cannot be controlled in the current global supply chain environments, where increased consumer demand in one country can foster manufacturers in another country (OECD, 2022b). There have been arguments on demand-side instruments in developed economies, saying that they incentivise manufacturers in developing economies, causing limited benefits to taxpayers in developed economies. These concerns have been evident in solar power rebates (ibid).

A place-based approach to demand instruments is a potential response to the above challenge, as demonstrated in public procurement innovations. Many governments have policies to prioritize purchasing goods and services from domestic, SMEs, and regional businesses. Given that governments are the largest purchasers in any country, the demand created for domestic SMEs can significantly support their development. For example, The New South Wales government of Australia has an innovative public procurement policy with different levels starting with the direct purchases from SMEs up to AU\$250,000, considering SMEs before other suppliers, up to AU\$3 million, and asking tenderers to include SMEs for purchases over AU\$3 million (New South Wales Government, 2021).

21.8 Supply-side policy instruments

Supply-side instruments can be categorised into two types encompassing those affecting (1) efficiencies, investment incentives, and access to inputs such as skills, knowledge, infrastructure, and utilities within firms or (2) complementary policies (competition, trade and investment policies, labor mobility, market functionality, and tax system) affecting industry dynamics. (OECD, 2022b). A few supply-push policy instruments are discussed next.

Vocational education and public school curriculum variations are common supply-push instruments that serve as complementary policy interventions that develop advanced technology skills and capabilities in the labor force. The limited availability of skilled labor in technology is a wide concern in the upgrading of technology industries (Karadayi-Usta, 2019). Education policies are generally not targeted strategies, and any industry or geography (depending on skill mobility) can benefit from the skill development effects. They have been widely adopted by many economies, including emerging economies. Singapore is historically a good example of a government's concerted efforts in upgrading skills over multiple decades. Australia has implemented the National STEM School Education Strategy 2016–26 (Australian Department of Education, 2025). The United States has STEM Education Policies (National Science and Technology Council, 2024) for promoting mathematical and digital literacy, problem-solving, critical analysis, and creative thinking skill development in students.

Adjusting the tax system to incentivise technology investments is a conventional approach in the form of a supply-side and within-firm instrument. The usefulness of tax rebates on technological innovation performance is empirically evident. Zhang and Song (2022) analyzed the effects of tax rebates on the innovation performance of Chinese mining firms and found empirical evidence for the positive effects of tax rebates. They argued that tax rebates provide an incentive effect rather than an antidriving effect on technological innovation. Another study by Yue et al. (2023) investigated Shanghai and Shenzhen A-share listed manufacturing firms during 2008–19 and found evidence for the positive effects of tax reduction on innovation, indicating an overall stimulating effect. The benefits of tax reductions are identified as supporting firms in reducing financing constraints in making technology investments.

Government interventions to stimulate university-industry partnerships through grants and subsidies and intellectual property measures are common. According to Zhang et al. (2022), the innovative city pilot policy, started in China in 2008, aimed to stimulate urban industry–university research collaborations and reported positive spillover effects in the forms of knowledge creation efficiency and knowledge transfer efficiency. In Australia, the Australian Research Council (ARC), the government-funded central research agency, promotes industry–university research collaborations through the ARC Linkage grant scheme and supports knowledge transfer through the ARC Training Centre grant scheme (<https://www.arc.gov.au/>). Such supply-push instruments stimulate knowledge creation and knowledge transfer for uplifting industry capabilities.

21.9 Policy design principles for enhancing Industry 4.0 adoption

The design of policy interventions for promoting, nurturing and driving Industry 4.0 technology adoption requires taking into account the barriers discussed in section 21.4 and the capability requirements shown in Fig. 21.2. Further, key theories such as Diffusion of Innovation (DOI) by Rogers et al. (2014) and the Technology Acceptance Model (TAM) by Davis et al. (1989) inform the development of policy design principles that are proposed next and shown in Fig. 21.3.

21.10 Employing a mix of policy instruments

Incorporating a blend of “supply-push” instruments, and “demand-pull” policy instruments and mission-oriented industry strategies are required to stimulate Industry 4.0 technology adoption. The mission here is to substantially increase the uptake of Industry 4.0 technologies for increased productivity, resilience, and sustainability. As Guerzoni and Raiteri (2015) argue, technology policies generate the highest impact when different policies interact. They reported evidence for the reinforcing effects of the interactions among different policies in the mix.

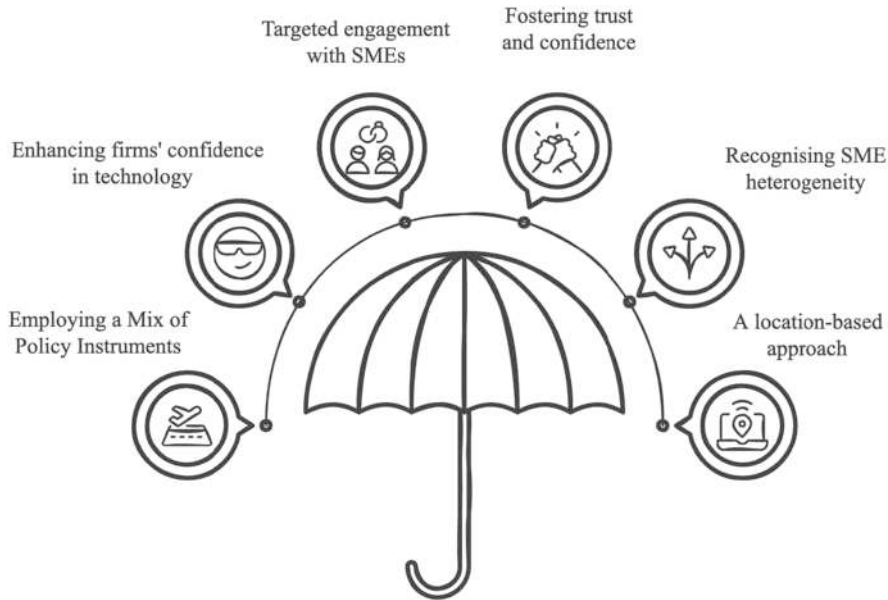


FIGURE 21.3 Policy design principles.

Following the discussion in Section 21.6, demand-side policy instruments such as innovative public procurement will create adequate demand for firms by creating a market for their technologically enhanced products. The assurance of larger demand reduces financial pressures on firms and uncertainties, and incentivises them toward investments in making technologically sophisticated products. Such demand-side instruments can reduce the financial pressures on SMEs in technology investments (Khanzode et al., 2021; Raut et al., 2020).

Tax credits and R&D subsidies are commonly used supply-side instruments to stimulate technology investments. They are widely used, and they primarily work to reduce the cost associated with technology adoption (Yue et al., 2023; Zhang & Song, 2022). However, Guerzoni and Raiteri (2015) argue that supply-side instruments are overestimated; a mix with innovative demand-side instruments can provide synergetic effects.

21.11 Enhancing firms' confidence in technology

A firm's technology adoption intentions are influenced by technology compatibility, usefulness, complexity, trialability, etc. (Davis et al., 1989; Rogers et al., 2014). Of those factors, the perceived usefulness of technology has been empirically confirmed to have significantly higher effects on the technology adoption intention of managers. Perceived usefulness is the extent to which a firm believes that using Industry 4.0 technologies improves its performance. For example, in an empirical study on Australian firms, managers' perceived usefulness was found to strongly influence their Industry 4.0 technology adoption

intentions (Nakandala et al., 2024). Further, perceived ease of use is described as a firm's belief that using a particular technology is effortless. Perceived compatibility of new technologies with the firm's existing technologies, structures, processes, and culture also influences technology adoption intentions. Raj and Jeyaraj (2023) established built-for-purpose technology centers for demonstrating advanced manufacturing technologies will support firms to develop confidence in selecting, implementing, using, and realizing benefits. Therefore, policy instruments leading to technology centers or facilities with relevant Industry 4.0 technologies that are available and accessible for firms is required.

21.12 Targeted engagement with small- and medium-sized enterprises

Recognizing that SMEs operate under time constraints and are constantly challenged by day-to-day operations demands, their reluctance to pursue digital transformation calls for closer engagement with SMEs in policy designs. The longer payback period of technology investments and SMEs' need for short-term financial performance for survival, compared to long-term goals, are known (Karadayi-Usta, 2019). A collaborative approach to policy design can help build the confidence of firms. In the policy delivery stage, it is important to offer supporting mechanisms to provide on-site assistance to SMEs. Such targeted support is meant to increase their participation in the policy implementation programs. Customized technology solutions through the understanding of the operational differences among firms need to be taken into account in policy designs. The effectiveness of policy implementation programs is higher when they closely engage with targeted firms in the policy design and delivery. An example of this approach can be in the LCR4.0 program in the Liverpool City Region, UK (<https://lcr4.uk/>).

21.13 Fostering trust and confidence

Trust and confidence in technology advisers is important for firms in their digital transformation attempts. According to industry insights (Sobel, 2020), building trust between firms and external parties involved in policy implementation is required and should be taken into account at the stage of designing policies. The involvement of neutral intermediaries between technology providers and firms is anticipated to build trust, thereby enhancing firm participation in policy implementation programs. The involvement of universities and other neutral knowledge partners in guiding firms in their digital strategy development, technology road mapping, and technology selections needs to be facilitated through policy designs.

21.14 Recognizing small- and medium-sized enterprise heterogeneity

The varying levels of technology use and technology levels in firms make the adoption of more sophisticated technologies challenging (Li et al., 2019). Many firms lack the

understanding of Industry 4.0 technologies and the benefits to their own operations, causing a bias toward avoiding digitalisation. For SMEs, the lack of standardization of operations and processes causes significant challenges in trying out off-the-shelf technology products in their operations (Müller, 2019). Given the heterogeneity among firms, codesign and cocreation of the technology centers with them will enable matching their operations requirements with technology solutions. For example, the difference in technology potential between large firms and SMEs is quite apparent when it comes to robots, where collaborative robots are more compatible with SME environments compared to industrial robots that require protected space and advanced skill sets for operation.

21.15 A location-based approach

Considering the locational concentration of economic activities and specialization in specific locations, location-based approaches can support upgrading their technology levels, addressing local economic and contextual conditions (OECD, 2022a). The benefits of such a concentrated approach also include resource efficiency and local technology ecosystem development. SMEs require networking opportunities with universities and other technology partners to develop both vertical and horizontal networks for their AC development (Nakandala et al., 2023). A location-based approach will enable knowledge transfer and spillover effects between universities and firms, as well as among firms colocated in a region.

21.16 Conclusion

The adoption of Industry 4.0 technologies presents significant benefits for firms, including increased efficiency, supply chain and operations resilience, and sustainability. However, despite these advantages, many firms, particularly SMEs, continue to lag in implementation due to a range of challenges, including financial constraints, management capability issues, lack of digital skills, and limited AC. This study has highlighted the critical barriers to Industry 4.0 adoption, and capability issues, recognizing the differences between large firms and SMEs in their digital transformations.

A key contribution of this study is its policy-driven approach, which addressed the limited existing research present in the Industry 4.0 adoption literature from a policy perspective. It considers both supply-side and demand-side policy instruments and proposes a set of actionable policy design principles aimed at boosting Industry 4.0 technology adoption by firms. These principles include employing a mix of policy instruments, targeted engagement with SMEs, fostering trust and confidence, recognizing the diverse needs of firms, and adopting a location-based approach. Firms are more likely to embrace Industry 4.0 technologies when they perceive benefits to their operations, have access to technology demonstration centers, and receive guidance from credible and neutral advisors. Additionally, tailored engagement strategies, including on-site support and

cocreation of technology solutions, are important responses to challenges encountered by SMEs.

Policy interventions are important, and their real effectiveness depends on careful design, execution, and ongoing evaluation, particularly the interactions among multiple policies in the mix. The heterogeneity among firms calls for an adaptive approach to policy that accommodates different capabilities and technology levels of firms. Future research should further explore mechanisms to measure policy effectiveness in the Industry 4.0 technology environment to develop further understanding of the policy approaches for sustainable digital transformation of firms.

AI disclosure

During the preparation of this work, the author(s) used Grammarly to refine the writing. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Barriers, best practices, and guidelines for implementation

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22.1 Introduction: challenges, opportunities, and solution approaches for digital transformation and sustainability implementation

The rise of Industry 4.0 and the sustainability practices within this domain have significantly transformed the manufacturing and service sectors. This digital transformation process provides businesses with numerous opportunities to optimize their operations, increase efficiency, and gain competitive advantages. However, this transformation also introduces various challenges. In this section, the barriers encountered during digital transformation processes will be defined, and best practices and guidelines to overcome these barriers will be provided. The role of digital applications and artificial intelligence (AI) in corporate sustainability, which forms the foundation of a sustainable future in the industry, is a critical part of this transformation. AI, data analytics, and other digital technologies are highlighted as essential tools for achieving sustainability goals. This introduction will provide readers with an overview of the challenges and solution approaches in the implementation process.

While the opportunities presented by Industry 4.0 enable businesses to conduct more efficient and sustainable operations, they also bring innovative solutions to environmental and social problems. Understanding the impact of digital transformation on sustainability and addressing the necessary strategies for managing this process successfully is of great importance for both academic research and industrial applications.

22.1.1 Concepts of Industry 4.0 and sustainability

Industry 4.0 is the fourth industrial revolution characterized by the integration of digital information and communication technologies (ICT) into the manufacturing and service sectors. This revolution is realized through the adoption of advanced technologies such as the Internet of Things (IoT), AI, big data analytics, cloud computing, cyber-physical systems, and smart factories. Industry 4.0 provides businesses with a competitive advantage by making production processes smarter, more efficient, and more flexible.

Internet of Things (IoT): IoT devices continuously collect data through sensors and transmit it to central systems, enabling real-time monitoring of operations. For example, IoT sensors on a production line can monitor machine performance and predict maintenance needs in advance.

Artificial Intelligence (AI): AI algorithms analyze large datasets, optimizing production processes. AI can be applied in a wide range of areas, from supply chain management to customer relations.

Big Data Analytics: Big data analytics helps businesses analyze the data they collect to improve decision-making processes. Data mining and machine learning techniques provide businesses with deep insights.

Cloud Computing: Cloud computing enables decentralized storage and processing of data. This offers flexibility and scalability, allowing businesses to respond quickly to changing demands.

Cyber-Physical Systems: Cyber-physical systems integrate physical processes with digital models, making production processes more precise and controllable.

For example, in a factory environment, IoT devices can collect real-time data from production machines, predict maintenance needs, and increase production continuity and efficiency by reducing downtime. Similarly, AI-based systems optimize production processes and maximize resource utilization. Big data analytics enables businesses to analyze production data and gain valuable insights to improve decision-making processes. Cloud computing provides flexibility and scalability by enabling decentralized storage and processing of data. Cyber-physical systems make it possible to integrate physical processes with digital models, making production processes more precise and controllable.

Sustainability is an approach that balances economic growth with environmental protection and social welfare. Sustainability includes goals such as preserving natural resources, reducing waste, increasing energy efficiency, and ensuring social equity. Corporate sustainability refers to businesses adopting these goals and expressing their long-term value creation strategies. Corporate sustainability strategies enhance businesses' environmental, social, and economic responsibilities while also increasing competitive advantage.

Sustainability encompasses environmental, social, and economic dimensions and requires the efficient and equitable use of resources for long-term well-being.

Environmental Sustainability: Focuses on conserving natural resources and minimizing environmental impacts. Key objectives include energy efficiency, waste management, and reducing the carbon footprint.

Social Sustainability: Aims to ensure societal well-being and social equity. It includes areas like workers' rights, occupational safety, and social responsibility projects.

Economic Sustainability: Aims for long-term financial sustainability for businesses. This is achieved through cost savings and operational efficiency.

Industry 4.0 technologies play a critical role in achieving sustainability goals in various ways, such as increasing energy efficiency, reducing waste, and optimizing resource use. For example, using smart sensors and data analytics to monitor and optimize energy consumption provides cost savings while reducing environmental impacts. IoT-based systems enable effective resource management across a wide range of areas, from energy consumption to water usage. AI and big data analytics can be used to monitor and analyze sustainability through key performance indicators (KPIs), helping businesses achieve their sustainability goals and evaluate progress toward those goals.

In this context, understanding the impact of digital transformation on sustainability is of great importance for both academic research and industrial applications. The technological innovations offered by Industry 4.0 not only increase production efficiency but also play a key role in achieving sustainability goals. Therefore digital transformation strategies need to be designed and implemented in alignment with sustainability principles. This integration allows businesses to maintain their competitive advantage while also achieving long-term sustainability goals.

In this new era, where sustainability and digital transformation are deeply intertwined, providing a comprehensive understanding of how businesses can use digital technologies to achieve their sustainability goals is the fundamental purpose of this chapter.

22.1.2 The impact of digital transformation on sustainability

Digital transformation plays a critical role in achieving sustainability goals by optimizing resource usage and increasing efficiency, thereby reducing environmental impacts (Beltrami et al., 2021; Lasi et al., 2014). For example, in a factory setting, IoT sensors can monitor energy consumption in real-time and automatically adjust systems to increase energy efficiency. These technologies lead to significant energy savings through real-time data collection and analysis (Atzori et al., 2010).

AI can contribute to environmental sustainability by reducing waste in production processes and enhancing supply chain management (Brynjolfsson & McAfee, 2014; Javaid et al., 2022). On a production line, AI algorithms can monitor machine performance and optimize maintenance schedules, reducing unnecessary energy consumption and waste production. Big data analytics enables businesses to track and analyze various sustainability indicators, such as energy and resource consumption, waste production, and environmental impacts (Manyika et al., 2011). These procedures help businesses make more informed decisions and optimize their sustainability strategies.

Digital technologies also contribute to social sustainability (Dyllick & Hockerts, 2002). Digital education and remote working opportunities increase social equity by providing access to more people (Means et al., 2014). Digital tools support equality in education by making learning materials accessible to a wider audience (Anderson, 2008). Remote working solutions help employees maintain a work-life balance and reduce workplace stress (Bloom et al., 2015). Additionally, digitalization can enhance workplace safety and employee satisfaction. For example, wearable technologies used for occupational safety can monitor workers' health and safety, helping prevent accidents (Chuah et al., 2016).

Moreover, digital transformation makes it easier for businesses to monitor and evaluate their sustainability performance. This enables them to implement sustainability strategies more effectively and analyze their outcomes. By leveraging these data, businesses can continuously improve their sustainability performance, fulfilling their environmental and social responsibilities.

The advantages offered by these technologies are not limited to environmental and social sustainability; they also contribute to economic sustainability. Digital transformation supports long-term financial sustainability by improving cost savings and operational efficiency. Big data analytics and AI provide insights that help boost efficiency. Digital technologies also give businesses a competitive edge. Technological innovations allow businesses to adapt quickly to market conditions and gain an advantage over competitors. In conclusion, digital transformation offers a comprehensive approach to achieving sustainable development goals and plays a critical role in shaping the sustainable future of both individual businesses and society.

22.1.3 Digital transformation and corporate sustainability strategies

Corporate sustainability strategies are closely integrated with digital transformation processes to drive long-term success (Bai et al., 2020). The use of digital technologies aligned with sustainability goals enables businesses to enhance their environmental and economic performance, providing a competitive edge.

Establishing a clear vision and mission for digital transformation and sustainability projects ensures organizational alignment (Hart & Milstein, 2003), with all members focused on shared goals (Kaplan & Norton, 1996). In pursuing these goals, organizations should identify short-term milestones that contribute to long-term objectives, using digital tools that enable phased project execution and increase success rates.

For example, digital transformation facilitates sustainability reporting by making environmental and social performance data more accessible and actionable (Ejsmont et al., 2020). Technologies like AI and big data analytics can track sustainability performance indicators as KPIs (Chen et al., 2014), helping businesses not only reach but continually assess their sustainability targets.

Digital transformation technologies—including AI, data analytics, IoT, and digital twins—each play a unique role in enhancing sustainability performance. For instance, big data analytics and AI enable real-time monitoring of metrics, optimizing resource use in areas like energy and waste management, which reduces both costs and environmental impact. Digital twin technology, by creating virtual replicas of physical assets, allows businesses to monitor and refine operations, identifying inefficiencies in real-time and driving continuous process improvement toward sustainability goals.

IoT devices and smart sensors provide continuous data feedback on metrics such as energy consumption, water use, and waste production, enabling companies to adjust and develop more sustainable operational strategies. Meanwhile, AI and big data have transformed corporate sustainability reporting. AI systems streamline compliance with sustainability standards by automating data collection and analysis, reducing manual effort while enhancing accuracy and speed. By continuously monitoring key indicators, AI also

enables businesses to focus on areas needing immediate action, forecast future performance, and support strategic planning and risk management.

Integrating digital transformation with sustainability strategies is crucial for long-term business success. Digital tools not only support environmental, social, and economic performance but also position businesses to meet sustainability goals while gaining a competitive advantage in the marketplace.

22.1.4 Barriers to implementation

The successful implementation of digital transformation and sustainability projects requires overcoming various barriers. These barriers can be technological, economic, organizational, and socio-cultural in nature. Each type of barrier presents different challenges and solutions on the path to achieving digital transformation and sustainability goals.

22.1.4.1 *Technological barriers*

The integration of digital transformation technologies often requires high initial costs. IoT sensors, cloud infrastructures, AI software, and other digital tools require significant investment (Armbrust et al., 2010; Furstenau et al., 2020). These costs can be a significant obstacle, especially for small- and medium-sized enterprises (SMEs), which may struggle to finance such investments due to their limited financial resources.

Integrating new technologies with existing systems can be complex. Making legacy systems compatible with IoT or AI-based new systems requires technical knowledge and skills. Data incompatibilities and integration errors are common issues in this process. Moreover, the rapid development and change of technological innovations make it difficult for businesses to stay up-to-date continuously. This situation necessitates ongoing training and updates, which also incur additional costs and time.

22.1.4.2 *Economic barriers*

Digital transformation and sustainability projects require substantial capital (Zhang et al., 2010). It can be particularly challenging for SMEs to secure this funding. The long payback period of these projects further complicates obtaining financial support. Investors and financial institutions generally expect high returns in the short term, while the benefits of digital transformation projects are usually seen in the long term.

The uncertainty of *Return On Investment* (ROI) can negatively impact businesses' decisions to invest in these projects. The ambiguity surrounding the returns of investments made in digital transformation projects can lead businesses to postpone or cancel these projects. Additionally, the risk of project failure makes businesses more cautious about engaging in digital transformation projects.

22.1.4.3 *Organizational barriers*

Organizations may resist change (Lee, 2008). This resistance can hinder the success of digital transformation and sustainability projects (Oláh et al., 2020). Employees might find it difficult to adapt to new technologies, necessitating training and skills development during

this process. Change management is key to successful digital transformation, but many organizations lack sufficient preparation in this area.

The lack of leadership can cause digital transformation projects to fail. If internal leaders do not support these projects or fail to provide the necessary vision, it could lead to project failures, since employees are often motivated by exemplary leadership. It is crucial for leaders to be knowledgeable about digital transformation and to motivate employees during this process. Without leadership support, the success of digital transformation projects is difficult to achieve.

22.1.4.4 Socio-cultural barriers

For global companies with diverse cultures, implementing digital transformation and sustainability projects can present challenges. Cultural differences such as collectivism may hinder the adoption of new technologies and sustainability practices. For instance, some cultures are more open to innovation, while others may be more conservative, which can affect the speed and effectiveness of digital transformation projects (Rajkumar et al., 2010).

The education and awareness levels of employees directly impact the success of digital transformation projects. A lack of adequate knowledge and awareness among employees regarding new technologies and sustainability can lead to project failures. Training programs and awareness campaigns play a critical role in overcoming these barriers. It is vital for businesses to involve their employees in the digital transformation process and provide the necessary training to ensure the success of these projects.

22.1.5 Best practices for overcoming barriers

Adopting best practices to overcome barriers in digital transformation and sustainability projects enables the successful and effective implementation of these initiatives. These practices range from strategic planning and employee engagement to technological investments and stakeholder collaborations.

22.1.5.1 Strategic planning and alignment

Successful digital transformation and sustainability projects begin with a clear vision and mission (Brundtland, 1987). Organizations should define their digital transformation and sustainability goals and how they intend to achieve these objectives. It is crucial that the entire organization understands and embraces this vision and mission (Enyoghasi & Badurdeen, 2021).

Identifying short-term gains to reach long-term goals is also essential. This approach ensures that projects are implemented in stages, increasing the likelihood of success. Achieving quick and tangible results in the initial stages boosts both the motivation of the project team and the support of top management. Short-term gains should align with long-term strategic goals and support the overall vision.

22.1.5.2 Employee engagement and training

Training programs should be organized to raise awareness and enhance the skills of employees regarding digital transformation and sustainability projects (Kumar et al., 2020).

Training programs should focus on the use of new technologies and sustainability principles. These programs not only increase the knowledge level of employees but also enable them to adapt more quickly and effectively to digital transformation processes (Schaltegger et al., 2016).

Employee participation and motivation in projects should be increased. This is crucial for the success of the projects. Employees' contributions to the projects should be encouraged, and their achievements should be rewarded. Open communication channels should be established to increase engagement, and employees' views and suggestions should be considered. This approach enhances employees' commitment to the projects and fosters the emergence of innovative ideas.

22.1.5.3 Technological investment and innovation

Before making large-scale investments, pilot projects and trials should be conducted. This approach can be used to test the effectiveness and feasibility of technologies. Pilot projects help minimize risks and allow for the successful implementation of technologies on a broader scale.

Organizations should foster a culture that encourages innovation. This culture supports employees in developing new ideas and integrating them into projects. An innovation-driven culture promotes continuous learning and development, contributing to the more efficient and effective execution of digital transformation processes. Additionally, open innovation platforms and collaborative projects can accelerate the development of innovative solutions.

22.1.5.4 Stakeholder collaboration and partnership

Collaborations between the public and private sectors can enhance the success of digital transformation and sustainability projects. These partnerships facilitate the sharing of resources and knowledge. Joint projects and initiatives leverage the strengths of both public and private sectors to develop more comprehensive and effective solutions.

Partnerships between academic institutions and industry can contribute to the development and implementation of innovative solutions. Collaborations between academia and industry support research and development activities and accelerate the practical application of new technologies. Such partnerships contribute to the more successful and effective execution of digital transformation and sustainability projects.

22.1.6 Guidelines and recommendations

The following steps and strategies are crucial for organizations adopting digital transformation and sustainability practices. These guidelines are essential for overcoming challenges encountered in the digital transformation process and achieving sustainability goals.

22.1.6.1 Planning and preparation process

Digital transformation and sustainability projects require robust strategic planning (Manyika et al., 2011; Sharma et al., 2021). During this process, it is important for

organizations to conduct a situation analysis and set clear objectives. Strategic plans provide roadmaps for achieving long-term goals and outline the necessary steps and resources to reach these objectives. Organizations should establish a clear vision and mission for the success of digital transformation and sustainability projects and communicate these goals throughout the entire organization (Feyzioğlu et al., 2023).

Digital transformation projects involve various risks. Therefore developing and implementing risk management strategies is critical. Identifying potential risks early and taking preventive measures to address them increases the likelihood of project success. Risk management should be an integral part of project planning and should be continuously reviewed and updated throughout the project lifecycle.

22.1.6.2 Project management approaches

Using agile methodologies in digital transformation projects enhances flexibility and speed (Mian et al., 2020; Chen et al., 2014). Agile methods allow project teams to adapt quickly and respond promptly to changing conditions. This approach helps manage projects more efficiently and effectively. Agile methods, with their short cycles and frequent feedback loops, enable dynamic project management.

The progress of projects should be regularly monitored and evaluated. This process is important to determine whether projects are moving in the right direction and to take corrective actions when necessary. Monitoring progress ensures that project goals are achieved and increases the success rate. Performance indicators should be established and reported at regular intervals to the project team and senior management.

22.1.6.3 Continuous improvement and adaptation

Continuous learning and feedback mechanisms should be established in digital transformation and sustainability projects (Elkington, 1998). These mechanisms ensure the continuous improvement and adaptation of projects. Feedback from employees and stakeholders is critical to the success of projects. Organizations can promote a culture of learning to develop innovative solutions and optimize implementation processes.

Projects need to be flexible and adaptable to respond quickly to changing conditions. Digital transformation projects should be continuously updated and improved in line with technological developments and market dynamics. Flexibility and adaptability guarantee the sustainability and long-term success of projects. Change management processes play an important role in this context, enhancing the adaptability of project teams.

22.1.6.4 Policy and regulatory considerations

Digital transformation and sustainability projects must comply with relevant regulations and standards (Dyllick & Hockerts, 2002). During this process, it is crucial to follow legal requirements and standards. Regulatory compliance ensures that projects are legally and ethically appropriate. Organizations should regularly review their compliance processes and make the necessary updates.

Public policies and incentives can enhance the success of digital transformation and sustainability projects. Government incentives and support programs facilitate project financing and accelerate the implementation process. Organizations can leverage these

incentives and support to execute their projects more effectively and achieve their sustainability goals.

22.2 Identifying implementation barriers

Identifying the barriers encountered during the implementation of digital transformation and sustainability projects is critical for ensuring their successful execution. In this section, barriers stemming from technological, financial, structural, cultural, legal, and regulatory aspects, as well as gaps in skills and capabilities, will be addressed.

22.2.1 Technological challenges

One of the most significant barriers encountered in the digital transformation process is technological challenges. *Infrastructure deficiencies, data integration issues, and cybersecurity concerns* make it difficult to adopt digital applications. Particularly, integrating new technologies with legacy systems requires substantial effort and costs. Upgrading or completely overhauling existing infrastructures can lead to significant expenses and technical challenges for businesses (Zhang et al., 2010).

Moreover, cybersecurity threats pose a significant risk in ensuring the safety of digital systems. Digital transformation projects necessitate the secure management and protection of data. **Cyber-attacks**, data breaches, and other security issues can threaten the integrity of digital systems and negatively impact project success. Developing and implementing robust cybersecurity strategies and measures are therefore essential (Armbrust et al., 2010).

Technological infrastructure investments are crucial for the successful adoption of digital transformation. Technologies like IoT and big data analytics require high-speed data processing capabilities and a reliable data storage infrastructure. Businesses lacking adequate infrastructure may find it challenging to adopt such technologies and risk losing their competitive edge (Chen et al., 2014).

Data security and cybersecurity remain at the forefront of technological challenges in digital transformation. IoT devices, in particular, are vulnerable to cyberattacks, presenting a significant risk for businesses. Such attacks can lead to data loss, system failures, and reputational damage. Thus enhancing cybersecurity strategies and improving data protection protocols is a must for organizations undergoing digital transformation (Beltrami et al., 2021).

Compatibility with legacy systems is another critical challenge. The integration of existing systems with new digital technologies can be complex due to technical knowledge gaps and incompatibilities (Furstenau et al., 2020). Issues such as data loss and system crashes during the integration process can lead to project failures, making it crucial for businesses to modernize their existing systems.

22.2.1.1 Recommended strategies

To overcome technological barriers, businesses are advised to adopt the following strategies:

- **Pilot projects and testing processes:** Before implementing on a large scale, conducting small-scale pilot projects can help identify potential issues and minimize risks associated with new technologies.
- **Cybersecurity measures:** Advanced security protocols and regular security audits should be implemented for IoT and other digital systems to enhance data protection.
- **Modernization of legacy systems:** Regular updates and, if necessary, complete overhauls of existing systems are essential to ensure compatibility with new technologies and to facilitate smoother digital transformation processes (Javaid et al., 2022).

22.2.2 Financial barriers

High initial costs pose a significant challenge for many organizations looking to invest in digital transformation projects. Transitioning to digital technologies often requires substantial investments, and the return on these investments may take a considerable amount of time to realize. The uncertainty surrounding the return on investment (ROI) for such projects can make them appear financially risky. This is particularly true for small- and medium-sized enterprises (SMEs), where these costs can be even more discouraging due to their limited financial resources (Zhang et al., 2010).

One of the major issues is the **long payback period** associated with digital transformation projects. Investors and financial institutions typically expect quick returns, while the benefits of digital transformation are often realized in the long term (Manyika et al., 2011). This discrepancy can make it difficult for businesses to secure the necessary funding, leading to delays or even cancellations of these projects.

Financial barriers not only limit the ability of companies to allocate resources to digital transformation but also reduce their overall interest in pursuing these initiatives. High costs and uncertain returns create hesitations among organizations, particularly SMEs, which often struggle with budget constraints (Bai et al., 2020). Therefore it is crucial to develop appropriate financing models and incentives that make these projects more financially sustainable.

22.2.2.1 Financing models and strategies

To overcome financial barriers, businesses should consider several strategies:

1. **Performance-based financing:** This model allows companies to pay based on the success of the digital transformation initiatives. By tying the cost of implementation to tangible outcomes, businesses can reduce upfront investments and financial risks (Brynjolfsson & McAfee, 2014).
2. **Government incentives and grants:** Many governments offer subsidies, tax breaks, and other forms of financial assistance to encourage businesses to adopt digital technologies. Leveraging these incentives can significantly reduce the financial burden on companies and make digital transformation projects more viable (Schaltegger et al., 2016).
3. **Cost-benefit analysis:** Conducting a detailed cost-benefit analysis helps organizations understand the potential financial returns and risks associated with digital transformation projects. This analysis aids in making informed decisions and justifying investments to stakeholders (Kaplan & Norton, 1996).

4. Public-private partnerships (PPPs): Collaborations between the public and private sectors can provide the necessary financial support and resources for large-scale digital transformation initiatives. Such partnerships can leverage both public funding and private sector expertise to drive innovation and sustainability (Hart & Milstein, 2003).

22.2.2.2 Managing financial risks

Effective management of financial risks is crucial to the success of digital transformation projects. Developing a comprehensive risk assessment strategy enables organizations to identify potential financial challenges early in the process and implement measures to mitigate them. This proactive approach helps businesses manage their resources more effectively and achieve their digital transformation goals while minimizing exposure to financial uncertainties (Ejsmont et al., 2020).

Risk identification and prioritization is a key step in managing financial risks. Organizations need to systematically identify all potential financial risks associated with their digital transformation initiatives, such as cost overruns, delays, and unexpected technological requirements. By prioritizing these risks based on their potential impact and likelihood, businesses can allocate resources and focus efforts on the most critical areas that may affect the project's financial viability (Bai et al., 2020).

Scenario analysis is another essential tool in financial risk management. Companies can create different financial scenarios, such as best case, worst case, and most likely scenarios, to understand how various factors could influence their digital transformation investments. This approach enables decision-makers to prepare for different outcomes and develop contingency plans, ensuring they are ready to act if the financial situation deviates from the expected path (Javaid et al., 2022).

Cost control and budget management are fundamental aspects of mitigating financial risks in digital transformation projects. Establishing a detailed budget and continuously monitoring expenses against this budget helps organizations track their financial performance and identify potential deviations early. This approach allows businesses to make adjustments before small issues escalate into significant financial problems. Moreover, implementing **agile project management methodologies** can help in maintaining flexibility and adaptability in budget allocations, responding promptly to changing requirements without compromising financial stability (Chen et al., 2014).

In addition, **investment in scalable technologies** plays a pivotal role in managing long-term financial risks. Investing in scalable digital solutions allows businesses to grow and adapt their technology infrastructure in line with their evolving needs without incurring excessive costs. Scalability helps reduce the risk of obsolete technologies and minimizes the need for frequent large-scale investments (Brynjolfsson & McAfee, 2014).

22.2.2.3 Leveraging financial strategies for sustainability

Financial strategies for supporting digital transformation should align with sustainability goals to ensure long-term success. **Circular economy principles** can be integrated into financial planning by prioritizing investments in technologies that promote resource efficiency and waste reduction. This approach not only helps in reducing operational costs but also enhances the sustainability of business practices (Schaltegger et al., 2016).

Sustainable finance and green bonds are becoming increasingly popular as a means of raising capital for digital transformation initiatives. These financial instruments are specifically designed to fund projects that deliver environmental and social benefits. By tapping into sustainable finance options, companies can secure lower-cost capital while also demonstrating their commitment to sustainability (Manyika et al., 2011).

Lastly, **digital ecosystem partnerships** can help distribute the financial risks associated with digital transformation. Collaborating with technology providers, financial institutions, and other stakeholders in a digital ecosystem allows businesses to share the costs and risks of technology adoption. These partnerships can also provide access to specialized expertise and resources that individual organizations might not possess, thereby reducing the overall financial burden (Kaplan & Norton, 1996)

22.2.3 Structural and cultural challenges

Organizational structure and culture can present significant barriers to digital transformation. Resistance to change among employees often slows down the transformation process. Digital transformation involves altering existing workflows and processes, which can create anxiety and resistance among employees. This resistance can significantly decrease the chances of success for transformation projects (Hamidianpour et al., 2016).

Organizational inertia is a common issue when implementing digital technologies. The reluctance to abandon established procedures and adopt new methods can hinder the integration of digital solutions. Additionally, the hierarchical structure in many organizations might slow down decision-making processes, leading to delays in digital initiatives (Uzule & Verina, 2023).

Communication and collaboration within the organization play a crucial role in the success of digital transformation projects. The lack of clear communication channels and insufficient coordination among departments can lead to misunderstandings, misalignment of objectives, and ultimately project failure (Menin, 2020). Improving internal communication, fostering a culture of collaboration, and promoting openness to new ideas are essential for overcoming these structural challenges.

Effective change management is key to addressing these barriers. Implementing change management strategies can help guide employees through the transformation process, reducing resistance and increasing engagement. Training programs, workshops, and continuous support play a significant role in helping employees adapt to new technologies and understand the benefits of digital transformation (Hamidianpour et al., 2016).

22.2.3.1 Recommended strategies

To overcome structural and cultural challenges, businesses are advised to adopt the following strategies:

- **Leadership and vision:** Strong leadership is essential in guiding the organization through digital transformation. Leaders should clearly communicate the vision and goals of the transformation, ensuring all team members understand the long-term benefits of adopting new technologies (Johnson-Cramer et al., 2007).

- **Employee engagement and involvement:** Engaging employees in the transformation process from the beginning can help reduce resistance. Involving them in decision-making and giving them a sense of ownership can motivate them to actively participate in the change (Hamidianpour et al., 2016).
- **Continuous training and development:** Providing continuous learning opportunities for employees helps them acquire the necessary skills to adapt to new technologies. Training programs should focus on enhancing both technical skills and change management capabilities (Menin, 2020).

22.2.4 Legal and regulatory barriers

Legal and regulatory barriers play a significant role in the adoption of digital technologies and sustainability practices. Regulatory compliance is often a complex process, particularly for multinational companies operating in different countries. Digital transformation projects must adhere to a variety of legal and regulatory requirements, which can create additional burdens for businesses (Dmitrik, 2020).

One of the primary challenges is the lack of clear standards and regulations related to digital technologies. This lack of standardized guidelines creates uncertainty, making it difficult for businesses to plan and execute digital transformation projects effectively (Haelterman, 2022). Inconsistent regulations across regions can result in companies facing different legal obligations, increasing the complexity and cost of compliance.

Data privacy and protection laws are critical aspects of regulatory compliance in digital transformation. As businesses collect and process vast amounts of data through digital platforms, they must ensure that they comply with data protection regulations such as the General Data Protection Regulation (GDPR) in Europe and the California Consumer Privacy Act (CCPA) in the United States. Noncompliance with these laws can lead to significant fines, legal actions, and reputational damage (Bamberger, 2010).

Cybersecurity regulations are also becoming increasingly stringent. Governments are implementing strict policies to protect critical infrastructure from cyber-attacks. These regulations often require companies to implement robust security measures, conduct regular risk assessments, and ensure that sensitive data is adequately protected (Chen et al., 2021). The cost and complexity of meeting these requirements can be a significant barrier for companies, especially small- and medium-sized enterprises (SMEs).

22.2.4.1 Recommended strategies

To navigate legal and regulatory barriers, businesses are advised to adopt the following strategies:

- **Engage with legal experts:** Companies should work closely with legal and regulatory experts to understand the specific requirements in their regions and industries. This approach helps ensure that digital transformation initiatives are fully compliant with existing laws and reduces the risk of legal issues (Dmitrik, 2020).
- **Implement a compliance framework:** Establishing a structured compliance framework can help businesses systematically address regulatory requirements. A comprehensive

framework should include regular audits, training for employees, and clear protocols for handling data and cybersecurity risks (Haelterman, 2022).

- **Advocate for standardization:** Companies can collaborate with industry bodies and policymakers to advocate for clearer and more standardized regulations. Such efforts can lead to the development of consistent guidelines that make it easier for businesses to comply across different regions (Bamberger, 2010).

22.2.5 Skills and Talent Shortage

The lack of skills and talent required for the successful implementation of digital transformation and sustainability projects poses a significant challenge. The absence of adequately qualified personnel with digital skills can negatively impact the progress and success of these projects. The rapid pace of advancements in digital technologies means that employees must continuously acquire new skills to keep up with these developments (Karaboğa et al., 2021).

The digital skills gap is a major barrier, particularly for small- and medium-sized enterprises (SMEs), which often lack the resources to attract and retain skilled professionals. Organizations that fail to invest in upskilling their workforce may find it difficult to adapt to new technologies, which can slow down or even halt their digital transformation efforts (Fahmy et al., 2022).

Continuous learning and development programs are essential to bridging this gap. Companies need to invest in training programs that focus on digital skills and competencies, such as data analytics, AI, and cybersecurity. These programs should be designed to enhance both technical and soft skills, empowering employees to adapt to changing roles and responsibilities in a digitally-driven environment (Sousa & Rocha, 2019).

Talent management strategies are also critical in addressing the skills shortage. Organizations must develop strategies to attract, develop, and retain talent with the skills necessary to drive digital transformation. This involves creating a culture that values continuous learning, providing career development opportunities, and offering competitive compensation packages to attract top talent (Čirčová & Blštáková, 2023).

22.2.5.1 Recommended strategies

To overcome the skills and talent shortage, businesses should consider implementing the following strategies:

- **Strategic partnerships with educational institutions:** Collaborating with universities and training institutions can help bridge the skills gap by developing customized training programs and internship opportunities for students in relevant fields. This approach ensures a steady pipeline of talent for future digital transformation projects (Karaboğa et al., 2021).
- **Upskilling and reskilling initiatives:** Investing in upskilling and reskilling initiatives helps current employees develop the competencies required for digital transformation. These initiatives should be aligned with the organization's strategic goals to maximize their impact on project success (Baral et al., 2022).

- **Creating a learning culture:** Fostering a culture of continuous learning encourages employees to take ownership of their professional development. Companies can implement mentorship programs, online learning platforms, and knowledge-sharing sessions to promote skill-building and knowledge transfer ([Lebedeva, 2019](#)).
- **Adopting agile workforce models:** An agile workforce model allows companies to adapt quickly to changing demands by utilizing a mix of full-time employees, freelancers, and contractors. This approach provides the flexibility to bring in specialized skills as needed without incurring long-term costs ([Nair, 2019](#)).

22.2.5.2 *Emphasizing diversity and inclusion*

Promoting diversity and inclusion within the workforce is another effective strategy for addressing skills shortages. Diverse teams bring a broader range of perspectives, ideas, and solutions to digital transformation challenges. Encouraging inclusivity not only strengthens the talent pool but also fosters innovation and creativity within the organization ([Karaboğa et al., 2021](#)). Creating a culture of diversity and inclusion has been shown to have a positive impact on problem-solving capabilities, team performance, and overall business innovation.

22.3 Overcoming implementation barriers: best practices

Adopting best practices to overcome barriers in digital transformation and sustainability projects ensures that these initiatives are implemented more effectively and successfully. This section will cover best practices in partnerships and collaborations, pilot projects and prototypes, training and skills development programs, innovative financing models, efficient use of existing resources, and transformation-oriented leadership and communication.

22.3.1 Partnerships and collaborations

Partnerships and collaborations are crucial for achieving success in digital transformation and sustainability projects. Collaborative efforts between academia, industry, and government can enhance knowledge sharing and resource allocation, thus supporting the overall success of projects. These partnerships allow for a broader knowledge base and the development of more effective solutions ([Rocha et al., 2021](#)).

For example, academic institutions can provide valuable research and development support, while industrial organizations contribute practical implementation skills. The synergy between these areas leads to innovative projects that have a higher likelihood of success ([Trencher et al., 2013](#)). Furthermore, international consortia can bring together expertise and experiences from different regions to create comprehensive solutions. By promoting global knowledge and resource sharing, these consortia enable projects to be executed more effectively and sustainably on a larger scale ([Macedo et al., 2020](#)).

Global collaborations in digital transformation and sustainability initiatives provide significant advantages in achieving common objectives. They encourage the integration of

diverse perspectives and the pooling of resources, leading to innovative strategies that address both local and international challenges (Larsson & Larsson, 2020).

22.3.1.1 Recommended strategies for effective partnerships

To enhance the impact of partnerships and collaborations, the following strategies can be implemented:

- **Stakeholder engagement:** Actively involve stakeholders from the early stages of the project to ensure that their interests and expectations are aligned with the project's goals. This approach fosters a sense of ownership and accountability among all parties involved (Rocha et al., 2021).
- **PPPs:** Collaborate with government entities to leverage funding opportunities, regulatory support, and public resources. These partnerships often lead to more robust project frameworks and greater scalability of solutions (Trencher et al., 2013).
- **Cross-sector collaboration:** Engage with partners from different sectors, such as technology firms, research institutions, and nongovernmental organizations (NGOs), to integrate diverse expertise and resources into the project (Macedo et al., 2020).
- **Transparent communication:** Maintain open and clear communication channels among all partners to ensure that information flows seamlessly. Transparency helps in building trust and facilitates better decision-making throughout the project lifecycle (Larsson & Larsson, 2020).

22.3.1.2 Benefits of international consortia

International consortia play a key role in the success of digital transformation and sustainability projects. These consortia gather global expertise, enabling organizations to leverage the collective knowledge and resources of different regions. This collaborative approach supports the development of innovative solutions that are not only efficient but also sustainable in the long term (Rocha et al., 2021).

International partnerships also allow for risk-sharing, where project challenges are distributed among the various stakeholders. This strategy reduces the financial burden on individual entities and increases the chances of overcoming technological and market-related obstacles (Trencher et al., 2013).

22.3.2 Pilot projects and prototypes

Small-scale trials and prototypes offer an effective way to mitigate the risks associated with large-scale digital transformation projects. Pilot projects are utilized to test the feasibility of new technologies and processes, identifying potential issues at an early stage. This approach allows organizations to refine and optimize projects before they are deployed on a broader scale, thereby increasing their chances of success (Barata et al., 2018).

Pilot projects are crucial in minimizing costs and risks by identifying weaknesses and areas for improvement before making a significant investment. By conducting these smaller-scale tests, companies can gain valuable insights into how new technologies perform in real-world scenarios, reducing the likelihood of costly errors during full-scale implementation (Tarasov, 2019).

Prototypes serve as a tangible way to test and validate new technologies and processes. They provide a hands-on evaluation of the project's potential performance, helping organizations understand the practical applications and limitations of their innovations (Qiang & Barukčić, 2021). By using prototypes, businesses can make necessary adjustments to ensure that the technology aligns with their strategic goals and operational needs.

22.3.2.1 Benefits of pilot projects and prototypes

Pilot projects and prototypes not only facilitate a smoother transition to large-scale implementation but also foster a culture of continuous improvement within the organization. They allow teams to iterate on solutions and refine processes based on real-time feedback, making the final deployment more robust and effective (Helmlinger, 2023).

These small-scale initiatives also enable organizations to be more agile and adaptable. In the rapidly evolving landscape of digital transformation, the ability to quickly pivot and make data-driven decisions is crucial. Pilot projects and prototypes give companies the flexibility to test different approaches and choose the one that best suits their needs, reducing the risk of failure (Guinan et al., 2019).

22.3.2.2 Recommended strategies for implementing pilot projects and prototypes

To maximize the impact of pilot projects and prototypes, organizations should consider the following strategies:

- **Set clear objectives:** Define clear goals and success criteria for each pilot project or prototype to ensure that the outcomes can be effectively measured and evaluated (Barata et al., 2018).
- **Involve key stakeholders:** Engage stakeholders early in the pilot process to gather diverse perspectives and gain their support. This involvement ensures that the pilot aligns with broader business objectives and secures buy-in from decision-makers (Qiang & Barukčić, 2021).
- **Iterate and optimize:** Use the insights gained from pilot projects to make iterative improvements. Continuously refining and enhancing the technology or process based on feedback will increase the likelihood of success in the final implementation (Helmlinger, 2023).
- **Scale with confidence:** Once a pilot project or prototype has proven successful, scale up gradually to full implementation, ensuring that each stage builds on the lessons learned from the previous phase (Tarasov, 2019).

22.3.2.3 Real-world application of pilot projects

In practice, companies across various industries have successfully used pilot projects to test new technologies before committing to full-scale rollouts. For example, manufacturing companies often deploy digital twins or IoT-based solutions on a small scale to monitor equipment performance and predict maintenance needs. This allows them to refine their strategies and reduce downtime without disrupting their entire production line (Barata et al., 2018).

Similarly, smart city initiatives often begin with pilot projects that focus on specific areas like traffic management or energy efficiency. These localized tests provide insights into how new technologies can be integrated into larger urban systems, paving the way for more extensive implementations that drive sustainable development (Guinan et al., 2019).

22.3.3 Training and talent development programs

The success of digital transformation heavily relies on the continuous development of employees' digital skills. Ongoing professional development and digital skills training enable employees to adapt more easily to new technologies, ultimately enhancing the project's success. These programs are designed to update employees' knowledge and skills, allowing them to integrate more quickly and effectively into digital transformation processes (Sousa & Rocha, 2019).

Investing in talent development programs not only contributes to the career growth of employees but also boosts their motivation. By empowering employees to actively participate in the digital transformation journey, these programs ensure that they have a vested interest in the success of these initiatives (Martínez-Morán et al., 2021). Well-structured training programs can significantly increase employees' engagement, making them more committed to the adoption and implementation of new technologies.

22.3.3.1 Benefits of continuous training and development

Continuous training and development programs play a critical role in bridging the skills gap that often hinders digital transformation projects. These initiatives help employees acquire the competencies needed to work with emerging technologies like AI, data analytics, and cybersecurity, fostering a more innovative and productive work environment (Barinova et al., 2019).

Additionally, organizations that prioritize training are better positioned to retain top talent. Providing opportunities for learning and growth creates a culture of continuous improvement, making the organization more attractive to skilled professionals. This focus on talent retention is essential for businesses that aim to maintain a competitive edge in the rapidly evolving digital landscape (Yang et al., 2023).

22.3.3.2 Recommended strategies for effective training programs

To maximize the impact of training and talent development, organizations should adopt the following strategies:

- **Customizable learning paths:** Create tailored training programs that address the specific needs of different departments and roles within the organization. This personalized approach ensures that each employee receives the relevant skills and knowledge necessary for their position (Zeng & Li, 2022).
- **Blended learning approaches:** Combine traditional face-to-face training with digital learning tools such as online courses, webinars, and interactive modules. This hybrid approach provides flexibility and allows employees to learn at their own pace, catering to various learning styles (Salveti & Bertagni, 2020).

- **Mentorship and coaching:** Establish mentorship programs where experienced employees guide and support their peers in learning new technologies and adapting to digital transformation. This peer-to-peer knowledge transfer accelerates the learning process and fosters a collaborative work culture (Guinan et al., 2019).
- **Continuous feedback and assessment:** Implement mechanisms to regularly assess the effectiveness of training programs. Continuous feedback from employees helps refine the training content and delivery methods, ensuring that they remain aligned with the evolving needs of the organization (Yang et al., 2023).

22.3.3.3 Promoting a culture of lifelong learning

Building a culture that encourages lifelong learning is essential for sustained growth in digital capabilities. Organizations should create an environment where employees are motivated to continuously enhance their skills, stay updated with technological advancements, and take ownership of their personal development. A commitment to lifelong learning not only improves individual performance but also drives the overall success of digital transformation initiatives (Barinova et al., 2019).

22.3.4 Innovative financing models

High initial costs are one of the major barriers to digital transformation projects. Innovative financing models such as performance-based financing and PPPs offer effective solutions to overcome these challenges. These models reduce the financial burden on businesses and help mitigate the risks associated with large-scale projects (Kim, 2015).

Performance-based financing is a model where repayment is directly tied to the success of the project. This approach allows businesses to implement digital transformation initiatives with reduced upfront costs, as payments are made based on the achievement of predefined outcomes. By aligning payments with project performance, this model not only minimizes financial risks but also encourages more responsible and results-driven project execution (Visconti & Morea, 2020).

PPPs play a crucial role in enhancing the financial sustainability of digital transformation projects. These partnerships combine the resources of the public sector with the expertise and capital of the private sector, making it possible to undertake larger, more comprehensive projects. PPPs are particularly effective in sectors where the benefits of digital transformation are shared between public entities and private companies, such as smart city initiatives or infrastructure projects (Sidorenko et al., 2019).

22.3.4.1 Benefits of innovative financing models

Innovative financing models are essential for ensuring the financial sustainability of digital transformation projects. By providing alternative funding mechanisms, these models allow businesses to pursue transformation initiatives without the need for substantial initial investments. This is particularly important for small- and medium-sized enterprises (SMEs), which often face challenges in securing financing for large-scale digital projects due to their limited financial resources (Kumar et al., 2020).

Additionally, performance-based financing and PPPs encourage a more collaborative and goal-oriented approach to project management. With performance-based models, the focus shifts from merely completing the project to achieving specific outcomes, which ultimately leads to higher levels of accountability and success (Visconti & Morea, 2020). Similarly, PPPs foster long-term partnerships between the public and private sectors, enabling both parties to share the risks and rewards of digital transformation efforts (Kim, 2015).

22.3.4.2 Recommended strategies for implementing innovative financing models

To effectively implement innovative financing models, businesses and governments should consider the following strategies:

- **Align financial incentives with project goals:** When using performance-based financing, it is crucial to establish clear, measurable project goals that align with the overall objectives of the digital transformation initiative. This ensures that payments are tied to tangible results, reducing financial risks for both the investor and the project sponsor (Sidorenko et al., 2019).
- **Leverage government support:** Governments can play a key role in facilitating access to financing for digital transformation projects by offering subsidies, tax breaks, and low-interest loans. These incentives can reduce the financial burden on companies, particularly SMEs, making it easier for them to embark on large-scale digital transformation efforts (Chen et al., 2021).
- **Develop a strong PPP framework:** For PPPs to be successful, it is essential to establish a well-defined framework that outlines the roles and responsibilities of both public and private entities. This framework should also include mechanisms for risk-sharing, performance monitoring, and dispute resolution to ensure that the partnership remains productive and sustainable (Kim, 2015).
- **Encourage financial innovation:** In addition to performance-based financing and PPPs, businesses should explore other innovative financing models such as crowdfunding, green bonds, and venture capital. These alternative funding sources can provide much-needed capital for digital transformation projects while also aligning with broader sustainability goals (Taylor et al., 2008).

22.3.4.3 Real-world applications of innovative financing

Several industries have successfully utilized innovative financing models to support digital transformation initiatives. For instance, smart city projects often rely on PPPs to fund the deployment of digital infrastructure, such as IoT-based traffic management systems and energy-efficient lighting solutions. These partnerships allow municipalities to leverage private sector expertise while minimizing public sector expenditure (Sidorenko et al., 2019).

Similarly, performance-based financing has been widely adopted in the healthcare sector, where companies invest in smart hospital technologies with the understanding that repayments will be made from the cost savings generated by the project. This model has proven effective in reducing operational costs while also driving financial sustainability (Visconti & Morea, 2020).

22.3.5 Efficient use of existing resources

Digital technologies enable businesses to make more efficient use of existing resources, which is a critical factor in achieving both cost savings and environmental sustainability. The integration of data analytics and IoT technologies significantly enhances resource optimization, helping companies reduce energy consumption and minimize waste production. This not only leads to financial savings but also contributes to reducing the environmental impact of business operations (Bibri, 2018).

For example, smart sensors and data analytics systems can monitor energy consumption in real-time, enabling businesses to adjust their operations for improved energy efficiency. By continuously optimizing energy use, companies can reduce their carbon footprint while cutting operational costs (Cao et al., 2023). Moreover, predictive analytics can identify inefficiencies in resource usage, allowing for more proactive management of resources and reducing wastage (Ruan et al., 2022).

22.3.5.1 Role of efficient resource use in sustainability

Efficient use of resources plays a critical role in achieving sustainability goals. By leveraging digital technologies, businesses can manage their resources more effectively, leading to improved sustainability performance. This not only supports the broader environmental objectives but also helps companies maintain a competitive edge by lowering costs and enhancing operational efficiency (Ji et al., 2023).

Furthermore, digital tools such as blockchain and AI-powered systems enable better tracking of resource use across the supply chain, providing transparency and accountability. These systems help companies identify areas where resources can be optimized, ensuring that waste is minimized, and resources are utilized to their full potential. For instance, predictive maintenance tools use IoT data to monitor equipment health, reducing the likelihood of breakdowns and improving overall resource utilization (Kristoffersen et al., 2021).

22.3.5.2 Recommended strategies for efficient resource use

To fully harness the benefits of digital technologies for resource optimization, organizations should consider the following strategies:

- **Adopt IoT and smart sensors:** Deploy IoT-enabled sensors to monitor resource usage in real-time. These data can be analyzed to make informed decisions about where to reduce consumption or improve efficiency (Bibri, 2018).
- **Leverage data analytics:** Use data analytics to identify patterns in resource use and predict future needs. This allows for more accurate planning and more efficient use of resources, reducing waste and costs (Cao et al., 2023).
- **Implement circular economy practices:** Incorporate digital solutions that support circular economy principles, such as reusing materials and reducing waste. Technologies like AI can help track resource flows and identify opportunities for recycling and repurposing materials, further improving sustainability (Kristoffersen et al., 2021).

- **Energy management systems:** Invest in digital energy management systems that continuously monitor and optimize energy usage. These systems can be integrated with renewable energy sources to further enhance efficiency and reduce reliance on nonrenewable resources (Ji et al., 2023).

22.3.5.3 Real-world application of resource efficiency

Many industries are already utilizing digital technologies to optimize resource use. In the manufacturing sector, for instance, companies use IoT-based systems to monitor the performance of machinery and manage energy consumption. By optimizing machine usage and reducing downtime, manufacturers can significantly cut their energy costs and improve productivity (Ruan et al., 2022).

Similarly, retail companies are using data analytics to track supply chain efficiency, helping to reduce inventory waste and improve resource allocation. These technologies enable businesses to better manage their supply chains, minimizing overproduction and ensuring that resources are used efficiently from procurement to end-of-life disposal (Ji et al., 2023).

22.3.6 Transformation-oriented leadership and communication

Leadership and communication play a crucial role in the success of digital transformation processes. Change leadership helps employees adapt to transformation more easily and ensures that the transformation process progresses smoothly. Strong leaders inspire digital transformation initiatives and motivate employees, making it easier to implement these projects effectively (Schwarzmüller et al., 2018).

Transformation-oriented leadership focuses on guiding the organization through the uncertainties and challenges that accompany digital transformation. These leaders create a vision for the transformation and communicate it clearly, ensuring that employees understand the purpose and benefits of the changes. A leader who embodies these qualities can drive engagement and foster a culture that embraces innovation and continuous improvement (Klein, 2020).

22.3.6.1 Role of communication in digital transformation

Transparent communication strategies are essential for ensuring that employees are fully engaged in the transformation process and have confidence in the projects. Open and effective communication helps employees stay informed about the progress of digital transformation initiatives and allows them to contribute their ideas and feedback (Abbu et al., 2022). This not only boosts morale but also leads to more collaborative efforts, improving the overall success of the transformation.

Effective communication also supports change management processes, which are critical for overcoming resistance to digital transformation. By fostering open dialogue and addressing concerns proactively, companies can ensure that employees are more receptive to changes, thereby reducing the friction that often accompanies major organizational shifts (Matsunaga, 2021).

22.3.6.2 Recommended strategies for leadership and communication

To maximize the impact of leadership and communication in digital transformation, organizations should implement the following strategies:

- **Develop a clear vision and communicate it consistently:** Leaders should articulate a clear vision for digital transformation, emphasizing the benefits and long-term goals. Consistent communication helps reinforce this vision, ensuring that all employees are aligned with the company's strategic objectives (Schwarzmüller et al., 2018).
- **Engage employees at all levels:** Include employees from all levels of the organization in the transformation process. By involving them early and often, leaders can foster a sense of ownership and commitment, making it easier to navigate the challenges of digital transformation (Klein, 2020).
- **Provide ongoing feedback:** Create channels for continuous feedback to keep employees informed about the progress of the transformation and address any concerns they may have. This fosters a culture of transparency and trust, which is crucial for long-term success (Matsunaga, 2021).
- **Training leaders in change management:** Equip leaders with the tools and knowledge they need to guide their teams through the complexities of digital transformation. This includes training in change management, communication strategies, and how to effectively support employees during the transition (Abbu et al., 2022).

22.3.6.3 Impact of leadership and communication on organizational performance

Strong leadership and effective communication not only contribute to the success of digital transformation projects but also improve the overall performance of the organization. By creating a culture of transparency, collaboration, and trust, leaders can help employees feel more connected to the company's mission, which in turn drives higher levels of engagement and productivity (Türk, 2023).

Organizations that prioritize open communication and strong leadership are better equipped to navigate the challenges of digital transformation. This ultimately leads to more successful project outcomes, increased employee satisfaction, and improved competitive advantage in the market (Larjovuori et al., 2018).

22.4 Guidelines and recommendations

This section outlines the key steps and strategies that organizations should follow to successfully adopt Industry 4.0 and sustainability practices. These guidelines are critical for overcoming challenges in the digital transformation process and achieving sustainability goals.

22.4.1 Planning and preparation process

Strategic planning is the cornerstone of successful digital transformation and sustainability projects. It involves a comprehensive analysis of the organization's current status, the

identification of long-term objectives, and the formulation of a detailed plan for achieving those goals. Strategic planning is not just about setting objectives; it provides a clear roadmap for the organization, outlining specific actions, resources, and timelines needed to meet the transformation goals (Stukalina, 2021). This approach ensures that all stakeholders are aligned with the organization's vision and objectives, fostering collaboration and focused efforts throughout the project lifecycle.

In digital transformation projects, **sustainability goals** must be integrated into strategic planning to ensure that the transformation contributes to long-term environmental and social objectives. This requires organizations to adopt a **holistic view** of their operations, considering not only financial performance but also the impact of their activities on the environment, society, and future generations (Schulte & Hallstedt, 2018). Companies that effectively incorporate sustainability into their strategic planning are better equipped to meet regulatory requirements, reduce operational risks, and enhance their brand reputation.

22.4.1.1 Key components of strategic planning

- **Current situation analysis (SWOT analysis):** Before embarking on any digital transformation initiative, organizations must conduct a thorough assessment of their current situation, including a **SWOT analysis** (strengths, weaknesses, opportunities, and threats). This analysis provides insights into the organization's internal capabilities and external opportunities, allowing them to craft a strategy that leverages their strengths while mitigating weaknesses (Dmitrieva & Shedko, 2023).
- **Goal setting and KPI development:** The next step in strategic planning is setting clear, measurable goals. Organizations should develop **Key Performance Indicators (KPIs)** that align with both short-term and long-term objectives. These KPIs serve as benchmarks for success, helping teams stay focused and measure progress throughout the project.
- **Resource allocation:** A critical component of strategic planning is determining how resources—financial, human, and technological—will be allocated. This ensures that projects have the necessary tools, talent, and capital to achieve their goals. Effective resource allocation is key to managing costs and optimizing outcomes, ensuring that resources are deployed where they can have the greatest impact (Schwarz Müller et al., 2018).
- **Stakeholder engagement:** Engaging stakeholders from the start is crucial to the success of digital transformation projects. This includes not only internal stakeholders such as employees and management but also external stakeholders like investors, suppliers, and customers. A well-planned stakeholder engagement strategy ensures that all parties are informed, aligned, and supportive of the transformation process (Larsson & Larsson, 2019).

22.4.1.2 Risk management

Digital transformation projects are inherently risky due to their complexity, scale, and the fast-changing nature of technology. **Risk management** is, therefore, a vital component of the planning process. By identifying potential risks early, organizations can develop mitigation strategies to avoid disruptions and ensure smooth project execution. Effective risk management involves:

- **Risk identification:** Organizations must first identify the risks that could affect their digital transformation projects, including **technological risks** such as system failures or cybersecurity threats, and **financial risks** like budget overruns or delayed ROI (Schulte & Hallstedt, 2018).
- **Risk mitigation strategies:** Once risks are identified, the next step is to develop **mitigation strategies**. For example, companies might invest in cybersecurity measures to reduce the risk of data breaches or implement contingency plans to address project delays (Vorontsova & Baranov, 2021).
- **Risk monitoring and control:** Risk management is not a one-time activity. It requires ongoing monitoring and control throughout the project's lifecycle. Organizations should implement **risk monitoring systems** that track potential risks in real-time, allowing teams to respond swiftly to any emerging issues (Achampong, 2010).

22.4.1.3 Benefits of strategic planning and risk management

- **Alignment with organizational goals:** By creating a clear roadmap, strategic planning ensures that all team members and stakeholders are working toward the same goals, increasing the likelihood of project success (Stukalina, 2021).
- **Proactive problem-solving:** Risk management helps organizations anticipate potential challenges and develop proactive solutions, reducing the likelihood of costly delays or failures (Schulte & Hallstedt, 2018).
- **Increased agility:** With a well-structured plan in place, organizations can adapt more easily to changes in the market, technology, or regulatory environment, ensuring that their digital transformation projects remain on track (Dmitrieva & Shedko, 2023).

22.4.1.4 Strategic planning and sustainability

For organizations pursuing both digital transformation and sustainability, the **integration of sustainability goals** into the strategic planning process is essential. This not only ensures compliance with regulations but also enables organizations to contribute positively to environmental and social outcomes. **Sustainability-driven strategic planning** emphasizes resource efficiency, waste reduction, and social responsibility, aligning the organization's goals with the broader global sustainability agenda (Schulte & Hallstedt, 2018).

22.4.1.5 Conclusion

In conclusion, a well-defined strategic plan and comprehensive risk management framework are essential for the successful execution of digital transformation and sustainability projects. By aligning resources, engaging stakeholders, and proactively managing risks, organizations can significantly increase their chances of achieving their long-term objectives.

22.4.2 Project management approaches

Effective project management is critical for the success of digital transformation and sustainability initiatives. Given the complexity and scale of such projects, organizations must adopt appropriate project management methodologies to ensure timely delivery, cost

control, and alignment with strategic goals. This section explores key project management approaches, such as agile methodologies and progress monitoring and control, both of which are instrumental in driving success in dynamic environments.

22.4.2.1 Agile methodologies

Agile methodologies have gained significant traction in managing digital transformation projects due to their flexibility, speed, and iterative approach. Unlike traditional waterfall project management, where each phase is completed before moving to the next, agile methodologies break projects into small, manageable increments or “sprints.” These short cycles allow teams to quickly adapt to new information, changing conditions, or stakeholder feedback, ensuring that the project remains aligned with business needs (Leong et al., 2023).

One of the core principles of agile methodologies is continuous feedback and collaboration. Teams work closely with stakeholders throughout the project, receiving regular input and making iterative improvements. This enhances the quality of the final product, reduces the likelihood of costly changes late in the project, and increases stakeholder satisfaction (Kose, 2021). Agile methodologies also emphasize cross-functional teams, where members from different departments collaborate closely, fostering innovation and breaking down silos that can impede progress.

22.4.2.2 Benefits of agile methodologies

- **Increased flexibility:** Agile methods enable teams to quickly adjust to changing project requirements, minimizing delays and maximizing responsiveness to market changes (Nerurkar & Das, 2017).
- **Higher efficiency:** By breaking projects into smaller, iterative cycles, teams can focus on delivering specific functionalities or improvements, reducing the risk of scope creep and ensuring steady progress (Lamacchia et al., 2020).
- **Enhanced collaboration:** Agile frameworks encourage ongoing communication between teams and stakeholders, facilitating problem-solving and ensuring alignment with organizational objectives (Schaltegger et al., 2016).
- **Improved risk management:** Agile methods allow for early identification of risks or issues and provide opportunities to address them before they impact the overall project timeline or budget (Alaidaros et al., 2018).

22.4.2.3 Implementing agile in digital transformation

To successfully implement agile methodologies in digital transformation and sustainability projects, organizations should:

- **Adopt a scalable agile framework:** Depending on the size of the organization or project, adopting scalable agile frameworks such as Scrum or Scaled Agile Framework (SAFe) can help ensure that agile principles are applied across teams and departments efficiently (Parveen, 2021).
- **Provide agile training and support:** Employees must understand agile principles and how to apply them effectively. Providing training on agile methodologies and tools

ensures that teams are equipped to operate within this dynamic environment (Alruwaili et al., 2019).

- **Encourage a culture of innovation:** Agile is not just a project management approach; it is a mindset. Creating a culture that encourages experimentation, collaboration, and continuous improvement is essential for successfully adopting agile methodologies (Kose, 2021).

22.4.2.4 Progress monitoring and control

Progress monitoring and control are essential components of project management. They ensure that projects stay on track, within scope, and on budget, while also achieving the intended objectives. Continuous monitoring provides project managers with real-time insights into project performance, allowing them to make data-driven decisions and adjust plans as needed (Lamacchia et al., 2020).

Monitoring progress involves tracking key milestones, timelines, and performance indicators (KPIs). By comparing actual progress against the project plan, project managers can identify deviations and take corrective actions. For digital transformation projects, where uncertainties are high and external conditions may change rapidly, regular monitoring is crucial for maintaining project momentum (Schaltegger et al., 2016).

22.4.2.5 Key elements of progress monitoring

- **Milestone tracking:** Tracking critical milestones helps ensure that major project deliverables are completed on time, reducing the risk of delays and budget overruns.
- **Budget control:** Regularly comparing actual spending against the budget helps organizations avoid overspending and make necessary adjustments (Chen et al., 2014).
- **Risk identification and response:** Effective monitoring includes tracking potential risks and implementing mitigation strategies to minimize disruptions. Agile methodologies also support ongoing risk assessment, as changes can be addressed iteratively (Alaidaros et al., 2018).

22.4.2.6 Tools for monitoring and controlling projects

Digital tools and software solutions play a critical role in progress monitoring and control. With the advent of project management platforms like Jira, Asana, and Trello, organizations can manage project timelines, allocate resources, and track deliverables with greater precision. These tools provide real-time dashboards, giving stakeholders access to up-to-date information on project status, which helps in maintaining transparency and accountability across all levels of the organization (Leong et al., 2023).

Another important tool is the balanced scorecard, which enables organizations to align business activities with strategic objectives. By using the scorecard to monitor KPIs, project managers can ensure that digital transformation projects are contributing to both operational goals and sustainability objectives (Kaplan & Norton, 1996).

22.4.2.7 *Benefits of effective monitoring and control*

- **Increased accountability:** Continuous monitoring keeps project teams accountable for meeting deadlines and staying within budget, leading to higher performance levels (Nerurkar & Das, 2017).
- **Proactive problem-solving:** Real-time data from monitoring tools enable project managers to identify issues early and implement solutions before they escalate (Javaid et al., 2022).
- **Transparency:** Sharing progress reports with stakeholders ensures that everyone remains informed and engaged, which improves collaboration and trust (Schaltegger et al., 2016).
- **Optimized resource use:** By regularly assessing resource allocation, organizations can ensure that resources are used efficiently, preventing bottlenecks and reducing waste [(Brynjolfsson & McAfee, 2014)].

22.4.2.8 *Conclusion*

Project management approaches such as agile methodologies and progress monitoring are critical for the successful execution of digital transformation and sustainability projects. Agile methods provide the flexibility and speed necessary to adapt to rapidly changing environments, while effective monitoring and control help ensure that projects are delivered on time, within scope, and on budget. By leveraging these project management techniques, organizations can improve their chances of achieving their transformation goals and enhancing their sustainability performance.

22.4.3 Evaluation and feedback mechanisms

Evaluation and feedback mechanisms are critical components of digital transformation and sustainability projects. They provide a systematic way to assess the effectiveness of initiatives, make necessary adjustments, and ensure that projects stay aligned with organizational goals. Establishing a solid framework for evaluation and feedback not only enhances the performance of current projects but also lays the foundation for continuous improvement.

22.4.3.1 *KPI tracking and analysis*

Key performance indicators (KPIs) play a vital role in measuring the success of sustainability and digital transformation projects. By defining specific KPIs, organizations can objectively track progress toward their goals. These indicators help in assessing how effectively resources are being used, the extent to which objectives are being met, and where there may be gaps in performance. Tracking KPIs provides several key benefits:

- **Objective measurement:** KPIs allow organizations to objectively measure project success, ensuring that decisions are based on data rather than intuition.
- **Resource optimization:** By analyzing KPIs, organizations can identify inefficiencies and optimize the use of resources, ultimately leading to cost savings.
- **Continuous monitoring:** Regular KPI tracking helps in detecting issues early, allowing for timely interventions and course corrections.

Advanced data analytics tools and **AI** can further enhance the process of KPI analysis. These technologies enable more sophisticated analysis, such as predictive modeling, which can forecast potential challenges and opportunities, thereby allowing organizations to take proactive measures.

22.4.3.2 Establishing effective KPI frameworks

To establish an effective KPI framework, organizations should:

- **Define relevant metrics:** Select KPIs that align with strategic objectives, such as energy efficiency, customer satisfaction, or operational efficiency.
- **Set realistic targets:** KPIs should have achievable targets that challenge the organization but remain realistic. Setting overly ambitious targets can lead to frustration and decreased motivation among team members.
- **Use technology for real-time tracking:** Leveraging digital tools for real-time tracking of KPIs ensures that the project team has the information they need to make data-driven decisions.

22.4.3.3 Continuous feedback loop

Creating a **continuous feedback loop** is crucial for fostering a culture of ongoing improvement. Feedback loops involve gathering input from various stakeholders, including employees, partners, and customers, throughout the project's lifecycle. This feedback provides valuable insights into what is working well and what requires adjustment, enabling teams to make informed decisions and drive successful outcomes. The benefits of a continuous feedback loop include:

- **Improved project adaptation:** Continuous feedback allows project teams to quickly adapt to changing conditions, improving overall project outcomes.
- **Increased employee engagement:** Regularly soliciting feedback from employees fosters a sense of ownership and involvement, motivating them to contribute positively to the project's success.
- **Identification of improvement areas:** Feedback helps in identifying areas of improvement that may not be immediately visible through KPI tracking alone.

22.4.3.4 Methods for collecting and analyzing feedback

- **Stakeholder surveys and interviews:** Conducting surveys and interviews with key stakeholders is an effective way to gather insights into the project's progress and identify potential areas for improvement.
- **Team retrospectives:** Retrospectives are regular meetings held by project teams to discuss what went well, what could be improved, and actionable steps for future improvements. These are especially common in **agile** environments.
- **Customer feedback mechanisms:** Involving customers and end-users in the feedback process ensures that the project meets their needs and expectations. This approach is especially important in sustainability projects, where stakeholder perceptions can have a significant impact on success.

22.4.3.5 Integration of feedback for improvement

The ultimate goal of evaluation and feedback mechanisms is to drive continuous improvement. Organizations must be prepared to **integrate the feedback** they receive into their processes and projects. This requires:

- **Agile adaptation:** Using an agile approach to incorporate feedback into the next phase of the project.
- **Transparent communication:** Ensuring that feedback is communicated clearly across the team so that everyone understands the reasons behind changes and supports their implementation.
- **Documenting lessons learned:** Documenting feedback and the lessons learned helps create a knowledge base that can be used to enhance future projects, reducing the likelihood of repeating mistakes and building on past successes.

22.4.3.6 Conclusion

In conclusion, evaluation and feedback mechanisms are essential for ensuring the success of digital transformation and sustainability projects. By tracking KPIs and establishing continuous feedback loops, organizations can achieve a high level of performance, make informed decisions, and foster a culture of continuous improvement. Effective evaluation and feedback processes not only help in achieving current project goals but also set the stage for sustained success in future initiatives.

22.4.4 Process improvement and flexibility

In the rapidly evolving landscape of digital transformation and sustainability, **continuous process improvement** and **organizational flexibility** are critical for maintaining a competitive advantage. Companies must be proactive in assessing and refining their processes to ensure that they remain efficient, scalable, and aligned with their strategic goals. By adopting a mindset of continuous improvement, organizations can respond effectively to market demands, technology shifts, and operational challenges.

22.4.4.1 Continuous improvement

Continuous improvement is a systematic approach to evaluating and enhancing business processes to achieve greater efficiency, productivity, and performance. In the context of digital transformation, continuous improvement focuses on optimizing workflows, reducing waste, and improving overall organizational performance. This approach is grounded in the principles of **lean management**, which emphasizes the elimination of nonvalue-added activities and the enhancement of value-creating processes. Key elements of continuous improvement include:

1. **Regular process reviews:** Organizations should conduct regular reviews of their key processes to identify inefficiencies and bottlenecks. These reviews help ensure that processes remain relevant and effective in light of evolving business needs.
2. **Employee involvement:** Engaging employees at all levels of the organization in the improvement process is essential. Employees often have valuable insights into day-to-day

operations and can suggest practical improvements that may not be immediately visible to management.

3. **Incremental changes:** Continuous improvement focuses on making small, incremental changes that, over time, lead to significant improvements in performance. This approach ensures that changes are manageable and sustainable, reducing the risk of disruption.

Lean and Six Sigma methodologies are commonly used frameworks for implementing continuous improvement initiatives. These frameworks emphasize data-driven decision-making, process optimization, and the elimination of inefficiencies, leading to measurable gains in productivity and quality (Kaplan & Norton, 1996).

22.4.4.2 Adaptability and flexibility

In addition to continuous improvement, **organizational flexibility** is crucial for navigating the uncertainties of digital transformation. As technology evolves and market conditions change, organizations must be able to adapt quickly to new opportunities and challenges. Flexibility allows businesses to pivot when necessary, whether that means adjusting product offerings, reconfiguring supply chains, or adopting new business models.

Adaptive strategies provide organizations with the tools to respond to external changes in a timely manner. These strategies involve being proactive in scanning the environment for emerging trends and threats and adjusting business operations accordingly. Flexibility also extends to resource management, where companies may need to reallocate capital, personnel, or technology to areas of greater strategic importance (Brynjolfsson & McAfee, 2014).

22.4.4.3 Benefits of continuous improvement and flexibility

1. **Enhanced efficiency:** By regularly refining processes, companies can reduce waste, streamline operations, and improve overall efficiency. This leads to cost savings and increased productivity, which are critical in highly competitive industries.
2. **Increased agility:** Flexibility allows companies to quickly adapt to changing market conditions, ensuring that they remain relevant and competitive. This adaptability is particularly important in industries undergoing rapid digital transformation, where the ability to pivot quickly can mean the difference between success and failure.
3. **Sustainability alignment:** Continuous improvement processes also support sustainability initiatives by identifying ways to reduce energy use, minimize waste, and optimize resource allocation. Organizations that embrace flexibility and continuous improvement are better positioned to meet sustainability goals and regulatory requirements (Hart & Milstein, 2003).

22.4.4.4 Strategies for achieving continuous improvement and flexibility

1. **Data-driven decision-making:** Leverage real-time data and analytics to drive decision-making. By continuously monitoring key metrics and performance indicators, organizations can identify areas for improvement and respond more quickly to emerging challenges.

2. **Agile project management:** Implement agile methodologies to maintain flexibility in project execution. Agile practices, such as iterative development and cross-functional teams, help organizations respond rapidly to changes and adjust project priorities as needed (Kaplan & Norton, 1996).
3. **Employee empowerment:** Foster a culture of continuous improvement by empowering employees to take ownership of their work and suggest improvements. Employee-driven innovation can lead to creative solutions and more effective problem-solving.
4. **Cross-functional collaboration:** Encourage collaboration across departments and business units to ensure that improvements are aligned with organizational goals. Cross-functional teams bring diverse perspectives and expertise, which can lead to more innovative and effective solutions (Schaltegger et al., 2016).

22.4.4.5 Conclusion

Process improvement and flexibility are essential components of successful digital transformation and sustainability initiatives. By embracing continuous improvement and fostering organizational adaptability, companies can maintain their competitive edge in an ever-changing business landscape. These strategies not only improve operational efficiency and responsiveness but also support long-term sustainability objectives.

22.5 Case studies: Successful implementation stories and examples

This chapter will provide an in-depth exploration of successful digital transformation and sustainability initiatives. By showcasing case studies from organizations of various sectors and scales, it aims to highlight the achievements and lessons learned in adopting sustainable practices. These examples will illustrate how different industries have effectively leveraged digital technologies to enhance operational efficiency, reduce environmental impact, and drive sustainable growth.

22.5.1 Case studies from industrial sectors

Large-scale manufacturers have achieved significant successes in digital transformation and sustainability initiatives. These achievements include developing smart factory applications, enhancing energy efficiency, reducing production waste, optimizing energy consumption, and significantly reducing carbon footprints. Such initiatives help companies meet their sustainability goals while also generating substantial cost savings.

22.5.1.1 Successful examples from large-scale manufacturers

22.5.1.1.1 Siemens' digital factories

Siemens has embraced Industry 4.0 technologies through its digital factories concept, leading to significant improvements in its manufacturing processes. By utilizing IoT and AI, Siemens has optimized energy consumption and minimized waste throughout its production lines. The use of digital twin technology—which creates virtual replicas of physical

products—has enabled the early detection of production errors, ultimately increasing energy efficiency. As a result, Siemens has managed to reduce energy consumption in its factories by 15%–20%, providing a model for resource-efficient and sustainable production practices (Siemens, 2023).

The digital twin concept has not only improved operational efficiency but also facilitated predictive maintenance, allowing Siemens to identify potential equipment failures before they occur. By implementing this approach, Siemens has minimized unplanned downtimes, resulting in both environmental and economic benefits. The integration of data analytics has enabled a closed-loop optimization process, driving continuous improvements in production quality and energy use.

22.5.1.1.2 Bosch's smart factories

Bosch has implemented a smart factory concept to achieve significant gains in production efficiency. By integrating IoT and AI technologies, Bosch has optimized its production lines and successfully reduced energy consumption by 30%. The use of smart sensors and data-driven decision-making has allowed Bosch to implement just-in-time production, reducing inventory and waste while enhancing operational agility (Bosch, 2021).

Bosch has also been a pioneer in implementing machine learning algorithms to optimize production scheduling and resource allocation. The result is a significant reduction in energy consumption during peak production periods, contributing to Bosch's broader sustainability goals. By reducing waste and improving energy efficiency, Bosch has demonstrated how digital tools can be harnessed to drive sustainability in industrial settings.

22.5.1.1.3 Procter and Gamble's data-driven supply chain optimization

Procter and Gamble (P&G) has utilized data-driven technologies such as big data analytics, machine learning, and the Industrial IoT (IIoT) to enhance its supply chain and manufacturing processes. P&G has collaborated with Microsoft to leverage the Azure platform and IIoT capabilities across more than 100 manufacturing sites globally. This digital transformation effort aims to optimize production, reduce downtime, and minimize waste, thereby improving overall efficiency. Through the use of predictive analytics and real-time monitoring, P&G has effectively reduced operational inefficiencies and maintenance costs, contributing to both environmental and economic efficiency (P&G, 2022).

P&G's strategy underscores the importance of data integration throughout supply chain operations, which has allowed the company to gain valuable insights into consumer demand patterns and enhance production planning. This has resulted in more responsive production cycles and optimized resource use, directly contributing to sustainability goals. P&G's digital transformation and commitment to responsible sourcing practices also highlight its effort to create a resilient and efficient supply chain that aligns with its sustainability targets.

22.5.1.2 A cautionary tale in industrial iot implementation: General Electric's Predix platform

General electric (GE) initially developed the Predix platform as a pioneering solution in its digital transformation strategy, intending to provide a comprehensive IIoT platform for real-time monitoring, predictive maintenance, and optimization of machinery performance.

The platform aimed to leverage data analytics and AI to foresee operational issues, minimize disruptions, and create an interconnected system across industrial assets. However, despite early success stories and ambitious goals, the Predix platform encountered significant obstacles, ultimately resulting in its underperformance.

22.5.1.2.1 Challenges and lessons from general electric's predix experience

1. **Overambitious goals:** GE set exceedingly high expectations for Predix, aspiring to establish it as the leading industrial IoT platform. The ambitious goals led to promises that exceeded the platform's initial capabilities, resulting in unmet expectations and customer dissatisfaction.
2. **Market readiness:** The industrial IoT market was less mature than anticipated, with many potential customers hesitant or unprepared to adopt advanced digital solutions on such a large scale. This mismatch in readiness limited Predix's early adoption and growth.
3. **Complexity of implementation:** Integrating Predix into existing operations required extensive workflow adjustments and infrastructure changes. These complexities posed substantial barriers to adoption, as many companies lacked the resources or flexibility to undertake such extensive restructuring.
4. **Lack of clear focus:** GE struggled to articulate a focused value proposition for Predix. This lack of clarity led to confusion about how Predix differentiated itself from other solutions, leaving potential users uncertain about its unique benefits.
5. **Intense competition:** The IoT and industrial analytics market saw rapidly evolving competition from more agile companies and platforms better able to adapt to changing market needs. This competitive environment made it difficult for Predix to secure a significant market share.
6. **Internal resistance:** Within GE, there was resistance to the organizational and cultural shifts required to support a successful digital transformation. This internal pushback hindered the platform's development and integration efforts.
7. **Financial constraints:** Broader financial challenges at GE often resulted in deprioritized investments in Predix. Limited resources affected the platform's development, marketing, and overall progress.
8. **Leadership changes:** Frequent shifts in leadership and strategic direction led to inconsistencies in the vision and execution of the Predix platform. This lack of continuity affected both employee commitment and market confidence in the platform's long-term viability.

GE's Predix platform offers a valuable learning experience for organizations considering large-scale digital transformations in industrial settings. The challenges faced by Predix underscore the importance of aligning market readiness, clear value propositions, and organizational support when pursuing ambitious digital solutions. By understanding these factors, businesses can better prepare for and mitigate risks associated with the complexities of digital transformation in the IIoT space.

22.5.1.3 Additional real-world example

22.5.1.3.1 Ford's sustainable manufacturing initiatives

Ford has been actively working on reducing the environmental impact of its production facilities through its global sustainability strategy. The company has integrated IoT

technologies and AI-driven energy management systems to monitor and optimize energy consumption in real time. Ford's "Zero Waste to Landfill" initiative, aimed at eliminating waste from its manufacturing operations, has also seen significant progress, with several facilities achieving zero-waste status ([Ford Motor Company, 2022](#)).

Ford has invested heavily in renewable energy sources, with a target of powering all its manufacturing plants with 100% renewable energy by 2035. The company has also employed water recycling technologies to minimize water consumption in production processes. These efforts underscore the potential of combining digital transformation with sustainability practices to achieve ambitious environmental goals.

22.5.1.3.2 Hypothetical example (fictional smart manufacturing journey)

A hypothetical example is XYZ Corporation, a large-scale manufacturer that has implemented smart manufacturing techniques to improve efficiency and sustainability. XYZ Corporation integrated IoT-enabled sensors throughout its production facilities to collect data on machine performance, energy use, and waste generation. By using AI to analyze these data, XYZ Corporation optimized its production schedules, reduced energy consumption by 18%, and cut down waste by 25%.

In addition, the company adopted digital twin technology to simulate production processes, allowing for the identification of inefficiencies before making changes to physical systems. This virtual testing environment enabled XYZ Corporation to implement improvements that minimized downtime and maximized resource efficiency. While fictional, this example illustrates the significant potential benefits of leveraging digital transformation technologies for sustainability in industrial settings.

22.5.2 Case studies: experiences from small and medium enterprises

Small and medium enterprises (SMEs) are the backbone of many economies around the world, providing employment opportunities and fostering innovation. Despite their smaller scale compared to large corporations, SMEs have made significant strides in digital transformation and sustainability. This section explores the success stories of SMEs from various industries that have leveraged digital technologies to enhance their sustainability practices. These examples underscore the adaptability and resilience of SMEs in the face of rapid technological changes, providing inspiration for similar organizations looking to initiate or expand their own sustainability initiatives.

22.5.2.1 Digital adaptation among small- and medium enterprises

Many SMEs have embraced digital transformation as a strategic tool for optimizing processes, reducing costs, and enhancing sustainability. These businesses often face unique challenges due to resource limitations, yet their flexibility and capacity for innovation can lead to remarkable successes when adopting new technologies. Several examples of how SMEs have successfully implemented digital strategies to enhance their environmental and operational sustainability will be delved here.

22.5.2.1.1 BrightFuture Solar: Internet of Things and artificial intelligence for energy efficiency

BrightFuture Solar, a medium-sized renewable energy company, has adopted IoT and AI technologies to enhance its solar energy production. By installing smart sensors in its solar panels, the company monitors energy output in real time, enabling predictive maintenance and more efficient energy management. The integration of AI-driven analytics has allowed BrightFuture Solar to optimize energy production, reducing operational costs by 20%. Additionally, the company has improved the reliability of its solar energy systems, ensuring consistent and sustainable energy output. These achievements underscore the role of data-driven technologies in achieving sustainability goals, even for smaller enterprises.

22.5.2.1.2 EcoPrint Manufacturing: 3D printing to minimize waste

EcoPrint Manufacturing, a small printing company, has embraced digital transformation by incorporating 3D printing technologies into its production line. By using 3D printing, the company has been able to significantly reduce material waste, which is traditionally high in conventional printing processes. EcoPrint has leveraged digital design tools to create precise prototypes, reducing the need for excess materials. Furthermore, the energy-efficient nature of 3D printing has enabled the company to cut down on energy usage, leading to a 15% reduction in operational costs. These advances have made EcoPrint a model for other SMEs in the manufacturing sector aiming to enhance efficiency and sustainability.

22.5.2.1.3 XYZ Factory: enhancing efficiency through automation

XYZ Factory, a hypothetical small-scale enterprise, provides an example of how IoT and automation can be used to improve production efficiency and sustainability. The factory integrated smart sensors throughout its production floor to gather real-time data on machine performance and energy usage. By analyzing these data, XYZ Factory identified inefficiencies and implemented corrective measures that reduced energy consumption by 20%. Moreover, the factory adopted predictive maintenance, reducing equipment downtime and improving overall productivity. This case highlights how small-scale manufacturers can leverage technology to achieve operational excellence and sustainability, even with limited resources.

22.5.2.1.4 ABC Workshop: reducing material waste with 3D printing

ABC Workshop, another hypothetical SME, implemented 3D printing technology to minimize material waste. This initiative allowed ABC to produce parts on-demand, significantly reducing inventory costs and excess material usage. By adopting 3D printing, ABC Workshop shortened production times by 30%, reduced material waste by 40%, and lowered energy costs by 20%. This transformation demonstrates how even small workshops can embrace cutting-edge technology to achieve sustainability goals.

22.5.2.1.5 EcoTech Solutions: Internet of Things for energy efficiency

EcoTech Solutions, a real SME in the technology sector, has successfully used IoT technology to improve energy management. By deploying smart meters and energy monitoring systems across its facilities, EcoTech has been able to identify peak energy usage times and implement strategies to reduce consumption during these periods. The

integration of IoT sensors and data analytics enabled EcoTech to decrease its overall energy consumption by 35%, while also enhancing workplace comfort for employees. This case illustrates the power of IoT in achieving both environmental and economic sustainability in smaller business contexts.

22.5.2.1.6 BrightTech Manufacturing: sustainable production practices

BrightTech Manufacturing, a small-scale production company, has taken significant steps toward sustainable production by integrating digital technologies. Through the adoption of 3D printing and smart sensors, BrightTech has reduced its material usage by 25%, contributing to a more sustainable manufacturing process. The company's approach to sustainability is twofold: reducing waste during production and using renewable materials whenever possible. By integrating sustainability into its core operations, BrightTech has positioned itself as a leader in the green manufacturing movement, providing a blueprint for other SMEs aiming to reduce their carbon footprints.

22.5.2.2 Success in renewable energy projects

22.5.2.2.1 SolarNow: IoT for optimized renewable energy

SolarNow, an SME specializing in renewable energy solutions in Africa, has used IoT-based energy monitoring systems to enhance the efficiency of its solar energy installations. By integrating real-time monitoring systems, SolarNow is able to track the performance of its solar panels and quickly identify maintenance needs, thereby maximizing energy production. This approach has improved energy efficiency by 20% and has expanded sustainable energy access in remote areas. SolarNow's success demonstrates the critical role that digital technologies play in optimizing renewable energy systems, especially for smaller enterprises aiming to make an impact in underserved regions.

22.5.2.2.2 AquaTech: smart water management solutions

AquaTech, a medium-sized enterprise in the water management sector, has leveraged IoT and big data analytics to improve water resource management. AquaTech's smart sensors monitor water usage across facilities, identify leaks, and optimize water distribution. Through these innovations, AquaTech has managed to save up to 30% of its water usage, significantly contributing to water conservation efforts. This case highlights the potential of digital transformation in achieving sustainability in water management, showcasing AquaTech's commitment to efficient resource utilization.

22.5.3 Public-private partnerships: achievements and gains

PPPs play a crucial role in the success of digital transformation and sustainability projects. By leveraging the strengths of both sectors, these collaborations can create impactful, scalable solutions. This section explores several examples of how joint efforts between the public and private sectors have driven progress in sustainability and digital transformation.

22.5.3.1 Outcomes from joint projects

Public and private sector collaborations are vital for achieving success in digital transformation and sustainability initiatives. For instance, the **SmartCity project** was launched through a collaboration between municipalities and technology firms. This project involved the deployment of smart sensors and data analytics systems citywide to monitor and optimize energy consumption and traffic congestion. Through this partnership, the city significantly improved energy efficiency and reduced carbon emissions, demonstrating the power of collaboration in addressing urban sustainability challenges.

22.5.3.2 Sustainable city project: a European case study

The **Sustainable City Project**, conducted in a European city, is another example of a successful PPP. The project aimed to enhance urban sustainability through smart city applications, renewable energy integration, and sustainable transportation solutions. The collaboration resulted in increased energy efficiency and a reduction in the city's carbon footprint. This case illustrates how PPPs can effectively address complex urban challenges and improve the quality of life for residents.

22.5.3.3 Renewable energy consortium: cross-sector collaboration

The **Renewable Energy Consortium**, established through the cooperation of multiple energy companies and public institutions, focused on developing renewable energy projects. By using IoT and big data analytics, the consortium optimized energy production and consumption data, contributing to energy security. This initiative highlights how PPPs can enhance the development and deployment of renewable energy, supporting the transition to a greener energy mix.

22.5.3.4 Smart city initiatives: Barcelona as a model

Numerous cities are implementing **Smart City Initiatives** through public-private collaborations. The **Barcelona Smart City Project** is a prime example, using IoT and data analytics to reduce energy consumption and traffic congestion. These projects contribute to improved urban living standards and help cities meet sustainability targets. The Barcelona initiative shows how smart technologies can be leveraged to create more efficient and environmentally friendly urban environments.

22.5.3.5 Renewable energy partnerships: Germany's Energiewende

Renewable Energy Partnerships are playing a pivotal role in expanding the use of renewable energy. **Germany's Energiewende** (Energy Transition) is a prominent example of how public and private sectors can work together to reduce reliance on fossil fuels and promote renewable energy. This collaboration has led to significant advancements in renewable energy infrastructure, contributing to Germany's efforts to reduce greenhouse gas emissions and transition to a sustainable energy system.

22.5.3.6 Sectoral collaborations for sustainability

Collaboration between organizations from different sectors also yields significant benefits for sustainability. For instance, partnerships between agricultural and technology companies have resulted in the development of **smart farming projects**. These initiatives help farmers optimize water and fertilizer use, increase productivity, and reduce environmental impacts. By utilizing data analytics and IoT technologies, smart farming contributes to achieving sustainability goals in agricultural production.

22.5.3.7 Circular economy collaborations: Ellen MacArthur Foundation

Circular Economy Collaborations have achieved great success through cross-sector partnerships. For example, projects led by the **Ellen MacArthur Foundation** in cooperation with major companies have increased recycling rates and reduced waste. These collaborations demonstrate the power of the circular economy model in promoting sustainable production and consumption practices.

22.5.3.8 Sustainable supply chain initiatives: Walmart and Procter & Gamble

Sustainable supply chain initiatives are another area where PPPs have had a positive impact. Companies such as **Walmart** and **Procter and Gamble** have collaborated on projects aimed at reducing carbon footprints and minimizing waste in their supply chains. By working together, these companies have made significant progress toward achieving sustainable supply chain management, setting an example for other organizations to follow.

22.6 Conclusion: advancing steps for sustainable transformation

This chapter summarizes the topics discussed in the previous sections and addresses the future steps in the realms of Industry 4.0 and sustainability. An emphasis has been put on strategies and measures that organizations should follow in digital transformation and sustainability initiatives, which are of critical importance for their continued success.

22.6.1 Overview and evaluation

Digital transformation and sustainability initiatives play a vital role in enhancing an organization's competitiveness while reducing its environmental impact in the modern business world. Technologies introduced by Industry 4.0, such as IoT, AI, big data analytics, and cyber-physical systems, enable companies to make their operations more efficient, flexible, and sustainable. These technologies offer significant benefits across various domains, including reducing energy consumption, improving waste management, and optimizing supply chains.

Moreover, the adoption of Industry 4.0 technologies facilitates better decision-making through data-driven insights, which allows organizations to identify inefficiencies and optimize their operations in real time. The synergy between digital transformation and sustainability fosters an environment where businesses can continuously innovate and

refine their practices to align with both economic and environmental goals. This dual focus not only enhances the resilience of organizations but also strengthens their ability to contribute to a more sustainable future.

When integrated with corporate sustainability strategies, digital transformation empowers businesses to achieve both economic and environmental goals more effectively. Sustainability initiatives not only help organizations fulfill their environmental responsibilities but also contribute to long-term cost savings and operational efficiencies. By enhancing the success of these projects, digital transformation supports organizations in achieving their sustainable development goals. Furthermore, the integration of sustainability into core business processes enhances brand reputation, attracts environmentally conscious customers, and fosters stronger relationships with stakeholders, which are all crucial for long-term growth.

22.6.2 Future steps and recommendations

In the future, organizations must take more advanced steps in their digital transformation and sustainability initiatives. To enhance the success of these projects, the following strategies and measures are recommended:

Strategic planning and integration: Organizations need to plan and integrate their digital transformation and sustainability strategies with a holistic approach. This ensures the effective and coordinated implementation of projects. Long-term goals should be set, and the necessary steps and resources to achieve these goals should be clarified through strategic planning. It is also essential to establish cross-functional teams that can bring together diverse expertise to ensure seamless integration across different business units.

Education and skill development: The success of digital transformation projects depends heavily on the development of employees' digital skills. Continuous training and professional development programs are crucial for easing the adaptation of employees to new technologies. Additionally, talent management strategies should ensure the recruitment and retention of personnel with the skills needed for digital transformation initiatives. Investing in upskilling and reskilling programs will not only enhance employees' capabilities but also foster a culture of continuous learning, which is key to sustaining innovation.

Policies and regulations: To facilitate the broader adoption of digital transformation and sustainability initiatives, suitable policies and regulations must be established. Governments and regulatory bodies should develop policies that encourage and support these projects. Regulatory compliance ensures that the projects are implemented in a legal and ethical manner. PPPs can also play a significant role in accelerating the adoption of sustainable technologies, by providing incentives, subsidies, and funding opportunities that make it easier for organizations to invest in transformative projects.

Technological investment and innovation: Organizations should increase technological investments in digital transformation projects and encourage innovation. Pilot projects and prototypes can be used to test the effectiveness and feasibility of technologies. Moreover, fostering a culture that promotes innovation is key to integrating new ideas into projects. Encouraging collaboration among different departments and with external partners, such as research institutions and technology providers, can lead to the development of more effective and innovative solutions. By staying at the forefront of technological advancements, organizations can create a competitive edge that drives both profitability and sustainability.

Continuous improvement and adaptation: Digital transformation projects should be continually reviewed and improved. Adaptive strategies enhance an organization's ability to quickly respond to changing conditions and unforeseen situations. This approach allows for more dynamic and flexible management of projects. Establishing feedback loops, where performance data are regularly collected and analyzed, can help organizations identify areas for improvement and implement timely adjustments. Additionally, fostering a culture of agility ensures that organizations remain resilient in the face of disruption and can capitalize on emerging opportunities.

In conclusion, digital transformation and sustainability initiatives are critical for ensuring the long-term success of organizations. The effective planning, implementation, and continuous improvement of these projects help organizations enhance their competitive advantage and achieve sustainable development goals. Therefore digital transformation and sustainability strategies must become an integral part of how organizations conduct their business. By committing to ongoing innovation, investing in people and technology, and fostering strong partnerships, organizations can build a sustainable future that benefits both the economy and the environment.

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Assessing readiness for Industry 4.0: key indexes and sustainable measures

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23.1 Introduction

This section begins by emphasizing the significance of readiness assessments in assisting organizations in their pursuit of successful technological adoption. These assessments facilitate the seamless integration of new technologies by identifying gaps and potential barriers. The section subsequently delves into the critical role that indexes play in the promotion of sustainable manufacturing. Indexes facilitate the measurement, monitoring, and enhancement of sustainability performance by organizations, thereby promoting more responsible and resilient industrial practices through the use of standardized metrics and benchmarks.

23.1.1 Importance of readiness assessment for technological adoption

In the context of technological adoption and Industry 4.0, "readiness" indicates an organization's thorough preparedness to integrate, implement, and leverage advanced digital technologies. It encompasses both the accessibility of advanced tools and systems and the capacity to synchronize these technologies with strategic business goals. Readiness evaluates if an organization possesses the requisite infrastructure, competencies, and vision to shift from traditional manufacturing methods to a more agile, data-driven, and interconnected operational framework. It is essentially an assessment of an organization's readiness to embark on a transformative digitalization journey, ensuring that technological adoption improves overall competitiveness and sustainability.

The dimensions of readiness assessment are complex, involving process, technology, and organization. The process dimension assesses the efficacy and flexibility of existing operational workflows and practices, highlighting the necessity for ongoing enhancement and innovation in production techniques. The technology dimension assesses the condition

of digital infrastructure, encompassing the complexity of hardware and software systems, along with the integration capabilities that facilitate seamless communication across diverse platforms. Simultaneously, the organizational dimension addresses human and cultural factors, including leadership commitment, employee competencies, and the strategic alignment necessary to propel and maintain digital transformation. Collectively, these dimensions provide a comprehensive framework for assessing readiness, guaranteeing that technological adoption is both viable and strategically embedded within contemporary manufacturing practices (Namjoshi & Rawat, 2022).

The theoretical basis for readiness assessments in technological adoption is firmly grounded in established frameworks that have historically shaped our comprehension of innovation implementation and diffusion within organizations. Two significant models in this domain are the Technology-Organization-Environment (TOE) framework and the Diffusion of Innovations (DOI) theory. Each presents a unique yet synergistic viewpoint, delivering a methodical framework to assess an organization's readiness for the incorporation of advanced digital technologies characteristic of Industry 4.0.

The TOE framework, created by Tornatzky and Fleischer, is significant in outlining the various dimensions that influence technological adoption (Tornatzky & Mitchell, 1990). This framework asserts that the adoption process is shaped by three essential contexts: technology, organization, and environment. Fig. 23.1 illustrates how external task environment factors, organizational attributes, and technology considerations converge to shape decisions regarding technological innovation. The technological context analyzes both internal and external technological attributes, encompassing the accessibility of advanced systems and their comparative benefits over current solutions. It evaluates factors, including compatibility, complexity, and observability of the new technology. The organizational context emphasizes the internal dynamics of the firm, including its structure, size, resource availability, and the strategic vision of its leadership. This dimension emphasizes the critical role of internal capabilities and managerial support in enabling change and leveraging technological innovations. The environmental context encompasses the external factors influencing adoption, including market competition, regulatory frameworks, and the socioeconomic landscape. These three dimensions offer a comprehensive framework for assessing readiness, as they collectively include the internal and external factors that

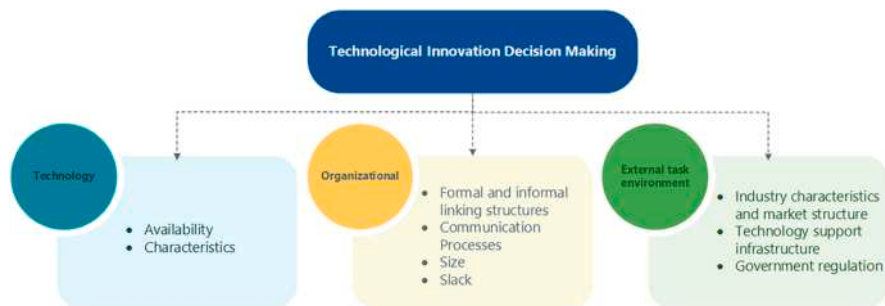


FIGURE 23.1 Technological innovation decision-making. A conceptual framework showing how the external task environment, organizational factors, and technology converge to drive technological innovation decision-making.

influence an organization's capacity to effectively adopt and gain advantages from Industry 4.0 technologies.

The DOI theory, popularized by Everett Rogers, elucidates the dynamics of the dissemination of new ideas and technologies within a social system (Rogers, 1995). The DOI theory delineates a sequence commencing with the recognition of an innovation, followed by interest, assessment, experimentation, and ultimately adoption or rejection. This theory is centered on several attributes of innovations—relative advantage, compatibility, complexity, trialability, and observability—that affect the rate and degree of adoption. By comprehending these attributes, organizations can discern obstacles and facilitators in the innovation process, thus methodically assessing their preparedness to adopt change. The DOI framework underscores both the attributes of the technology and the significance of communication channels, social systems, and temporal factors in the adoption process. This comprehensive approach enables decision-makers to formulate targeted strategies that promote seamless transitions, increase acceptance, and ultimately guarantee that technological investments produce measurable benefits.

When combined, these frameworks facilitate a systematic assessment of readiness by providing a thorough array of perspectives for organizations to evaluate their preparedness. The TOE framework offers a systematic, multidimensional analysis that elucidates the interaction among internal resources, external pressures, and the inherent characteristics of the technology (Satyro et al., 2024). It emphasizes that preparedness is not exclusively dictated by the availability of sophisticated tools or systems but is also contingent upon organizational culture, strategic orientation, and the external ecosystem. Simultaneously, the DOI theory enhances this analysis by exploring the intricacies of how innovations are perceived and adopted by individuals and groups within the organization (Ayanwale & Ndlovu, 2024). By concentrating on elements such as perceived advantages, usability, and social dynamics, DOI theory assists organizations in identifying particular areas necessitating improvement—be it augmenting training programs, refining communication channels, or modifying technology to align more effectively with current processes (Evan, 2009).

Furthermore, these frameworks emphasize the significance of a dynamic and iterative methodology for evaluating readiness. Both the TOE and DOI recognize that technological adoption is an ongoing process characterized by learning, adaptation, and enhancement. They promote the continual evaluation and enhancement of strategies in response to changing technological environments and fluctuating market dynamics (Hradecky et al., 2022). This progressive strategy is especially pertinent to Industry 4.0, characterized by continuous innovation and digital transformation. As organizations move toward integrated, data-driven operational models, the capacity to adapt and adjust readiness assessments in real time is crucial. The systematic methodologies offered by these theories allow organizations to sustain a competitive advantage while ensuring that their adoption strategies are sustainable and aligned with overarching economic and environmental objectives (Chaudhuri et al., 2024).

The TOE framework and Diffusion of Innovations theory are essential for developing a thorough, systematic assessment of readiness for technological adoption. They assist organizations in recognizing the internal and external factors that affect adoption, while elucidating the intricate processes by which innovations infiltrate social systems. Collectively, these frameworks establish a strong basis for creating readiness assessments

that are both stringent and flexible, facilitating the successful incorporation of Industry 4.0 technologies and the achievement of sustainable manufacturing practices.

In the modern manufacturing environment, the motivations and necessities for technological adoption are complex and interconnected, influenced by a combination of external and internal factors. Companies function in an environment marked by swift technological advancements, fierce global competition, and changing market dynamics. Competitive pressures necessitate that organizations perpetually innovate and integrate advanced technologies to sustain or improve their market position. As competitors increasingly utilize automation, data analytics, and intelligent manufacturing solutions, companies that fail to adapt risk losing their competitive advantage or becoming obsolete (Horváth & Szabó, 2019). Market demands exacerbate this pressure, as consumers now anticipate products that are not only high in quality and reliability but also manufactured through processes that prioritize efficiency, customization, and sustainability. Moreover, regulatory modifications—especially those focused on environmental sustainability, occupational safety, and equitable trade practices—serve as substantial external influences. These regulations frequently require the implementation of sophisticated monitoring, reporting, and compliance systems, compelling firms to adopt technological enhancements that guarantee conformity to rigorous standards and promote transparency in operations.

The internal impetus to embrace new technologies is motivated by the strategic need to optimize operations and improve organizational performance. Digital transformation has become a crucial strategic necessity in contemporary manufacturing. This transformation transcends the simple implementation of new tools or systems; it necessitates a comprehensive reengineering of business models, processes, and organizational cultures to fully leverage digital technologies (Strazzullo, 2024). Companies are driven by the necessity to attain operational efficiencies, minimize production expenses, and enhance product quality. Advanced analytics, automation, and intelligent manufacturing platforms facilitate the streamlining of intricate production processes, the reduction of waste, and the optimization of resource allocation. These technological integrations allow companies to shift from reactive troubleshooting to proactive management, with data-driven insights guiding all strategic decisions. By doing so, organizations are more adept at responding rapidly to demand fluctuations, managing supply chain complexities, and adapting to market disruptions.

The significance of digital transformation as a strategic necessity is paramount. In contemporary manufacturing, it acts as a catalyst for significant organizational transformation by effectively merging digital and physical systems. Technologies like the Internet of Things (IoT), artificial intelligence (AI), and big data analytics serve not only as operational instruments but also as catalysts for a new epoch characterized by real-time monitoring, predictive maintenance, and agile decision-making (Samadhiya et al., 2024). Digital transformation reconfigures conventional manufacturing paradigms by instilling a culture of perpetual innovation and enhancement. It enables organizations to transcend isolated operations, promoting improved collaboration among various functions and establishing more agile, integrated supply chains (Nayyar et al., 2024). Consequently, digital transformation establishes a solid basis for sustainable growth, guaranteeing that technological investments yield concrete competitive advantages while aligning with overarching economic and environmental goals.

The motivation for technological adoption in manufacturing is influenced by a complex interaction of external pressures and internal necessities. Competitive forces, market demands, and regulatory requirements constitute the external foundation that compels innovation and compliance, whereas internal motivators like the quest for operational excellence and the strategic impetus for digital transformation highlight the necessity for a holistic and proactive approach to technology integration. By adopting digital transformation, contemporary manufacturers improve their operational efficiency and strategically position themselves to succeed in a rapidly evolving and interconnected global market.

Readiness assessments offer a methodical framework for organizations to assess their preparedness for the integration of new technologies, especially within the realms of Industry 4.0 and sustainable manufacturing (Barletta et al., 2021; Nick et al., 2020; Saad et al., 2019). Fundamentally, these assessments assist firms in pinpointing precise deficiencies in their processes, technological competencies, and organizational frameworks. Readiness assessments identify deficiencies—such as obsolete IT infrastructure, inadequate technical expertise, or misaligned operational processes—allowing decision-makers to determine where investments and enhancements are most essential. This gap analysis optimizes resource allocation and ensures that financial, human, and technological capital are focused on areas that will provide the maximum benefit, thereby improving overall operational efficiency.

In addition to gap identification, readiness assessments are essential for risk mitigation. Through systematic analysis of existing capabilities and vulnerabilities, organizations can proactively mitigate potential barriers to successful technological adoption. The early identification of risks—ranging from cybersecurity vulnerabilities to operational bottlenecks—enables companies to formulate and execute mitigation strategies before expanding digital transformation efforts. Moreover, the comprehensive insights obtained from readiness assessments facilitate informed decision-making. Leaders can utilize data-driven assessments to formulate strategic plans that are pragmatic and future-oriented, ensuring that the integration of new technologies corresponds with overarching business goals and long-term growth strategies.

Connecting these evaluations to sustainable manufacturing practices enhances their significance. In the current manufacturing environment, sustainability has transitioned from a marginal issue to a fundamental component of corporate strategy. Readiness assessments that include sustainability metrics guarantee that technological adoptions are efficient, competitive, and environmentally and economically sustainable in the long term. By incorporating environmental performance indicators and adhering to circular economy principles, these evaluations facilitate organizations' transition from conventional linear production models to more sustainable, closed-loop systems. This integration promotes practices that minimize waste and continuously repurpose resources, thus diminishing environmental impacts and enhancing resilience to regulatory and market changes.

Furthermore, the advantages encompass promoting the implementation of circular models in Industry 4.0 settings (Ciano et al., 2025). Readiness assessments can function as a guide for implementing closed-loop systems by pinpointing strengths and weaknesses in existing practices and emphasizing opportunities for innovation. This may involve reengineering products for enhanced recyclability, refining resource recovery methodologies, or utilizing digital technologies to optimize the complete production lifecycle. By doing

so, organizations attain enhanced resource efficiency while generating cost savings and competitive advantages that are essential in the current dynamic market.

Nonetheless, it is crucial to acknowledge that although readiness assessments provide considerable advantages, they also present challenges and limitations. Data constraints, for example, can present a significant obstacle. In numerous organizations, data may be disjointed, inconsistent, or obsolete, complicating the execution of a thorough assessment. The interpretation of readiness metrics, especially those pertaining to organizational culture and human capital, may be subjective. This subjectivity may result in discrepancies in assessment outcomes, potentially impacting the consistency and reliability of the findings. Moreover, incorporating these evaluations with existing legacy systems and established processes can be intricate, as organizations may face resistance to change or challenges in reconciling new insights with conventional operational frameworks (Awodele et al., 2024).

Notwithstanding these challenges, the overarching potential of readiness assessments remains persuasive. They provide a balanced viewpoint by facilitating targeted resource distribution, reducing risks, and improving strategic planning, while ensuring that technological integration promotes sustainable manufacturing practices. By persistently enhancing assessment methodologies and tackling intrinsic challenges, organizations can optimize the advantages of readiness assessments, facilitating a more seamless transition to innovative, efficient, and sustainable manufacturing systems in the context of Industry 4.0 (Yaqub & Alsabban, 2023).

23.1.2 Role of indexes in facilitating sustainable manufacturing

Indexes are composite indicators that consolidate multiple performance dimensions into a single, coherent metric in the context of industrial readiness and sustainable manufacturing. To offer a comprehensive assessment of an organization's readiness to implement advanced digital technologies while simultaneously achieving sustainability objectives, these indexes are intended to capture a diverse array of data points, including technological infrastructure, process efficiency, environmental performance, and resource circularity. Indexes empower stakeholders to evaluate current performance, identify critical gaps, and make informed decisions about future investments and enhancements by simplifying intricate, multidimensional data into a format that is easily comprehensible.

Traditional metrics that prioritized operational and financial indicators, including production output, machine utilization, and cost efficiency, were the primary tools used to evaluate manufacturing performance throughout history. Although these isolated metrics were effective in assessing economic performance, they frequently failed to capture the more complex and broader challenges that modern industries are confronted with, which are becoming more interconnected with environmental sustainability and digital transformation (Khan et al., 2025). The transition to integrated, composite indexes is a paradigm shift that has resulted in the expansion of traditional performance metrics to encompass sustainability metrics, including energy consumption, carbon emissions, waste management, and circular economy principles. This integration supports a more resilient and future-oriented manufacturing ecosystem by aligning industrial readiness assessments with long-term environmental and economic sustainability goals.

The components and methodological foundations of these indexes have also undergone significant refinement in parallel with this conceptual evolution. The Smart Industry Readiness Index (SIRI), the Industrial Transformation Technology Index (ITTI), and the Consumer Sustainability Industry Readiness Index (COSIRI) are key indexes that illustrate this sophisticated methodology. Each of these indexes is designed to include a comprehensive set of indicators that encompass the technological, organizational, and environmental domains. Their design entails the integration of a variety of submetrics into a single overall score through composite indicators, which aggregate diverse data. Normalization techniques are implemented to guarantee comparability across various scales and contexts. These methods convert raw data into standardized formats, which facilitates accurate and equitable aggregation. Weighting schemes are subsequently implemented to determine the relative significance of each indicator, which is a reflection of the criticality of specific dimensions as determined by expert judgment and empirical evidence. This methodological rigor guarantees that the resulting indexes are both robust and reliable, capable of delivering actionable insights that are based on a fair evaluation of performance across multiple domains.

In addition to their construction, these indexes play a critical role in performance measurement and benchmarking. They serve as strategic instruments that enable organizations to evaluate their current status in relation to industry standards and best practices. Companies acquire a comprehensive comprehension of their operational efficiency and competitive position by contrasting the aggregated scores generated by these composite indexes with predetermined benchmarks. This benchmarking process not only emphasizes strengths but also exposes performance gaps that may otherwise remain concealed. Organizations can prioritize targeted improvements in areas such as environmental management, process optimization, and technology integration with the assistance of such insights. The clear, quantifiable metrics that these indexes provide enable decision-makers to monitor the impact of strategic initiatives, track progress over time, and adjust their approaches as necessary to meet the changing demands of the industry.

Furthermore, indexes are essential for strategic decision-making, as they offer actionable insights that inform resource allocation, technology investment, and long-term planning. These indexes can be used by decision-makers to determine the most effective allocation of capital and human resources, thereby identifying areas that necessitate urgent upgrades or strategic shifts. For instance, an organization may consider investing in advanced machinery or digital training programs in response to a low score in technological readiness, while initiatives focused on energy efficiency or waste reduction may be motivated by deficiencies in environmental metrics. Indexes facilitate the adoption of a proactive planning approach by leaders, as they anticipate challenges before they escalate into substantial risks by incorporating these diverse performance indicators. In the context of sustainable manufacturing, the capacity to anticipate and mitigate risks—whether they are associated with regulatory changes, market disruptions, or technological obsolescence—can be the deciding factor between resilience and vulnerability. This proactive approach is particularly advantageous.

Additionally, the integration of digital technologies with sustainability objectives is a critical component of these indexes (Mem et al., 2021). These composite tools vividly illustrate the interconnections between sustainability objectives and digital transformation

initiatives. However, digital technologies—including the IoT, AI, and advanced data analytics—are essential for facilitating Industry 4.0 readiness (Alijoyo, 2024; Attaran et al., 2024; Soori et al., 2023). Conversely, these technologies directly contribute to environmental and economic sustainability when they are employed to monitor and optimize resource usage, reduce waste, and improve process efficiencies. The dual emphasis on sustainability and Industry 4.0 readiness fuels innovations that promote economic and environmental resilience (Saleh & AlShafeey, 2025). This comprehensive strategy not only guarantees that technological investments generate operational enhancements but also aligns them with the overarching societal objectives of sustainability, thereby easing the transition to more circular, environmentally friendly manufacturing models.

Nevertheless, the development and application of these indexes are not without their own set of challenges and constraints. Many organizations encounter significant challenges with fragmented, inconsistent, or outdated data, which can undermine the precision of readiness assessments. Consequently, data quality continues to be a significant obstacle. Standardization issues also present challenges, as various sectors and regions may utilize distinct metrics and methodologies, which complicates cross-comparison and benchmarking. Furthermore, the ever-changing nature of digital technologies necessitates that indexes be consistently improved to ensure their relevance and efficacy (Fang & Liu, 2024). The necessity of rigorous validation and iterative updates is underscored by the subjective interpretation of specific qualitative metrics, such as organizational culture or leadership commitment, which can result in inconsistencies. The continuous improvement of these tools is crucial to ensure that they remain reflective of the current state of manufacturing and are able to keep pace with industrial and technological changes, despite the challenges they face.

In the future, the value and applicability of these composite indicators are expected to be further enhanced by emerging trends in index development. Innovations such as real-time data integration, IoT analytics, and AI-driven insights are poised to revolutionize the assessment of industrial readiness and sustainability. These developments will facilitate the development of dynamic, continuously updated indexes that offer real-time feedback on performance and risk factors, thereby facilitating more agile decision-making processes. Additionally, the integration of these state-of-the-art technologies is expected to encourage increased collaboration among academia, government, and industry, resulting in the development of new policies and standards that encourage sustainable manufacturing practices. These indexes can be essential tools for monitoring compliance, shaping regulatory frameworks, and incentivizing best practices across the manufacturing ecosystem, as governments and regulatory bodies increasingly acknowledge the significance of sustainability in industrial development. The policy implications are substantial.

In conclusion, the development of integrated, composite indexes in sustainable manufacturing and industrial readiness is a substantial improvement in the measurement and enhancement of performance. These indexes offer a comprehensive framework for risk mitigation, strategic planning, and benchmarking by combining traditional performance metrics with sustainability measures and advanced analytical techniques. By providing decision-makers with clear, actionable insights, they ensure that technological advancements are in harmony with sustainability goals, while also guiding resource allocation, technology investments, and long-term planning. The ongoing refinement of these indexes,

in conjunction with emerging trends in real-time data and AI-driven analytics, will be crucial in the development of policies and standards that promote a sustainable, resilient industrial future as the manufacturing landscape continues to evolve, driven by environmental imperatives and digital transformation (Agarwal & Ojha, 2024).

23.2 The Smart Industry Readiness Index

This section offers a thorough examination of the index and its practical application in assessing the readiness of manufacturing for the digital era. It initiates with an overview and development of SIRI, delineating its conceptual foundations and evolution. The section subsequently explores the key components and evaluation criteria, providing a detailed explanation of the definition and measurement of each index element. Subsequently, it addresses the advantages and obstacles that organizations may encounter when implementing SIRI, emphasizing both operational enhancements and potential impediments. Lastly, this section provides real-world case studies, with a particular focus on Pepperl+Fuchs and Haier, to demonstrate the potential of SIRI to facilitate strategic, technology-driven transformations in manufacturing environments.

23.2.1 Overview and development of Smart Industry Readiness Index

Industry 4.0 has arisen as a transformational influence, redefining production processes with sophisticated automation, data analytics, and digitalization. In Singapore, the momentum for Industry 4.0 intensified after a 2017 study in collaboration with Accenture, indicating that over 70% of local manufacturers intended to use Industry 4.0 solutions by 2020 (EDB, 2018). Notwithstanding this confidence, firms frequently grapple with fundamental questions regarding the initiation of digital changes, the quantification of their prospective advantages, and the formulation of a sustainable strategy for comprehensive implementation.

In addressing these problems, the Singapore Economic Development Board (EDB), in conjunction with a consortium of business executives, technology specialists, and academic collaborators, initiated the development of the Smart Business Readiness Index (SIRI) (EDB, 2018). This initiative was partially driven by insights from McKinsey's 2017 global expert survey on digital manufacturing, which identified the absence of a coherent vision, comprehensive strategy, and structured roadmap as significant obstacles to successful Industry 4.0 implementation (Alicke et al., 2017). SIRI was conceived as a pragmatic, organized framework to assist firms in comprehending Industry 4.0, delineating their desired results, and executing the incremental measures required to advance along the digital maturity continuum.

The creation of SIRI commenced with a comprehensive literature analysis of concepts and frameworks pertinent to Industry 4.0, encompassing various industry reports, landscape analyses, and company surveys. SIRI utilized foundational models, including the Reference Architectural Model for Industry 4.0 (RAMI 4.0) established by Plattform Industrie 4.0, while also integrating insights from other significant references, particularly the Industry 4.0

Maturity Index released by the German Academy of Science and Engineering (acatech) and the Bersin model for human capital development by Deloitte (ZVEI, 2015). This extensive evaluation demonstrated that the SIRI framework incorporated both technological precision and organizational factors, assuring its applicability across various industrial environments.

An advisory council of professionals from academia and industry was assembled to validate and enhance the technological robustness of SIRI. Their contributions guided the creation of the SIRI framework and its associated assessment matrix, which was later tested with a cohort of manufacturers situated in Singapore. The organizations varied from small- and medium-sized enterprises (SMEs) to multinational corporations (MNCs) within discrete and process manufacturing sectors. A prototype workshop with senior management, engineering, and operations teams, alongside the core SIRI development team, produced useful feedback that was integrated into the final version of the framework.

SIRI evaluates firms based on three fundamental dimensions—process, technology, and organization—reflecting the complex nature of Industry 4.0 developments as shown in Fig. 23.2. SIRI assists companies in identifying deficiencies, establishing strategic priorities, and assessing progress, serving as a fundamental instrument for facilitating targeted enhancements, ensuring consistent benchmarking, and ultimately steering manufacturers toward enduring competitiveness in a progressively digitized industrial environment.

23.2.2 Key components and evaluation criteria

SIRI provides a systematic framework for enterprises to evaluate their preparedness for the Industry 4.0 transition. This paradigm comprises three fundamental components—technology, process, and organization—each essential for facilitating a smooth transition to the "facility of the future." SIRI delineates eight fundamental pillars that encapsulate the critical domains of Industry 4.0 adoption. By assessing a company's maturity across five pillars, SIRI



FIGURE 23.2 Smart Industry Readiness Index framework.

offers a comprehensive overview of preparedness, emphasizing both strengths and opportunities for enhancement.

23.2.2.1 Key components

This section delineates the primary elements of the SIRI framework, which are intended to evaluate the maturity of an organization in the digital age. It encompasses three key areas: operation, which assesses production efficiency through real-time analytics; supply chain, which guarantees seamless material management; and product lifecycle, which integrates digital tools from design to end-of-life. Furthermore, automation and connectivity are dedicated to optimizing data flow and minimizing manual labor, while Intelligence employs sophisticated analytics to facilitate proactive decision-making. Finally, talent readiness and structure & management address the human and governance factors necessary to drive and sustain digital transformation.

23.2.2.1.1 Operation

The operation pillar focuses on the planning and execution of processes involved in producing goods and services. Under Industry 4.0, the goal remains to convert raw materials and labor into market-ready outputs at the lowest cost and highest quality; however, companies increasingly leverage new technologies—such as real-time data analytics and wireless communications—to optimize workflows and reduce inefficiencies. When assessing the operation pillar, SIRI examines how well an organization integrates these technologies to streamline production, monitor performance, and decentralize process control. Higher maturity indicates sophisticated use of data-driven insights and robust automation practices that reduce waste, improve responsiveness, and enhance overall productivity.

23.2.2.1.2 Supply chain

The supply chain pillar addresses the planning and management of raw materials and inventory, from the point of origin through to the end customer. Industry 4.0 enables connected and digitized supply chains through sensor networks, central data hubs, and analytics engines that allow seamless communication across all nodes in the value chain. In evaluating this pillar, SIRI considers how effectively a company integrates real-time tracking, demand forecasting, and end-to-end visibility. Advanced maturity in this pillar typically manifests as reduced lead times, greater flexibility, enhanced transparency, and the ability to orchestrate complex supply networks both within and beyond the enterprise.

23.2.2.1.3 Product lifecycle

The product lifecycle pillar encompasses the entire journey of a product—from initial concept and design, through manufacturing and delivery, to eventual disposal or recycling. Historically, robust product lifecycle management (PLM) has been a cornerstone of manufacturing operations. Under Industry 4.0, however, shorter product cycles and increased customization pressures call for a more integrated and dynamic approach. Companies with higher maturity in this pillar often utilize digital twins, advanced simulation tools, and unified data platforms to link design, engineering, production, and

customer feedback. SIRI's evaluation criteria here focus on how effectively organizations leverage such technologies to accelerate innovation, personalize offerings, and manage lifecycle stages seamlessly.

23.2.2.1.4 Automation

Automation has long been integral to modern manufacturing, but Industry 4.0 elevates its significance by connecting it to real-time data, flexible production lines, and autonomous decision-making. The automation pillar in SIRI assesses the extent to which a company deploys technology to monitor, control, and optimize the production and delivery of products and services. Higher-level maturity reflects not only the reduction of manual tasks but also the ability to adapt quickly to changing market demands—producing smaller batches, customizing products on demand, and maintaining consistent quality. Thus, advanced automation enables both operational efficiency and strategic agility.

23.2.2.1.5 Connectivity

The connectivity pillar examines how effectively machines, equipment, and computer-based systems communicate across the production value chain. As Industry 4.0 technologies evolve, the volume of data generated from IoT-enabled devices continues to grow, making secure and reliable data exchange a fundamental requirement. SIRI evaluates the sophistication of networking infrastructure, data protocols, and systems integration. High connectivity maturity implies that disparate systems—once isolated—are unified, allowing data to flow seamlessly from the shop floor to the enterprise layer. This integration underpins advanced analytics, remote monitoring, and real-time decision-making.

23.2.2.1.6 Intelligence

Where automation and connectivity serve as the operational backbone of Industry 4.0, Intelligence is its analytical core. The intelligence pillar addresses how data are processed, analyzed, and leveraged to drive strategic and operational decisions. Companies at advanced levels of maturity in this pillar utilize cloud computing, big data analytics, and machine learning algorithms to uncover insights from vast amounts of operational data. This enables predictive maintenance, demand forecasting, and other intelligent applications that can anticipate disruptions, optimize production parameters, and support more proactive decision-making. Ultimately, high intelligence maturity translates into greater adaptability, continuous improvement, and data-informed innovation.

23.2.2.1.7 Talent readiness

Implementing Industry 4.0 technologies requires more than just technical infrastructure; it also depends on having a workforce capable of driving and sustaining these initiatives. The talent readiness pillar evaluates the skills, mindset, and organizational culture needed to support digital transformation. This includes continuous learning programs, cross-functional collaboration, and a proactive approach to workforce development. Companies with higher maturity in talent readiness typically have established pathways for upskilling and reskilling employees, fostering a multiskilled and flexible workforce. As the industry landscape becomes increasingly dynamic, robust talent development ensures organizations remain competitive and can adapt quickly to emerging opportunities.

23.2.2.1.8 Structure and management

Finally, the structure and management pillar captures the organizational design and leadership practices that guide Industry 4.0 initiatives. Structure refers to the formal and informal systems of roles, responsibilities, and governance; management focuses on how individuals and teams are mobilized toward shared goals. Under Industry 4.0, hierarchical structures often give way to more agile, collaborative models that encourage experimentation and cross-departmental synergy. SIRI's evaluation criteria consider whether a company's strategic vision, leadership commitment, and governance framework effectively support innovation and rapid decision-making. High maturity in this pillar typically correlates with clear accountability, robust change management, and the capacity to coordinate complex digital projects across the enterprise.

23.2.2.2 Evaluation criteria

Building on the three building blocks—technology, process, and organization—and the eight pillars discussed previously, the SIRI further refines its assessment through 16 dimensions. These dimensions offer a granular view of the specific areas in which a company must develop capabilities to achieve Industry 4.0 readiness. Each dimension is evaluated on a six-level maturity scale (Levels 0–5), and the resulting scores are integrated into a prioritization matrix that helps organizations focus on the most critical, high-impact improvement opportunities.

SIRI's 16 dimensions capture the full breadth of an organization's Industry 4.0 readiness by examining how processes, technologies, and organizational practices interrelate. While each of the eight pillars highlights a major thematic area, these 16 dimensions delve deeper into the specific components that drive digital transformation, as shown in [Fig. 23.3](#).

By examining each of these dimensions, organizations gain a nuanced understanding of how Industry 4.0 principles manifest across various operational, technological, and managerial domains. To provide a clear roadmap for advancement, SIRI employs a six-level scale that measures the maturity of each dimension as shown in [Fig. 23.4](#). The scale ranges from Level 0 ("undefined") to Level 5 ("intelligence"), with each level denoting a distinct stage of progress:

This structured progression helps companies pinpoint their current status and chart an incremental path forward, ensuring that transformation initiatives are both methodical and aligned with organizational capacity.

Once the 16 dimensions have been evaluated, SIRI aggregates and interprets these maturity levels using a prioritization matrix. This matrix is designed to identify

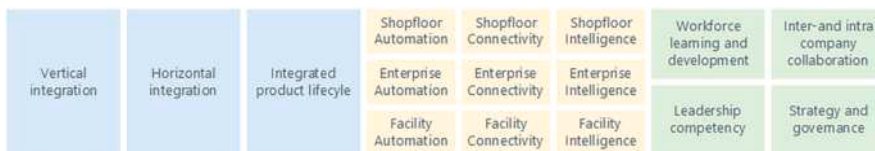


FIGURE 23.3 Smart Industry Readiness Index dimensions.

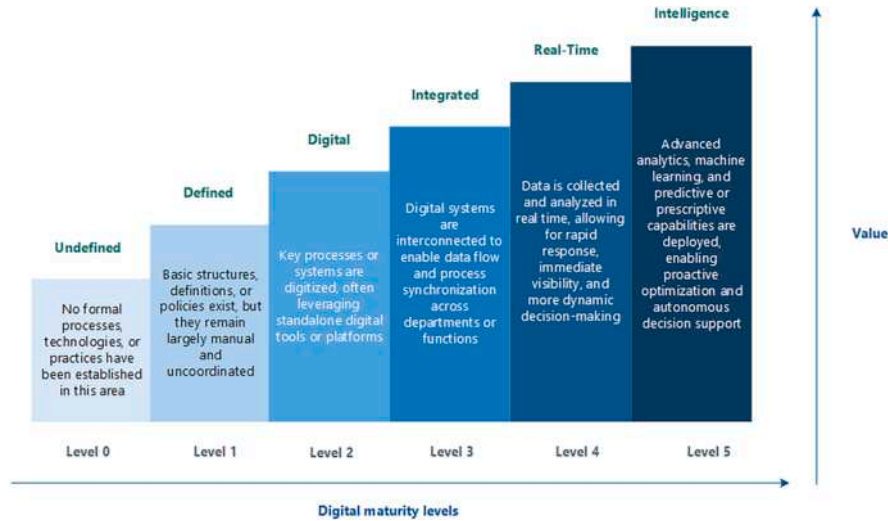


FIGURE 23.4 Smart Industry Readiness Index's six-level scale for measuring maturity across each dimension.

high-priority areas where improvements will bring the most significant impact, both in the short and long term. The matrix typically incorporates three key factors:

1. **Cost:** It reflects the financial and resource requirements needed to advance a particular dimension from its current maturity level to a higher level.
2. **Key performance indicators (KPIs):** It represents the operational or strategic impact that improvements in a given dimension will have on overall performance.
3. **Proximity to industry best-in-class:** It indicates how far a company is from the leading standards or benchmarks in that dimension, highlighting the potential competitive advantage of rapid improvement.

The outcome of this prioritization process is often summarized via the TIER framework, which stands for:

- **T (assessment matrix score):** The aggregated maturity level scores across the 16 dimensions.
- **I (cost profile):** The estimated investment or effort required to elevate a specific dimension.
- **E (key performance indicators):** The quantified benefits (e.g., efficiency gains, cost reductions, quality improvements) that align with organizational goals.
- **R (industry best-in-class benchmark):** The external reference points indicating the gap between current practices and leading-edge standards.

By weighting these factors according to organizational objectives—such as return on investment, strategic importance, or time-to-impact—the prioritization matrix offers a data-driven, directional view of where to focus transformation efforts. Dimensions that score high on strategic impact and are relatively close to best-in-class (with manageable cost implications) may be flagged as immediate priorities. Conversely, dimensions that require

extensive resources but offer lower near-term benefits can be scheduled for phased or long-term development.

In summary, SIRI's evaluation criteria and scoring methodology offer a robust, scalable means of guiding Industry 4.0 initiatives. By measuring maturity across 16 dimensions—each assessed on a six-level scale—and applying a structured prioritization model, manufacturers can strategically direct their transformation efforts, optimizing both operational performance and long-term competitiveness.

23.2.3 Benefits and challenges

Implementing the SIRI can be revolutionary for manufacturers aiming to adopt Industry 4.0. SIRI delivers a systematic, data-informed methodology to evaluate existing capabilities and prioritize enhancements, thereby delivering a definitive path for digital transformation. Nonetheless, the progression toward Industry 4.0 maturity entails numerous hurdles that enterprises must meticulously navigate. The subsequent sections delineate the principal advantages and prevalent obstacles faced when implementing SIRI.

23.2.3.1 Benefits

A primary advantage of SIRI is its comprehensive viewpoint on digital transformation. SIRI provides decision-makers with a holistic perspective of their existing capabilities by assessing various dimensions, including technology, procedures, and organizational issues. This comprehensive viewpoint assists manufacturers in circumventing fragmented strategies that may overlook critical aspects like talent preparedness or organizational connectedness. Consequently, firms can build transformation programs that tackle interconnected challenges and guarantee enduring sustainability.

SIRI also enables strategic planning and alignment at different tiers of a business. By analyzing assessment ratings from many locations, managers can uncover discrepancies in preparedness and recognize possible synergies. If one plant exhibits superior levels of shop floor automation compared to another, knowledge-sharing activities may be implemented to replicate optimal practices. This not only expedites digital adoption but also fosters a more collaborative culture, wherein teams unite behind shared transformation objectives.

Moreover, SIRI's systematic assessment methodology can guide industry-wide strategic planning and policy formulation. Governments and industry associations frequently utilize aggregated SIRI data to pinpoint sector-wide deficiencies, prioritize resource distribution, and formulate specialized support initiatives. Consequently, technology suppliers and consultancy firms can customize their services to resolve common issues identified by SIRI assessments, thus fostering a beneficial cycle of innovation and assistance within the manufacturing ecosystem.

The prioritizing matrix integrated into SIRI assists organizations in optimizing their investments. The matrix identifies areas where resources might generate optimal returns by assessing aspects such as cost, performance impact, and proximity to industry best practices. This data-centric methodology drives manufacturers to prioritize immediate gains before strategizing for more intricate or resource-demanding enhancements in the long run.

23.2.3.2 Challenges

Notwithstanding its benefits, the deployment of SIRI can present considerable hurdles, especially for firms that lack the requisite internal expertise or capacity to perform comprehensive evaluations. The framework's 16 characteristics and six maturity levels necessitate comprehensive data gathering and analysis, which can be laborious and resource-demanding. Smaller manufacturers may struggle to devote the requisite staff or budget, thereby impeding the transformation process.

A prevalent difficulty pertains to corporate culture and change management. Adopting an Industry 4.0 attitude frequently necessitates the acquisition of new skills, enhanced collaborative workspaces, and a willingness to engage in experimentation. Despite SIRI identifying distinct areas for enhancement, internal opposition may emerge if employees fear job displacement or are reluctant to embrace unfamiliar technologies. Leaders must consequently allocate resources to communication, training, and incentives to cultivate a supportive culture that supports ongoing learning and innovation.

Furthermore, data governance and cybersecurity issues may impede organizations' readiness to integrate systems and exchange information. Given that SIRI prioritizes connectivity and intelligence, which depend on extensive data collection and analysis, firms must implement stringent data protection protocols. Ensuring regulatory compliance, reducing cyber threats, and fostering stakeholder confidence are essential elements of any transformation strategy.

Ultimately, reconciling immediate operational requirements with enduring strategic objectives can be challenging. Although SIRI can assist in pinpointing high-impact areas, daily pressures—such as production deadlines and cost management—may eclipse long-term investments in digital infrastructure or workforce development. Companies may find it challenging to rationalize substantial capital expenditures if quick profits are not apparent. It is crucial to align SIRI-driven projects with current performance measures and financial objectives to sustain momentum and ensure continued support from top management.

In conclusion, SIRI provides firms with a robust framework for navigating their Industry 4.0 trajectories, offering actionable insights and directing resource allocation. The advantages—spanning extensive diagnostics to sector-wide benchmarking—can be significant, particularly when firms dedicate themselves to a thorough, data-informed transformation approach. However, difficulties pertaining to resource limitations, cultural obstacles, data security, and the equilibrium of operational requirements must be meticulously addressed. By identifying and proactively tackling these obstacles, manufacturers can use SIRI's ability to foster sustainable, long-term growth in a progressively competitive industrial environment.

23.2.4 Case studies: application of Smart Industry Readiness Index in manufacturing

23.2.4.1 Case study 1: Pepperl+Fuchs

This case study is drawn from [WEF \(2022\)](#). Pepperl+Fuchs (P+F) is a prominent producer of industrial sensors and process automation devices. In 2018 the business designated its Singapore facility to conduct a trial of the Overall SIRI Assessment (OSA). This location was selected for its strategic significance: it contains final assembly lines for diverse input/

output (I/O) production, in addition to an integrated logistics and distribution center. Throughout the years, P+F has enhanced its distribution capabilities and implemented new processes at the Singapore site, rendering it an optimal place to evaluate the alignment of the company's current operations with Industry 4.0 objectives.

During the initial OSA in 2018, the overall maturity level of the Singapore facility was determined to be below the "Broad Middle" average for similar facilities. Notwithstanding this discovery, P+F leadership acknowledged it as an opportunity to restructure and enhance the site's operational plan. The evaluation specifically identified Vertical and Horizontal Integration, along with Workforce Learning and Development, as critical areas for enhancement. P+F implemented organized learning and development programs to enhance the skills of long-tenured personnel and cultivate a culture more amenable to digital transformation. The organization aimed to provide a robust basis for enhanced automation and data-driven decision-making by enhancing these human-capital activities.

A subsequent reevaluation occurred between 2019 and 2020, yielding an updated overview of the Singapore site's advancement. The results demonstrated that multiple enhancements had been implemented, particularly in the integration of shop floor and enterprise-level technologies. The location commenced the investigation of real-time data communication technologies to facilitate proactive monitoring and control across several manufacturing lines. These improvements highlighted the necessity of a methodical strategy for Industry 4.0 implementation—one that harmonizes technological enhancements with concurrent investments in personnel and processes.

P+F intends to use the insights gained in Singapore at three additional test locations within its global network. The unwavering dedication from senior leadership, along with a well-defined strategy based on SIRI's organized framework, has enabled the organization to achieve steady advancements in automation, connectivity, and workforce preparedness. P+F's senior management indicated that the SIRI-based strategy offers "team-wide visibility and guidance," which will be essential for maintaining momentum. Through this approach, Pepperl+Fuchs intends to further its digital transformation initiatives, thereby solidifying its status as an innovative leader in industrial automation systems.

23.2.4.2 Case study 2: Haier

This case study is drawn from (WEF, 2022). Established in 1984, Haier Group is a prominent Chinese multinational corporation recognized for its cutting-edge home appliances and consumer electronics, catering to over one billion people across 160 nations. In its continuous effort to maintain competitiveness in a digital environment, Haier has adopted developing technologies, including AI, advanced robotics, and the Industrial IoT (IIoT). This progressive strategy has positioned 28 of its facilities within the World Economic Forum's Global Lighthouse Network, highlighting the company's preeminence in digital manufacturing excellence.

Haier utilized the SIRI to obtain a comprehensive assessment of its digital transformation efforts across various industrial locations. By evaluating each site according to SIRI's three foundational components—process, technology, and organization—the corporation acquired insights into the alignment of its varied operations with Industry 4.0 best practices. The multisite Official SIRI Assessment (OSA) assisted Haier in identifying performance

discrepancies among facilities, allowing leadership to disseminate best practices from its highest-performing "Lighthouse" sites to those in earlier phases of digital maturity.

The OSA results demonstrated that Haier's facilities typically achieved performance at or above top-decile criteria across various SIRI dimensions, notably excelling in areas like Shop Floor Intelligence. Nonetheless, the evaluation also underscored particular areas for enhancement. Certain locations necessitated more advanced facility automation, leading Haier to invest in equipment enhancements, standardized maintenance protocols, and improved operator training. Furthermore, aspects such as vertical integration and inter- and intracompany governance have surfaced as critical elements for enhancing comprehensive connection and collaboration with suppliers and distributors. By solving these deficiencies, Haier seeks to optimize its global value chain and enhance efficiency and responsiveness in production and distribution.

The multisite SIRI review has provided Haier with a more defined strategy for enhancing its digital capabilities and maintaining innovation. Employing SIRI's structured grading methodology, the organization may now prioritize investments according to measurable performance deficiencies and prospective profits. This method promotes a culture of ongoing enhancement, as the exchange of knowledge among facilities expedites the implementation of innovative manufacturing techniques. By integrating strategic planning and operational execution inside the SIRI framework, Haier is positioned to sustain its competitive advantage and address the changing demands of customers in a progressively digital environment.

23.3 The Industrial Transformation Technology Index

This section examines the ITTI, which provides a comprehensive framework for evaluating technological transformation in manufacturing. It commences with an overview and development of ITTI, outlining its conceptual foundations and evolution. The section subsequently delineates the key components and evaluation criteria, offering a comprehensive understanding of the index's quantification of the various facets of industrial transformation. Subsequently, it investigates the advantages and obstacles associated with the implementation of ITTI, emphasizing its capacity to enhance efficiency and address potential challenges that organizations may encounter. Lastly, the section provides a variety of case studies, such as those from PepsiCo, Tata Steel, Cipla, and Specialty Plastics, to illustrate the practical application of ITTI in a variety of manufacturing environments.

23.3.1 Overview and development of Industrial Technology Transformation Index

The ITTI was inaugurated by the Ministry of Industry and Advanced Technology as part of the Technology Transformation Program, in partnership with the Abu Dhabi Department of Economic Development, during the World Government Summit in February 2023 ([Industrial Technology Transformation Index, 2023](#)). ITTI serves as a comprehensive assessment tool designed to evaluate the digital maturity and sustainability preparedness

of manufacturing facilities, offering stakeholders a definitive roadmap for improving competitiveness and resource efficiency. ITTI is founded on the ideas of Industry 4.0 and sustainable production, aimed at highlighting the essential importance of technology adoption, environmental responsibility, and operational efficiency in the manufacturing industry.

ITTI is distinguished by its value chain-oriented approach, enabling manufacturers to comprehensively understand and evaluate their operations—from raw material procurement and production processes to logistics and end-of-life concerns. ITTI provides specific recommendations for continuous improvement by assessing a facility's current capabilities and comparing them to best practices. The evaluation process is generally conducted in a single on-site visit, during which assessors collect data on several performance metrics and stakeholder feedback. The findings are combined into a tailored report detailing both immediate "quick wins" and long-term strategic plans for technology-driven transformation.

In framework design, ITTI integrates quantitative measurements with qualitative insights to establish a systematic assessment of digital and sustainability maturity. Essential features include Industry 4.0 technology, such as automation, connectivity, and sophisticated analytics, alongside sustainability requirements encompassing resource management, energy efficiency, and environmental impact. This dual emphasis guarantees that manufacturers not only seek technology advancements but also integrate responsible and resilient methods across their operations. The index offers a comprehensive overview of an organization's existing position and highlights specific areas where enhancements can produce substantial benefits, such as cost reduction, decreased carbon emissions, or improved product quality.

In addition to functioning as a diagnostic instrument, ITTI emphasizes the actual implementation of its results. The methodology facilitates manufacturers in identifying and ranking essential use cases for transformation by mapping each participating company across many readiness dimensions, thus aligning enhancement initiatives with the most critical organizational requirements. This prioritization approach is particularly beneficial in extensive or multisite settings, where leadership must deploy resources wisely to tackle various operational difficulties. In the context of the UAE, ITTI's consolidated data have identified the 10 most significant use cases among local manufacturers, emphasizing the convergence of frequency, potential commercial impact, and overall preparedness.

Over time, ITTI's recurrent evaluations and expanding repository of benchmarks can foster a cycle of perpetual innovation inside the manufacturing sector. Insights derived from each review inform policy-making, capacity-building initiatives, and specific industry assistance measures. Thus ITTI not only offers an evidence-based framework for tailored corporate transformation plans but also enhances a wider ecosystem of collaborative learning. ITTI is positioned to significantly influence the evolution of manufacturing by providing a transparent, scalable framework for assessing and enhancing digital and sustainability maturity, fostering an agile, resource-efficient, and future-oriented industry.

23.3.2 Key components and evaluation criteria

ITTI is based on five fundamental design principles—intuitive, insightful, forward-looking, modular, and swift—designed to provide a thorough yet efficient evaluation of

digital and sustainability maturity in manufacturing. These principles guarantee that the ITTI framework is accessible to a diverse array of stakeholders, while accurately reflecting the intricate reality of contemporary industrial processes. ITTI aims to provide a concise, actionable overview of current performance while minimizing disruptions to daily production processes.

ITTI is characterized by its value chain-based design, which divides the manufacturing organization into discrete but interconnected functions: research and development (R&D), engineering, marketing, sales, supply chain management (both inbound and outbound), manufacturing, and customer service. Furthermore, ITTI assesses enterprise administration, strategy and organization, and sustainability in addition to these core operating domains. Fig. 23.5 illustrates the ITTI dimensions across the core manufacturing value chain, supported by a technology backbone and strategic considerations for enterprise automation, strategy, and sustainability. By synchronizing its evaluation categories with the inherent progression of materials, information, and decision-making, ITTI offers a comprehensive viewpoint on the integration of technology adoption and sustainability practices across each phase of the industrial lifecycle.

23.3.2.1 Key components

ITTI is a comprehensive framework that evaluates the digital and operational maturity of a manufacturing enterprise in multiple dimensions. It commences by conducting an assessment of R&D and engineering, with an emphasis on collaborative product lifecycle management, digital integration, and innovation. The framework subsequently evaluates marketing and sales to guarantee that commercial strategies and production capabilities are in alignment. Supply chain management, on the other hand, is dedicated to achieving transparency and efficiency in inventory control, logistics, and sourcing. Furthermore, manufacturing/production evaluates the optimization of the shop floor, quality, and

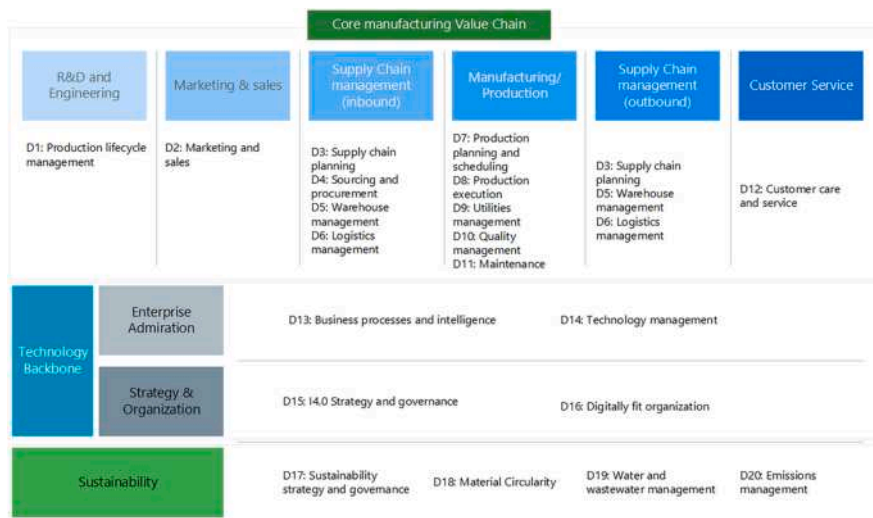


FIGURE 23.5 Industrial Technology Transformation Index framework.

maintenance, while customer service evaluates the transition from basic support to proactive, data-driven engagement. Enterprise administration evaluates the resilience of technological infrastructure and process integration, while strategy and organization evaluates the cultural readiness and leadership vision for digital transformation. Lastly, sustainability guarantees that environmental stewardship and resource management are integrated into the organization's long-term operations.

23.3.2.2 Research and development and engineering

The R&D and Engineering component of the ITTI assesses the efficacy of an organization in managing the initial stages of the product lifecycle, including conceptual design, prototyping, engineering validation, and product launch. This component places a significant emphasis on product lifecycle management, which encompasses the processes, digital tools, and collaborative practices that drive innovation. In particular, ITTI is interested in the presence of cross-functional collaboration, well-defined workflows (e.g., process definition), integrated digital platforms (e.g., E2E integration), and the seamless exchange of information between various teams, including design, engineering, and manufacturing. Companies can refine product features, improve user experience, and reduce time-to-market by integrating customer feedback loops into design decisions. In the final analysis, R&D and engineering establish a foundation for long-term competitiveness by guaranteeing that products are created with a combination of technical rigor and market responsiveness.

23.3.2.3 Marketing and sales

The marketing and sales component of the ITTI encompasses the entire commercial lifecycle, from lead generation and channel management to customer retention and contract execution. This dimension assesses the extent to which organizations effectively nurture leads through the qualification and proposal stages by integrating digital and offline channels to develop cohesive marketing strategies. ITTI emphasizes the significance of seamless coordination between marketing, sales, and production planning to guarantee consistent messaging and timely fulfillment by analyzing end-to-end processes. Furthermore, performance metrics—which encompass everything from lead conversion rates to postsales satisfaction—provide insights into the extent to which a company's marketing and sales functions are aligned with its overarching growth objectives. A mature marketing and sales operation not only enhances revenue generation but also utilizes data-driven insights to enhance customer relationships, anticipate market trends, and refine product offerings throughout the entire enterprise.

23.3.2.4 Supply chain management

Supply chain management encompasses a wide range of activities, including inbound procurement and third-party logistics, as well as factory storage, manufacturing operations, and outbound distribution, as outlined in the ITTI. This dimension evaluates the extent to which organizations maintain transparent and efficient sourcing and procurement processes (e.g., spend transparency, supplier relationship management, end-to-end source-to-pay) while effectively planning and synchronizing demand and supply (e.g., demand planning,

supply planning, S&OP collaboration). It also assesses warehouse management, which concentrates on inventory oversight and material flow, as well as logistics management, which encompasses transportation, fleet management, and timely delivery to customers or intermediate warehouses. ITTI emphasizes the significance of cross-functional collaboration, real-time data visibility, and digital integration in reducing lead times, optimizing inventory levels, and improving the overall resilience of the supply chain by analyzing these interconnected functions. In the dynamic manufacturing landscape of today, mature organizations in this dimension are capable of rapidly adapting to market fluctuations, minimizing costs, and maintaining high levels of service quality—essential factors for sustaining a competitive advantage.

23.3.2.5 Manufacturing/production

ITTI includes manufacturing/production, which encompasses the complete range of shop floor activities, including raw material intake, production planning, packaging, and outbound logistics. This dimension assesses the extent to which organizations optimize resource consumption (e.g., utilities management, which emphasizes operational efficiency and energy use), leverage automation to improve supervision and intelligence (e.g., automation), and schedule and execute daily, weekly, or monthly production runs (e.g., production planning and scheduling). Quality management is a critical component of this dimension, as it evaluates both quality assurance and quality control processes to guarantee consistent product quality and adherence to industry standards. Maintenance is equally critical, encompassing strategy, failure analysis, and root cause investigation to extend the lifespan of equipment and minimize downtime. ITTI emphasizes the potential of real-time data visibility, cross-functional coordination, and predictive analytics to achieve operational excellence, thereby reducing costs, improving throughput, and ensuring consistent high-quality product in a rapidly evolving manufacturing environment. This is achieved by evaluating these interconnected areas.

23.3.2.6 Customer service

Customer service evaluates the efficiency of an organization's postsales engagement, customer care, and support processes. This dimension assesses the maturity of customer service operations on a six-level scale, ranging from Level 0 (basic, ad hoc responses) to Level 5, which is fully virtual and predictive. The presence of formal SOPs, dedicated staff, and analog or digital tools for tracking customer issues (Levels 0–2) is a key consideration. Additionally, the transition to personalized and predictive support (Levels 3–4) through data-driven insights and integrated communication channels is a critical factor. At the most advanced maturity level (Level 5), organizations frequently employ virtual platforms, automated interactions, and robust analytics to provide proactive resolutions, thereby enhancing a seamless, on-demand experience for customers. It is important to note that strategic customer care not only enhances satisfaction and loyalty but also provides valuable feedback loops that inform continuous product and process improvements across the enterprise. This is emphasized by ITTI in its assessment of these evolving practices.

23.3.2.7 Enterprise administration

Enterprise administration is the organizational and technological infrastructure that facilitates secure data management, cross-functional collaboration, and strategic decision-making within the ITTI. This component encompasses two critical dimensions: Technology management and business processes and intelligence. ITTI assesses the efficacy of an organization's implementation of end-to-end process integration, utilization of digital platforms, and utilization of advanced analytics to generate actionable insights under the business processes and intelligence category. Technology management emphasizes the extent to which emerging technologies are adopted and protected to generate business value, with a particular emphasis on a company's overall technology strategy, enterprise architecture, data governance, and cybersecurity measures. ITTI emphasizes the importance of robust enterprise administration in a rapidly evolving industrial landscape, as it not only streamlines daily operations but also improves organizational agility, resource allocation, and long-term competitiveness. This is achieved by analyzing these elements.

23.3.2.8 Strategy and organization

In the ITTI, strategy and organization assesses the extent to which a manufacturing enterprise's leadership vision, organizational structure, and digital capabilities are in alignment with the overarching objectives of Industry 4.0. This component consists of two critical dimensions: Digitally-Fit Organization and I4.0 Strategy and Governance. The former evaluates the clarity of an organization's Industry 4.0 roadmap, which encompasses strategic planning, implementation frameworks, and reporting mechanisms. The latter, on the other hand, concentrates on cross-functional collaboration, capability development, and cultural readiness. ITTI emphasizes the importance of transparent governance, continuous learning, and leadership-driven transformation by evaluating these areas. A company's agility in adapting to technological advancements, market shifts, and evolving customer demands is significantly enhanced when its strategic direction and organizational culture are aligned with digital innovation. This, in turn, enables the company to maintain its competitiveness in an industrial landscape that is constantly evolving.

23.3.2.9 Sustainability

Sustainability is a component of the ITTI that evaluates the extent to which a manufacturing enterprise integrates environmental stewardship, responsible resource management, and long-term resilience into its operations. Sustainability strategy and governance, material circularity, water and wastewater management, and emissions management are the four dimensions into which this component is divided. ITTI assesses the extent to which organizations establish explicit sustainability objectives, incorporate environmental considerations into decision-making, and maintain transparent oversight frameworks through sustainability strategy and governance. Material circularity emphasizes the importance of eco-design principles and circularity fundamentals, including the reduction, repurposing, and recycling of materials, to ensure that products and processes generate minimal waste throughout their lifespans. In the interim, water and wastewater management evaluates the methods by which organizations optimize their water consumption, treat and discharge wastewater, and reduce the risks associated with water scarcity or

pollution. Finally, emissions management assesses the extent to which businesses monitor, mitigate, and compensate for their greenhouse gas emissions, considering variables such as emissions intensity and energy mix. The critical role of sustainability in maintaining compliance, building brand trust, and safeguarding long-term competitiveness in a rapidly evolving industrial landscape is underscored by ITTI by addressing these interlinked areas.

23.3.2.10 Evaluation criteria

The 20 ITTI dimensions encompass both technological and organizational enablers, offering a comprehensive perspective on an enterprise's preparedness for digital transformation and sustained resource efficiency. This comprehensive approach highlights essential interdependencies—such as the connection between production automation and labor skill enhancement—thus assisting organizations in formulating strategies that tackle many aspects of Industry 4.0 preparedness concurrently. Furthermore, the framework's comprehensive design allows for targeted prioritization, enabling decision-makers to concentrate on the most critical gaps and match initiatives with overarching corporate objectives. This comprehensive evaluation strategy enables firms to innovate, adapt, and prosper in a context where technical progress and sustainability concerns are increasingly interconnected.

ITTI uses a six-level maturity scale, from Level 0 (ad hoc) to Level 5 (self-optimizing), as shown in Fig. 23.6, to assess an organization's advancement across these aspects. At the lower end of the spectrum, corporations may have irregular or informal processes with limited digital integration, while organizations at the upper end exhibit predictive analytics, autonomous decision-making, and ongoing optimization. Between these extremes are distinctly delineated waypoints—defined (Level 1), digital (Level 2), integrated (Level 3), and predictive (Level 4)—that assist firms in monitoring their progression toward complete

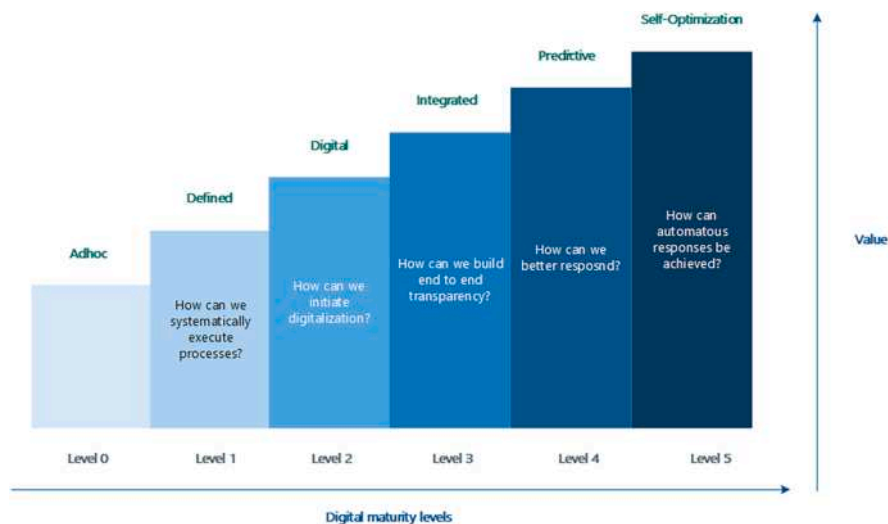


FIGURE 23.6 Industrial Transformation Technology Index's six-level scale for measuring maturity across each dimension.

digital transformation. This organized advancement defines immediate objectives while also revealing the overarching idea of a highly interconnected, self-regulating production ecosystem.

Subsequent to the maturity evaluation, ITTI employs a prioritizing process, commonly known as the “DxF” framework, which evaluates two principal indicators: direction and focus. Direction assesses the disparity between the company's existing maturity level, its aspirational objectives, and industry-leading benchmarks, thereby facilitating pragmatic goal-setting for the forthcoming 2–3 years. Focus on the essential areas tackles the company's most urgent difficulties or “pain points,” ensuring that enhancement initiatives are aligned with particular operational requirements and industry contexts. Through the integration of these two indicators, ITTI provides a definitive framework that prioritizes enhancement opportunities while aligning them with strategic goals and resource limitations.

The assessment process concludes with a comprehensive report, usually presented in a debrief session, which outlines the Ministry of Industry and Advanced Technology (MoIAT), summarizes the facility's Industry 4.0 readiness, details the company's operational profile, and offers targeted recommendations for immediate and future transformation initiatives. This report structure promotes iterative advancement, enabling manufacturers to periodically conduct the ITTI evaluation to evaluate enhancements, readjust priorities, and hone their strategic direction. The essential elements and assessment standards of ITTI provide firms with a stringent yet adaptable framework for enhancing their technological proficiencies and promoting sustainability goals throughout the whole value chain.

23.3.3 Benefits and challenges

Implementing ITTI can provide substantial strategic and operational benefits for manufacturing enterprises. ITTI offers a comprehensive assessment of digital and sustainability maturity, enabling decision-makers to evaluate their performance against industry-leading practices. This overview identifies particular areas for improvement while also emphasizing overarching trends and patterns throughout the value chain. Consequently, firms can formulate explicit recommendations for enhancement—customizing interventions to their specific operational settings and linking them with overall corporate goals.

Furthermore, ITTI provides a valuable instrument for facilitating evidence-based decision-making, especially with the adoption and expansion of Industry 4.0 principles. Manufacturers can pinpoint the most significant investment opportunities, ranging from enhancing manufacturing technology to refining personnel competencies and organizational frameworks, through quantitative measurements and qualitative evaluations. The effortless implementation of ITTI significantly improves its utility; enterprises can perform evaluations without revealing confidential information, thereby rendering the framework available to all stakeholders and facilities. Furthermore, ITTI's systematic review approach helps expedite firms' advancement in the digital era, allowing them to remain at the forefront of swiftly changing market and technical trends.

A significant advantage in specific jurisdictions, such as the UAE, is that the implementation of ITTI can enhance a company's In-Country Value (ICV) ranking and potentially facilitate access to public contracts. By methodically exhibiting digital and sustainability

proficiency, firms can enhance their trust with governmental entities and industry associates, thus setting themselves advantageously for future partnerships and expansion.

Notwithstanding these benefits, enterprises frequently encounter various obstacles when using ITTI. Resource limitations—encompassing financial, technological, and human capital—can present a considerable obstacle, particularly for small and medium-sized firms. Although ITTI's modular design aims to reduce disruption, executing assessments and applying suggested enhancements necessitate time, financial resources, and specialized knowledge. Organizational culture is crucial; securing buy-in from both employees and management may need explicit communication of ITTI's advantages, along with targeted training initiatives to bridge skill gaps and cultivate a mindset conducive to digital transformation.

A further difficulty emerges from data management and security. The extensive scope of ITTI involves the collection and analysis of intricate operational data, thereby heightening concerns regarding confidentiality and cyber threats. To resolve this challenge, firms must establish stringent data governance protocols, balancing transparency with protection. Furthermore, reconciling immediate operational requirements with overarching strategic objectives can be challenging. Although ITTI prioritizes sustainability and ongoing enhancement, daily production demands or short-term financial objectives may eclipse comprehensive transformation efforts. This tension requires explicit priority strategies—an aspect where ITTI's prioritization technique can assist, contingent upon businesses' dedication to ongoing implementation.

In conclusion, ITTI provides a robust framework for enhancing digital maturity and sustainable practices, offering explicit suggestions and enabling strategic alignment. Effective implementation necessitates meticulous planning, sufficient resources, and robust stakeholder involvement to surmount prevalent challenges, including cultural opposition, data security issues, and the conflict between immediate production demands and long-term transformation objectives. By proactively confronting these problems, manufacturers may fully capitalize on ITTI's promise to foster innovation, operational excellence, and sustainable growth.

23.3.4 Case studies: application of Industrial Transformation Technology Index in manufacturing

23.3.4.1 Case study 1: PepsiCo

This case study is drawn from [MoIAT \(2024\)](#). PepsiCo, a prominent entity in the food and beverage sector, utilized the ITTI to improve operational excellence, sustainability, and innovation within its manufacturing processes. Through the “All Things AI” project, the corporation aimed to enhance product quality, ensure stringent compliance and safety standards, and prioritize a customer-centric approach, while cultivating a workforce adept at facilitating continuous digital change. PepsiCo recognized a significant opportunity for AI implementation and process improvement across many functions by aligning its strategy roadmap with ITTI principles.

PepsiCo's initiatives centered on the systematic enhancement of production performance, especially using AI-driven solutions. Sound and visual detection technologies were

implemented to guarantee uniform chip texture and shape, while sophisticated peeling algorithms improved potato processing to minimize material waste and increase cost efficiency. The technology enhancements were accompanied by sustainability goals, such as responsible resource management and waste reduction—a strategy that closely matches ITTI's focus on harmonizing digital maturity with environmental stewardship.

PepsiCo prioritized talent preparedness to facilitate these breakthroughs. Understanding that organizational culture and personnel competencies are essential for successful digital efforts, R&D management teams implemented extensive training programs to provide operators, engineers, and managers with the necessary expertise to embrace AI-driven processes. This emphasis on workforce development also cultivated a collaborative atmosphere that promoted experimentation and interdisciplinary problem-solving—key features of ITTI's comprehensive approach to change.

The advantages of PepsiCo's "All Things AI" initiative were both measurable and strategic. Annual savings of AED 1,100,000 were achieved in packing costs, while enhancements in peeling efficiency resulted in an additional AED 1,000,000 in savings. Product offers aligned more closely with client needs due to data-driven design and focused production techniques. Automating specific monotonous chores allowed staff to focus on higher-value activities, ultimately enhancing a culture of creativity. Moreover, PepsiCo's choice to synchronize its digital initiatives with sustainability objectives emphasized the company's dedication to responsible expansion, thereby reinforcing its competitive edge in a changing market.

PepsiCo's experience illustrates how ITTI may assist manufacturers in incorporating sophisticated technologies, environmental efforts, and effective workforce strategies to realize significant operational improvements. By pinpointing intervention points—from AI-enhanced quality control to labor skill enhancement—the company effectively improved product quality, decreased expenses, and reinforced its client orientation. PepsiCo's transformation story demonstrates that cultural preparedness and employee empowerment are essential for maximizing the benefits of digital innovation. PepsiCo exemplifies how an ITTI-aligned framework may promote lasting enhancements in efficiency, sustainability, and organizational resilience within the evolving food and beverage sector.

23.3.4.2 Case study 2: Tata Steel

This case study is drawn from [MoIAT \(2024\)](#). Tata Steel, a leading global steel manufacturer, initiated a comprehensive transformation to tackle increasing raw material expenses, changing supply chain needs, and heightened sustainability expectations. Utilizing the ITTI methodology, the corporation prioritized diversity, equality, and inclusion (DEI) as fundamental principles to enhance operational performance and organizational resilience. Tata Steel sought to modernize its plants, decrease resource consumption, and establish a more adaptive, progressive organization by incorporating Industry 4.0 technology into its manufacturing processes.

The establishment of a robust digital infrastructure was fundamental to Tata Steel's transformation journey. The corporation installed more than a thousand sensors throughout its buildings, producing millions of data points for real-time analysis and decision-making. The data were input into digital twins for essential process equipment, facilitating predictive

maintenance and optimization of plant operations. Simultaneously, a centralized cloud solution—internally referred to as the Integrated Remote Operation Center (JROC)—enabled remote monitoring and control, assisting Tata Steel in coordinating intricate manufacturing operations across many locations. The technological developments were supported by a collaborative network of partners, including Google, Microsoft, Tata Communications, and IBM, which collectively oversaw the substantial increase in data to 25 petabytes by 2023.

Tata Steel prioritized cultural transformation, emphasizing the creation of an inclusive atmosphere conducive to the success of individuals from varied backgrounds. By integrating its ITTI-driven plans with DEI activities, the company cultivated cross-functional teams that encompassed a wide array of perspectives. This inclusive strategy enhanced staff engagement while also expediting horizontal integration and innovation. The outcomes have been remarkable: three of Tata Steel's European facilities received Lighthouse certification from the World Economic Forum, highlighting their position as worldwide standards for digital manufacturing. In financial terms, the company achieved a projected AED 5.1 billion in EBITDA savings in 2020—5 years into its transformation journey—primarily owing to enhanced process efficiencies, optimized resource allocation, and more robust supply chain operations. Tata Steel's experience illustrates that integrating technological innovation with a dedication to diversity, equity, and inclusion may produce significant advantages, enhancing the company's competitive position in a dynamic industrial environment.

23.3.4.3 Case study 3: Cipla

This case study is drawn from [MoIAT \(2024\)](#). Cipla, a prominent worldwide pharmaceutical entity, initiated a comprehensive digital transformation project informed by the ITTI, with the objective of enhancing operational efficiency and compliance across over 20 manufacturing facilities within a two-year timeframe. A primary impetus for this program was Cipla's objective to improve real-time data capture and visibility, increasing data transparency from 20% to 80% across essential activities. Utilizing ITTI's structured methodology, Cipla systematically identified high-impact digital and analytics applications, such as process simulation for yield enhancement and dynamic workforce planning to maximize human resources. The initiative that commenced as a pilot in eight facilities rapidly extended to more than 20 locations, highlighting the scalability and adaptability of the selected solutions.

A vital aspect of Cipla's progression was technological enhancements designed to safeguard its infrastructure for the future. The company established an IoT-enabled framework integrated with edge computing and AI, facilitating the capture, analysis, and routing of data to appropriate use cases with low delay. This architecture was additionally reinforced with an enterprise-scale "third platform" for data management, facilitating smooth interaction across various sites and activities. Cipla concurrently prioritized talent preparedness, acknowledging that the effective implementation of new technologies necessitates a digitally proficient and motivated staff. The organization cultivated a culture conducive to innovation and continual improvement through organized training programs, a committed transformation office, and leadership forums.

The outcomes of this transition were substantial. Cipla reported enhancements of 20%–80% in operational outcomes across many production lines, indicating increases in both efficiency and quality. Furthermore, its rapid expansion to over 20 outlets within two years highlights the efficacy of a meticulously planned digital strategy. The company's focus on data-driven decision-making established the foundation for a "lighthouse factory," a facility that exemplifies best-in-class Industry 4.0 practices acknowledged by external standards. Cipla effectively illustrated how an ITTI-directed strategy may facilitate swift, sustainable change throughout a global industrial network by synchronizing technical investments with comprehensive talent development.

23.3.4.4 Case study 4: Specialty Plastics

This case study is drawn from [MoIAT \(2024\)](#). A prominent specialized plastics company in the energy, oil, and water pipeline industries aimed to minimize unplanned downtime by transitioning from a reactive to a proactive maintenance approach. Utilizing the ITTI, the company pinpointed its low-density polyethylene (LDR) production lines—specifically the hyper compressor—as pivotal failure areas contributing to elevated operational expenses and recurrent interruptions. By increasing transparency in essential operational processes, the company established a more resilient, data-informed strategy for maintenance. Through the utilization of sophisticated monitoring systems and predictive analytics, the organization achieved an average of 44 days' notice for significant potential failures, allowing for the scheduling of preventive measures with minimal disruption to production.

Essential components of this change involved digital modeling of the most failure-prone equipment, such as packing seals and control valves, enabling maintenance teams to identify early indicators of deterioration before failures. The transition to a proactive maintenance strategy included the implementation of new standard operating procedures (SOPs) for shutdown and restart processes, resulting in decreased downtime and enhanced overall system reliability. Consequently, the organization attained a 27-day lead time for scheduled maintenance while substantially reducing repair expenses and productivity losses. By integrating predictive skills into daily operations—bolstered by cross-functional collaboration and continuous training—the organization built a more resilient culture that prioritizes early detection and long-term asset health. The ITTI framework was crucial in assisting the specialty plastics company in developing a sustainable, proactive maintenance approach, hence enhancing productivity and profitability in a competitive market.

23.4 Consumer Sustainability Industry Readiness Index

This section introduces the COSIRI, a framework that evaluates the extent to which manufacturing organizations integrate sustainability into their operations from a consumer perspective. The initial section provides a comprehensive overview and development of COSIRI, which serves as the foundation for its development and formation. The section then delineates its primary components, deconstructing the fundamental dimensions that motivate sustainable practices throughout the industry. The following section delves into the advantages and obstacles of implementing COSIRI, identifying the potential for

improved sustainability and the obstacles that companies may face. The section concludes with a case study of HP Inc., which illustrates the practical application of COSIRI in the manufacturing sector.

23.4.1 Overview and development of Consumer Sustainability Industry Readiness Index

The COSIRI was developed in reaction to the growing significance of sustainability, net-zero pledges, and environmental stewardship within the manufacturing industry. COSIRI, collaboratively developed by the World Economic Forum (WEF), the International Centre for Industrial Transformation (INCIT), and Capgemini Invent, provides a standardized methodology for evaluating and benchmarking an organization's environmental, social, and governance (ESG) maturity (INCIT, 2024). The COSIRI initiative expands beyond the limited focus of existing industry indices on operational efficiency and digitalization to encompass comprehensive sustainability dimensions, allowing manufacturers to align their practices with global climate objectives and changing stakeholder expectations.

COSIRI fundamentally functions as a "personal health assessment" for a company's sustainability preparedness. Rather than delivering a fixed overview, it presents a systematic, iterative approach for assessing ESG performance across all aspects, promoting ongoing enhancement and strategic adjustment. In creating the index, the project's collaborators aimed to fulfill the increasing demand for concrete, grassroots insights—data that would clarify the application of sustainability principles in daily operations and enable organizations to enhance their transformations in accordance with global emissions reduction objectives.

COSIRI-24, the premier assessment model of the framework, shows this comprehensive approach. The assessment encompasses 24 variables across four fundamental components—strategy and risk, sustainable business processes, technology, and organization and governance—addressing corporate ESG strategies, climate risk management, supply chain practices, and workforce development. COSIRI-24 integrates sustainability into every aspect of a company's operations, including R&D, warehousing, logistical partnerships, and external communications, rather than treating it as a separate endeavor.

COSIRI has prioritized comparability and scalability in its development, acknowledging that businesses of varying sizes and phases in their sustainability efforts need tools that may be customized to their own circumstances. Regardless of being a nascent firm in need of foundational advice or a multinational corporation readying for investor evaluation, entities can utilize COSIRI's defined criteria to assess performance relative to local, regional, and worldwide counterparts. This comparability underscores competitive advantages while indicating potential gaps that may require additional investment, legislative modifications, or stakeholder involvement.

From a governance standpoint, COSIRI-24's multistakeholder framework embodies the prevailing industry opinion that sustainability cannot be realized through isolated initiatives. The World Economic Forum's endorsement highlights the index's worldwide significance, while INCIT's participation contributes extensive expertise in industrial change. Simultaneously, Capgemini Invent provides strategic consulting expertise,

guaranteeing that the index remains forward-looking and responsive to evolving commercial, regulatory, and technology landscapes.

In conclusion, COSIRI's development signifies a concerted endeavor to connect overarching sustainability objectives with tangible, real-world execution. COSIRI assesses an organization's ESG maturity through 24 interconnected dimensions and integrates these assessments within a framework that fosters continuous learning, enabling manufacturers to prioritize enhancements, gain stakeholder support, and exhibit accountability to investors, regulators, and the wider community. As climate and environmental concerns ascend on global business and policy agendas, COSIRI is prepared to lead a more unified, data-informed, and inclusive strategy for sustainability in manufacturing.

23.4.2 Key components and evaluation criteria

COSIRI is structured around four overarching building blocks—strategy and risk management, sustainable business process, technology, and organization and governance—each of which is further subdivided into specific dimensions as shown in Fig. 23.7. This arrangement ensures a comprehensive examination of how sustainability principles are integrated into an organization's strategic, operational, technological, and cultural frameworks.

23.4.2.1 Key components

An organization's sustainability performance is evaluated across key dimensions by the comprehensive framework known as COSIRI. It commences by conducting an evaluation of strategy and risk management to guarantee that business objectives are effectively integrated with clear, ESG-driven objectives and that potential sustainability risks are effectively mitigated. The framework then evaluates operational practices, such as sustainable procurement, efficient supply chain management, and direct environmental impacts, to reduce waste and emissions. It also assesses the adoption of circular product lifecycles and

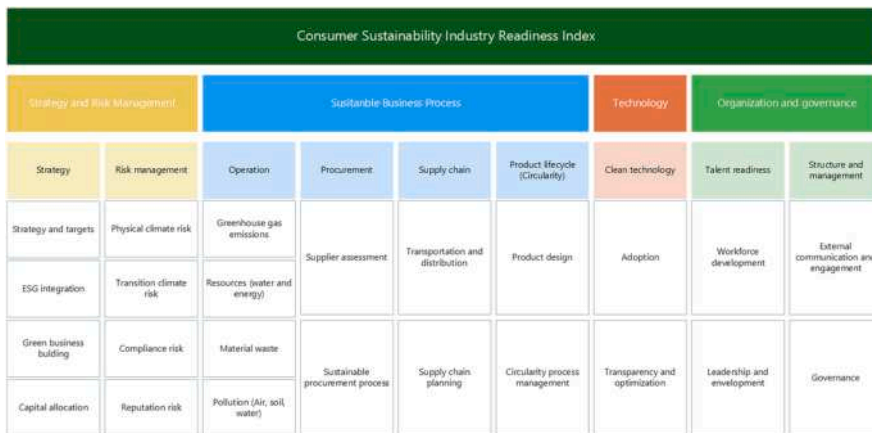


FIGURE 23.7 Consumer Sustainability Industry Readiness Index framework.

clean technologies, while also underscoring the significance of Talent Readiness and robust structure and management to facilitate sustainable innovation and governance.

23.4.2.1.1 Strategy

Strategy is the primary focus of the COSIRI in terms of the clarity with which a company defines its sustainability objectives and how they are aligned with its overarching business objectives. This dimension evaluates the degree to which organizations establish ambitious, quantifiable objectives—such as emissions reductions or resource conservation—and incorporate environmental, social, and governance (ESG) factors into their long-term planning. COSIRI evaluates whether sustainability is integrated into the corporate culture, as opposed to being treated as a separate initiative, by evaluating factors such as capital allocation, green business modeling, and cross-functional alignment. Companies that implement an effective strategy not only comply with regulations but also actively pursue opportunities for innovation and competitive advantage.

23.4.2.1.2 Risk management

Risk management in COSIRI is closely associated with strategic planning and pertains to the company's capacity to identify, evaluate, and mitigate a variety of sustainability-related risks. These may encompass physical climate risks (e.g., extreme weather events), transition risks (e.g., altered regulations or market preferences), compliance risks (e.g., evolving legal requirements), and reputation risks (e.g., stakeholder backlash or negative public perception). COSIRI emphasizes the organization's capacity to safeguard its brand and ensure operational continuity by analyzing the frameworks and processes that govern risk monitoring and response. Not only does effective risk management prevent costly disruptions, but it also establishes the company as a forward-thinking, trustworthy partner for regulators, customers, and investors.

23.4.2.1.3 Operation

COSIRI assesses the methods by which companies manage their direct environmental footprint in the operation dimension, with a particular emphasis on greenhouse gas (GHG) emissions, resource usage (water, energy), material waste, and pollution (air, soil, water). This evaluation demonstrates the extent to which environmental considerations are incorporated into routine decision-making and the efficiency of daily production processes. COSIRI identifies both strengths and areas for improvement by analyzing metrics such as energy intensity, waste reduction targets, and pollution control measures. Ultimately, a more resilient and competitive business model is the result of a strong commitment to resource efficiency, cost savings, and regulatory compliance, as indicated by a high-performing Operation dimension.

23.4.2.1.4 Procurement

Procurement examines the sustainability practices within a company's sourcing and supplier management processes. This encompasses the sustainable procurement process, which guarantees that purchasing decisions are in accordance with broader environmental or social objectives, and supplier assessment, in which organizations evaluate vendor performance on ESG criteria. Procurement teams can effect significant change upstream in

the supply chain by fostering transparency, collaboration, and long-term partnerships. This approach reduces the overall environmental impact and enhances social responsibility. The critical role that sourcing plays in shaping corporate sustainability is underscored by COSIRI, which encourages companies to select and incentivize suppliers who follow rigorous standards and share similar values.

23.4.2.1.5 Supply chain

The supply chain dimension of COSIRI expands the focus beyond inbound materials and procurement to include transportation and distribution, warehouse operations, and end-to-end planning. Effective supply chain management necessitates the optimization of routes, the reduction of lead times, and the reduction of emissions, all of which reduce costs and environmental impacts. COSIRI evaluates the extent to which organizations monitor and supervise these activities, as well as their capacity to implement digital tools for predictive analytics and real-time visibility. Companies can more effectively respond to market fluctuations, reduce their carbon footprint, and provide consistent value to customers by promoting sustainable, streamlined logistics.

23.4.2.1.6 Product lifecycle (circularity)

In this dimension, COSIRI evaluates the degree to which organizations incorporate circular economy principles into product design, manufacturing, and end-of-life strategies. Circularity process management, which pertains to the manner in which organizations manage reuse, repair, or recycling, and product design—which emphasizes material selection, modularity, and recyclability—are critical factors. Over the course of a product's entire lifespan, a circular approach can substantially diminish carbon emissions, waste generation, and resource extraction. Businesses can distinguish themselves in an increasingly eco-conscious market and establish new revenue streams in product recovery and remanufacturing by incorporating circular thinking into research, development, and manufacturing.

23.4.2.1.7 Clean technology

The clean technology dimension measures the extent to which a company adopts and scales environmentally friendly innovations to enhance efficiency and reduce its ecological footprint. This encompasses the utilization of digital platforms for resource optimization and monitoring, as well as emissions-reducing equipment and renewable energy sources. COSIRI assists organizations in identifying both long-term investments and "quick wins" by assessing adoption rates, cost-benefit analysis, and ongoing technology upgrades. A proactive approach to climate challenges is indicated by a strong performance in Clean Technology, which demonstrates the company's readiness to capitalize on emerging opportunities and maintain compliance with evolving regulations.

23.4.2.1.8 Talent readiness

Under talent readiness, COSIRI investigates how well an organization's workforce is equipped to execute sustainability initiatives. This entails evaluating leadership involvement and workforce development programs, including training and certification, to determine the dedication of senior executives to advancing ESG objectives. Also included

in effective talent readiness are the capacity to incorporate sustainability considerations into daily operations and cross-functional collaboration. COSIRI motivates organizations to allocate resources toward people-centric strategies that cultivate engagement, innovation, and a collective sense of accountability for environmental stewardship by emphasizing deficiencies in accountability structures, culture, or skill sets.

23.4.2.1.9 Structure and management

Finally, structure and management looks at the organizational frameworks, decision-making processes, and governance models that support sustainability. This dimension pertains to the clarity of roles and responsibilities, the transparency of reporting mechanisms, and the efficacy of stakeholder engagement, which encompasses internal communication and external partnerships. COSIRI assesses the extent to which the corporate governance structure is integrated with sustainability, which in turn affects resource allocation and strategic priorities. Cohesive, consistent ESG policies that align all tiers of the organization are frequently associated with a strong performance in structure and management, resulting in more robust accountability and sustained improvements over time.

23.4.3 Benefits and challenges

The implementation of the COSIRI can provide numerous benefits for manufacturing enterprises of all scales, delivering both short-term and enduring value. A significant advantage is COSIRI's on-site evaluation method, in which qualified assessors collaborate directly with the company to collect precise data and contextual insights. This approach guarantees data precision by recording real-time operating parameters and validating sustainable initiatives on-site. Consequently, firms obtain a detailed 360° report that includes scores for each of the 24 characteristics, best-in-class comparisons, and GHG emissions profiles, offering a definitive roadmap for enhancement. The prioritization matrix included in the final assessment assists organizations in ranking their sustainability targets based on potential effect and feasibility, while expert recommendations aid in addressing detected deficiencies.

In addition to diagnostic insights, COSIRI fosters creativity and mitigates risk. By identifying opportunities to optimize processes and minimize environmental impacts, firms can discover new efficiencies, generate innovative revenue streams, and bolster their resilience to climate-related disruptions. The star insignia and rating system provide an extra incentive, enabling participants to convey their sustainability accomplishments to external stakeholders—such as customers, investors, and regulators—thus enhancing brand reputation and stakeholder trust. The integration of directed enhancement and publicly acknowledged standards helps foster enduring involvement and ongoing progress in ESG (environmental, social, and governance) efforts.

Notwithstanding these advantages, companies may face many obstacles when implementing COSIRI. Initially, resource limitations—encompassing financial, technological, and human capital—can present obstacles, particularly for smaller firms that lack specialized sustainability teams or comprehensive data infrastructures. Collecting, validating, and analyzing the information necessary for a COSIRI assessment can be labor-intensive,

requiring interdisciplinary collaboration among departments that may not have previously collaborated. Cultural resistance within the firm can impede the adoption of proposed changes, especially if employees lack awareness of the long-term advantages of sustainability initiatives. Establishing explicit communication channels and thorough training programs is essential for obtaining buy-in at all organizational levels.

Ultimately, concerns regarding data confidentiality and security may emerge, as COSIRI depends on comprehensive operational metrics, emissions data, and supply chain information. Organizations must implement stringent data governance processes to safeguard sensitive information while granting assessors the necessary visibility for a substantive evaluation. Reconciling data-sharing requirements with privacy and competitive factors can be intricate, especially in sectors where proprietary methods or trade secrets serve as crucial competitive advantages.

COSIRI offers a robust platform for firms aiming to evaluate their sustainability performance, pinpoint significant enhancements, and convey their ESG advancements to stakeholders. By proactively tackling issues concerning resource allocation, organizational culture, and data security, manufacturers can maximize COSIRI's potential to promote sustainable growth, encourage innovation, and establish enduring resilience amid increasing environmental and market pressures.

23.4.4 Case studies: application of Consumer Sustainability Industry Readiness Index in manufacturing

23.4.4.1 Case study 1: HP Inc.

This case study is drawn from [INCIT \(2024\)](#). HP Inc. has long recognized the importance of sustainability in driving both innovation and responsible growth. In pursuit of ambitious climate targets—including a 65% reduction in Scope 1 and 2 greenhouse gas (GHG) emissions by 2025 (relative to 2015), a 50% cut in value chain GHG emissions by 2030 (relative to 2019), and net-zero emissions by 2040—HP has prioritized circularity, deforestation countermeasures, and water conservation as key pillars of its environmental strategy. To gain deeper insights into its progress and benchmark against industry peers, HP collaborated with the World Economic Forum and leveraged the COSIRI at its Singapore manufacturing site.

Through this assessment, HP validated several strengths in its sustainability transformation. One notable highlight was structured sustainability governance at both the corporate and site levels, ensuring that global objectives are translated into locally relevant actions. In tandem, HP's focus on circularity—including an increase in recycled plastic content within devices and packaging redesigns to reduce single-use plastics—has propelled the company toward its 2030 goal of achieving 75% product and packaging circularity by weight. As of 2022, HP also expanded its planet partners recycling program to 60 countries, recycling over one billion print cartridges.

The COSIRI assessment nonetheless pinpointed areas where HP could refine its sustainability initiatives. In particular, it revealed gaps in data consolidation at the site level, especially within logistics and warehousing—challenges that mirrored HP's own internal evaluations. By addressing these data-related issues, HP aims to gain a more

granular understanding of supply chain impacts at local facilities, thereby enabling more effective and targeted sustainability actions. Overall, the COSIRI framework provided HP with a quantitative measure of the impacts of its sustainability efforts, affirmed existing best practices, and pinpointed specific improvement opportunities that can be scaled across the organization's global footprint.

23.5 Future directions

This section delineates the changing landscape of readiness indexes in manufacturing and their potential to facilitate sustainable practices and digital transformation. It commences by analyzing the Evolution and Adaptation of Indexes, emphasizing the evolution of these composite tools from static performance metrics to dynamic, adaptive instruments that are in accordance with the rapid changes in technology and industry requirements. The subsequent section explores advanced analytical and data integration techniques, with a particular emphasis on the role of state-of-the-art techniques, including AI, machine learning, and real-time data integration, in improving the predictive capabilities and responsiveness of these indexes.

Furthermore, the discourse on contextual relevance and customization delves into the significance of customizing readiness indexes to satisfy the unique operational, sectoral, and regional needs of a variety of manufacturing environments, thereby guaranteeing that the metrics are both actionable and precise. The section then transitions to collaborative and ecosystem-based approaches, where it promotes stakeholder engagement and cross-industry partnerships as essential for the development of standardized, robust metrics that accurately reflect the multifaceted nature of contemporary manufacturing.

The section critically evaluates issues such as data quality, standardization hurdles, and the necessity of continuous refinement to keep up with technological advancements and industry disruptions in addressing emerging challenges and risks. In conclusion, future research directions and strategic implications delineate promising avenues for further investigation, including real-time analytics, IoT integration, and innovative normalization techniques. The discussion also includes how these advancements can inform strategic decision-making, policy formulation, and the overall sustainability agenda in manufacturing.

23.5.1 Evolution and adaptation of indexes

The dynamic interplay between the evolving demands of sustainable industrial practices and technological advancements has characterized the evolution and adaptation of readiness indexes in manufacturing. Initially, readiness assessments were based on static, isolated performance metrics that were primarily concerned with operational efficiency and cost-effectiveness. Although these initial measures were beneficial for assessing short-term productivity, they provided only a limited perspective on the more extensive strategic challenges of digital transformation. However, it became increasingly apparent over time that these conventional metrics were inadequate to capture the multifaceted nature of

industrial progress in the era of Industry 4.0 (Ma et al., 2024). This realization prompted the creation of composite indexes, which are integrated tools that are intended to encompass a broader range of indicators, such as technological infrastructure, process efficiency, and, most importantly, sustainability metrics.

The conceptual framework that underpins readiness indexes underwent substantial refinement as industries began to adopt digital transformation. A fundamental comprehension of performance gaps and opportunities was provided by early indexes; however, they frequently lacked the ability to dynamically integrate real-time data or adapt to rapidly changing technological landscapes. Modern indexes have transformed into agile, continuously updated instruments as a result of the introduction of sophisticated digital tools, including IoT sensors, big data analytics, and AI-driven decision support systems. These sophisticated models are now capable of integrating a wide range of datasets, allowing for a more nuanced evaluation of an organization's readiness to not only adopt new technologies but also to align these initiatives with long-term sustainability objectives (Rashid & Kausik, 2024).

In addition, the growing significance of environmental and social factors in industrial performance has had a substantial impact on the adaptation of readiness indexes. The incorporation of sustainability metrics, including energy consumption, carbon footprint, and waste management, into composite indexes is indicative of a more extensive paradigm shift in manufacturing. This change acknowledges that to guarantee long-term economic sustainability, operational excellence must be in harmony with environmental stewardship and social responsibility. Consequently, contemporary readiness indexes now fulfill a dual function: they serve as benchmarks for technological preparedness and as indicators of an organization's ability to operate sustainably in a resource-constrained, complex world (Javaid et al., 2022).

Lessons learned from early implementations also contribute to the continuous evolution of these indexes. Ongoing methodological refinements have been necessitated by initial challenges, including the necessity for subjective judgments in specific performance areas, standardization difficulties, and data quality issues. The development of more robust normalization techniques, sophisticated weighting schemes, and real-time data integration methods that improve the reliability and responsiveness of these tools is currently the primary focus of both researchers and practitioners. This iterative process guarantees that readiness indexes continue to be pertinent as technological landscapes and manufacturing practices evolve.

In the future, the strategic value and adaptability of readiness indexes in manufacturing are expected to be further enhanced by emerging trends. The integration of AI and advanced analytics is expected to result in the development of more predictive and prescriptive models that are capable of identifying potential risks and opportunities before they fully manifest. Furthermore, the integration of dynamic sustainability indicators that monitor environmental impacts in real time will become more prevalent in future indexes as the push for sustainable manufacturing intensifies. This development will not only facilitate proactive planning and risk mitigation but also stimulate innovations that enhance economic and environmental resilience.

In essence, the evolution and adaptation of readiness indexes in manufacturing encapsulate a broader narrative of industrial transformation. From their humble beginnings as static

performance metrics, these indexes have developed into sophisticated, multidimensional tools that are essential for assisting organizations in navigating the intricacies of digital transformation and sustainable development. The future of manufacturing will be significantly influenced by the ongoing evolution of these organizations, which is being driven by technological advancements, methodological refinements, and an ever-deepening commitment to sustainability. This will ensure that organizations are not only prepared for the challenges of today but also equipped to thrive in a rapidly changing industrial landscape.

23.5.2 Advanced analytical and data integration techniques

The evolution of manufacturing readiness indexes is being significantly influenced by the rapid emergence of advanced analytical and data integration techniques. These methods utilize the capabilities of AI, machine learning, and big data analytics to convert static assessment tools into dynamic, perpetually updated instruments. These advanced methods allow readiness indexes to capture real-time performance metrics and provide a more nuanced understanding of an organization's operational landscape by integrating vast datasets from internal systems, IoT sensors, and external sources.

The capacity to rapidly and accurately process and analyze large volumes of data is the foundation of this transformation. For example, machine learning algorithms have the ability to detect intricate patterns and correlations in the data, which may be difficult to detect using conventional statistical methods. This capability not only improves the indexes' accuracy but also provides them with predictive insights. Thus decision-makers can transition from a reactive to a proactive stance, identifying potential risks and future trends before their full realization. Consequently, readiness indexes are indispensable instruments for strategic planning, providing the necessary foresight to navigate the uncertainties of contemporary manufacturing environments.

Another critical component of these sophisticated analytical methods is the incorporation of real-time data. Readiness indexes can be updated in real time to reflect the most recent changes in operational performance, technological advancements, and sustainability measures through continuous monitoring and automated data feeds ([Rame et al., 2024](#)). This dynamic updating process guarantees that the indexes remain pertinent and current, regardless of the rapid evolution of external conditions and manufacturing processes. Additionally, the comprehensive assessment of industrial readiness is facilitated by the seamless integration of a variety of data sources, including machine performance logs and environmental impact assessments. It is essential for the effective decision-making process as it bridges the gap between isolated metrics and offers a comprehensive perspective ([Aldoseri et al., 2024](#)).

Advanced analytics not only improve the accuracy and timeliness of readiness indexes but also enhance their robustness by implementing more effective normalization and weighting schemes. Organizations can guarantee that each indicator in the composite index is precisely calibrated to accurately reflect its true impact on overall performance by employing sophisticated algorithms. This methodological rigor reduces the biases that frequently accompany manual data interpretation, resulting in more dependable and actionable insights. The outcome is a collection of readiness indexes that not only assess current performance but also function as dynamic instruments for predicting future trends, thereby enabling more resilient and agile operational strategies.

In conclusion, the incorporation of sophisticated analytical and data integration methodologies represents a substantial advancement in the creation of manufacturing readiness indexes. These next-generation tools provide comprehensive insights into both operational efficiency and sustainability performance, as well as enhanced accuracy and predictive capabilities, by utilizing AI, machine learning, and real-time data. In the digital era, manufacturing will continue to evolve, and these advanced techniques will be essential for maintaining readiness indexes that are adaptive, robust, and in alignment with the strategic imperatives of sustainable development and Industry 4.0.

23.5.3 Customization and contextual relevance

The customization and contextual relevance of readiness indexes for manufacturing are a critical frontier in their evolution. A one-size-fits-all approach is no longer adequate to capture the distinctive challenges and opportunities across different sectors as industries become more diverse and complex. Rather, it is anticipated that future readiness indexes will be customized to the unique operational realities of a variety of organizations, including small and medium-sized enterprises and large multinational corporations. These indexes will also be expected to reflect the unique market dynamics, regulatory environments, and technological maturity levels that are present in different regions and industries.

This customization enables a more detailed assessment of performance by aligning the metrics and indicators with the distinctive strategic priorities of each organization. For example, the relative significance of sustainability measures against digital transformation metrics may vary significantly between a traditional chemical processing plant and a high-tech automotive manufacturer (Feroz et al., 2021). These indexes become more precise and actionable by adapting the weighting schemes and normalization techniques to the contextual specifics of each sector. This enables companies to identify targeted areas for improvement that are directly relevant to their operational context.

Additionally, the utility of readiness indexes is improved by contextual relevance, which guarantees that the insights they offer are directly applicable to the current external conditions. In a time when market conditions, technological advancements, and environmental policies are changing at a rapid pace, the capacity to contextualize and personalize performance assessments is essential (Martínez-Peláez et al., 2023). This customized method enables the creation of unique strategies that address specific regional or sectoral challenges, optimize resource allocation, and promote continuous innovation. In essence, future readiness indexes will not only function as reliable benchmarks for digital and sustainable transformation but will also enable organizations to navigate the intricacies of contemporary manufacturing with greater agility and precision by incorporating contextual relevance and customization.

23.5.4 Collaborative and ecosystem-based approaches

The future development of manufacturing readiness indexes is increasingly being driven by collaborative and ecosystem-based approaches. In the intricate industrial landscape of the present day, it is impossible for a single organization to independently comprehend the multifaceted nature of digital transformation and sustainability. Rather, it has become

imperative to cultivate an environment of collaboration among academic institutions, governmental bodies, technology providers, and industry leaders. These partnerships ensure that readiness indexes are comprehensive and responsive to the rapidly changing dynamics of modern manufacturing by combining a variety of expertise and insights (Rodríguez-Espíndola et al., 2022).

The principle of cocreation is the foundation of these collaborative approaches. Their distinctive perspectives on operational challenges, technological trends, and sustainability imperatives are contributed by stakeholders throughout the manufacturing ecosystem. This collective intelligence not only improves the quality of the underlying data but also facilitates the development of standardized metrics and methodologies. For instance, public-private partnerships can be instrumental in the establishment of shared data standards and best practices (Jiaqi, 2023). This standardization enhances the comparability and reliability of readiness indexes, rendering them more advantageous for benchmarking performance across various sectors and regions.

Additionally, ecosystem-based methodologies foster continuous learning and knowledge sharing, which are indispensable for innovation (Rabelo Neto et al., 2024). Organizations can develop more effective and adaptable solutions by collaborating to identify common challenges and opportunities through the open sharing of their experiences and insights. This collaborative spirit enables the dissolution of conventional silos, thereby enabling a more comprehensive understanding of industrial performance that includes both sustainable practices and digital capabilities. Consequently, readiness indexes transform into dynamic instruments that not only evaluate present performance but also predict future trends and risks, thereby facilitating proactive strategic planning.

Another substantial advantage of collaborative methodologies is their capacity to generate contextual relevance (Cao & Zhang, 2011). Organizations can guarantee that the resulting tools are finely tuned to the specific requirements of various industries and regions by involving a wide range of stakeholders in the index development process. This customized method enables organizations to compare their performance to that of their peers who are operating in comparable circumstances, while simultaneously pinpointing areas that require enhancement. Furthermore, collaboration promotes an adaptive feedback loop, in which indexes are continuously refined in response to real-world insights and emerging technological advancements. Consequently, readiness assessments are guaranteed to be current, robust, and consistent with the changing objectives of digital transformation and sustainability. Lastly, the strategic decision-making and risk mitigation are improved by the collective expertise that is acquired through collaborative networks. The complex interplay between technological innovation, operational efficiency, and environmental stewardship is more effectively captured by readiness indexes developed through ecosystem-based approaches, which incorporate a variety of viewpoints and expertise. Resilience against market disruptions and regulatory changes is also promoted by this holistic perspective, which also supports effective resource allocation and investment decisions (Nunes et al., 2022).

In conclusion, the evolution of readiness indexes in manufacturing has been significantly altered by collaborative and ecosystem-based approaches. These methods improve the accuracy, adaptability, and strategic value of readiness assessments by leveraging the power of collective expertise and fostering cross-sector partnerships. Such collaborative models

will be essential in fostering resilience, driving innovation, and achieving long-term economic and environmental sustainability as manufacturing continues to evolve in an increasingly interconnected and dynamic environment.

23.5.5 Addressing emerging challenges and risks

Addressing emerging challenges and risks is a critical element in the ongoing development of manufacturing readiness indexes. Despite the fact that these indexes provide substantial strategic benefits by incorporating a variety of performance metrics, they are also confronted with a number of persistent and evolving challenges. Data quality is a significant obstacle. Many organizations continue to struggle with fragmented, inconsistent, or outdated datasets, which can compromise the reliability and accuracy of the indexes. It is essential to ensure that the data inputs are comprehensive and accurate, as readiness assessments are heavily reliant on them. Additionally, standardization concerns introduce an additional layer of complexity. The absence of uniform standards can render cross-comparison and benchmarking less effective, as various industries and regions frequently employ a variety of metrics and methodologies. The development of robust normalization and weighting schemes that can reconcile these discrepancies while still capturing the unique aspects of each context is required due to the diversity in measurement techniques.

The rapid pace of technological advancement poses risks in terms of adaptability, besides data-related challenges. To maintain their relevance, readiness indexes must be continuously refined as new digital technologies are introduced. The dynamic nature of digital transformation necessitates an agile framework that can integrate real-time data and predictive analytics, as the metrics and indicators that are currently in use may quickly become obsolete. The indexes' utility in a rapidly changing industrial landscape is contingent upon this continuous evolution. In addition, the subjective interpretation of qualitative indicators, such as organizational culture or leadership commitment, can result in significant variability in assessment results. The necessity of continuous methodological enhancements and iterative validation processes is underscored by these interpretative challenges.

In addition to these technical and methodological issues, the more extensive challenge is the integration of these tools into the decision-making frameworks of diverse organizations. In addition to technological and analytical sophistication, a profound comprehension of the specific operational contexts is necessary to guarantee that the insights obtained from readiness indexes are both actionable and in alignment with long-term strategic objectives. Consequently, a balanced approach that integrates collaborative stakeholder engagement with continuous technological refinement is necessary to address emerging challenges and risks, ensuring that these tools can adapt to both current needs and future uncertainties (Tripathi et al., 2024). In this manner, the continuous development of readiness indexes will not only solidify their strategic value but also ensure their status as essential instruments for navigating the intricacies of sustainable manufacturing and digital transformation.

23.5.6 Future research directions and strategic implications

Future research directions and strategic implications are a critical frontier in the continuous development of readiness indexes in manufacturing. There is a clear imperative

for additional interdisciplinary research to refine the underlying methodologies and enhance the strategic value of these composite metrics as they become increasingly central to guiding digital transformation and sustainable practices.

The development of dynamic, real-time indexes that continuously integrate data from IoT sensors, AI-driven analytics, and advanced big data techniques is emerging area of exploration in the field of research. These dynamic models have the potential to provide predictive insights that not only capture current performance but also predict future trends and risks, thereby allowing organizations to proactively adjust their strategies. In an effort to enhance the reliability and accuracy of composite indexes, researchers are conducting an increasing number of investigations into innovative normalization and weighting schemes. These studies frequently concentrate on the calibration of indicators across a variety of industrial contexts, thereby addressing the distinct operational, technological, and sustainability challenges of various sectors (Shabur, 2024). Additionally, there is an increasing demand for the incorporation of qualitative dimensions—including stakeholder engagement, leadership dynamics, and organizational culture—into these quantitative frameworks, which requires the development of innovative mixed-method approaches (Garrido-Moreno et al., 2024).

The implications of these research advancements are profound from a strategic perspective. By furnishing a robust, data-driven foundation for resource allocation, technology investments, and risk mitigation strategies, enhanced readiness indexes can function as indispensable instruments for strategic decision-making. These indexes will likely influence policy formulation and industry standards as they evolve, serving as benchmarks that drive regulatory frameworks and encourage best practices throughout the manufacturing ecosystem. Policymakers can utilize the information obtained from advanced readiness assessments to develop supportive measures that promote innovation and guarantee that industrial transformation is consistent with economic and environmental sustainability objectives.

Moreover, the dual imperative of modern manufacturing is emphasized by the integration of sustainability metrics with emerging analytical techniques: achieving operational excellence while promoting environmental stewardship (Dharmayanti et al., 2023). Strategic leaders will be better prepared to implement comprehensive transformation initiatives that not only increase productivity but also contribute to long-term resilience and resource efficiency as future research continues to bridge the gap between global sustainability objectives and digital technologies. The development of adaptive, forward-thinking readiness indexes that can effectively navigate the complexities of an increasingly dynamic industrial landscape will be facilitated by the ongoing convergence of research and strategy.

In conclusion, the methodological robustness of readiness indexes is expected to be improved through the integration of real-time data, refined predictive analytics, and a more nuanced integration of qualitative factors in future research. From a strategic perspective, these developments are on the brink of revolutionizing the way in which organizations approach sustainable manufacturing and digital transformation. They provide a comprehensive framework that facilitates proactive planning, effective policy-making, and continuous improvement in a global market that is rapidly evolving.

23.6 Conclusion

The critical role of readiness assessments in navigating the transition to Industry 4.0 and embedding sustainable practices into manufacturing operations has been emphasized by the journey through this chapter. We have observed that customized frameworks can provide profound insights into an organization's current capabilities, identify areas for improvement, and ultimately direct strategic investments in sustainable measures and digital technologies by analyzing key indexes such as SIRI, ITTI, and COSIRI.

SIRI demonstrates a comprehensive approach to the assessment of digital transformation, with an emphasis on the integration of advanced automation and connectivity, as well as operational efficiency. Companies such as Pepperl+Fuchs and Haier have utilized these insights to optimize their production processes and expedite innovation, as evidenced by the detailed evaluation criteria and case studies.

ITTI expands upon this by exploring the technical aspects of transformation, emphasizing the importance of intelligent data-driven decision-making, manufacturing optimization, and R&D. ITTI is a reliable indicator of industrial competitiveness and technological maturity, as evidenced by practical examples from global industry leaders including PepsiCo, Tata Steel, Cipla, and Specialty Plastics.

COSIRI serves as a bridge between environmental responsibility and digital readiness. COSIRI offers a roadmap for companies such as HP Inc. to improve their environmental stewardship and remain competitive in a market that is increasingly driven by eco-conscious consumers by incorporating sustainability into every layer of the manufacturing process, from strategic planning and risk management to operations and customer engagement.

Going forward, this chapter's discourse on future directions underscores the necessity of these indexes' ongoing development. Organizations must adopt advanced analytical tools, embrace collaborative approaches, and customize these frameworks to their specific contexts as digital technologies advance and the pressures for sustainable practices intensify. In addition to a steadfast dedication to the integration of circular economic models into the fabric of industrial strategy, the integration of innovative technological solutions will be necessary to address emerging challenges and risks.

In summary, the thorough analysis of SIRI, ITTI, and COSIRI in this chapter serves to underscore that Industry 4.0 readiness is not solely contingent upon technological advancements; it also involves strategic alignment, sustainable practices, and ongoing improvement. These indexes are indispensable instruments that enable organizations to make well-informed decisions, foster innovation, and, in the end, establish a competitive advantage in a global marketplace that is becoming more intricate and environmentally conscious.

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Environmental impacts of digitalization based on life cycle assessment

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24.1 Introduction

Digitalization, considered the driver of the fourth industrial revolution, is happening in every part of society and across sectors, and emerging as a key component of current sustainable development strategies. Also referred to as Industry 4.0, the Fourth Industrial Revolution is characterized by increasing automation and the use of smart machines and factories, enabling real-time decision-making and the efficient and agile manufacture, improvement, and distribution of products (Ghobakhloo, 2020). Industry 4.0 technologies are not only essential for enhancing the productivity and performance of manufacturing through advanced production systems, but they also play a key role in driving low-carbon transition efforts globally.

In light of urgent climate challenges, digital transformation presents significant opportunities to reduce energy consumption, environmental impact, and greenhouse gas (GHG) emissions. In this regard, digital technologies such as big data analytics, artificial intelligence (AI), the Internet of Things (IoT), blockchain, intelligent robotics, cloud, and edge computing among others, can accelerate and improve the effectiveness of environmental regulations by aiding in the reduction of resource consumption and emissions. The growing application of AI to optimize energy and resource usage and the use of distributed ledger technology (DLT) to facilitate the circular economy are just two examples of how the digital shift may help and accelerate the green transition. Digitalization has the potential to make the

industrial, manufacturing, agricultural, mobility and various system more sustainable and promote positive behavioral shifts, fair business models and system(s)-wide optimization. According to research by Accenture and the World Economic Forum's Digital and Climate Network ([World Economic Forum & Accenture, 2022](#)), digital technologies might help reduce emissions in high-emission sectors like energy, materials, buildings, and mobility by up to 20% by 2050 if they are broadly implemented. By 2030, these industries may reduce emissions by 4 to 10%, depending on the pace of adoption, through a reduction or avoidance of resource use (e.g., fuel, electricity, and raw materials). However, it is crucial to recognize that new and emerging technologies can also have potentially adverse social and environmental impacts that demand consideration, necessitating a comprehensive understanding of their overall impacts, limitations, and risks.

As our world becomes increasingly digitalized and interconnected, there is a growing awareness of the environmental impact associated with digitalization. The information industries, and the Information and Communication Technology (ICT) sector in particular, are the backbone of digital transformation. Currently, the ICT sector accounts for 1.8%–2.8% of global GHG emissions, comparable to the aviation industry, and is projected to exceed 14% of worldwide GHG emissions by 2040, surpassing half of the current relative contribution of the entire transportation sector ([Belkhir & Elmeligi, 2018](#)). Despite ongoing technical progress driving high-energy efficiency gains, the digital carbon footprint is increasing by about 8% annually due to exponential growth in digital “volumes” such as devices, network traffic, computing instances, and stored data ([Itten et al., 2020](#)). Moreover, digital transformation raises concerns regarding high-energy consumption, which largely comes from fossil-based electricity, toxic disposal of systems, and electronic waste (e-waste) issues ([Dwivedi et al., 2022](#)).

The impact of digitalization on energy, materials, and ecosystems raises questions about whether the increased electricity and material use will be offset by efficiency gains and sustainable behaviors driven by digital innovations ([Andersen et al., 2021](#)). Current research and initiatives often fall short of providing a robust environmental rationale for their sustainable implementation, particularly when accounting for their overall impacts. A consistent and comparable framework and methods for assessing ICT and digital solutions' impact are therefore, crucial for empowering stakeholders to make informed decisions and foster the development of climate-positive digital solutions.

One of the most common methodologies for quantifying the environmental impacts is life cycle assessment (LCA). LCA is a systematic analysis of the environmental impacts of a product, material, process, or other measurable activity throughout its entire life cycle, from raw material extraction to end-of-life disposal ([ISO, 2006a](#)). LCA models the environmental implications of the many interacting systems that make up industrial production. Such an approach would help identify areas of concern, potential improvements at each production stage, and avoid suboptimal solutions when evaluating digital solutions ([Gäbel et al., 2004](#); [Valderrama et al., 2012](#)). Furthermore, because of its comprehensive approach, LCA is a multicriteria method that can evaluate a broad range of environmental impacts, such as climate change, the depletion of fossil and mineral resources, effects on human health, and ecosystems, facilitating the identification of potential burden shifting through its comprehensive approach. Leveraging the LCA framework, the consortium of the European Parliament has established methods and tools to measure the net carbon impact of green

digital technologies on the environment and climate, which consider the full life cycle emissions of the ICT solutions (European Green Digital Coalition, 2024).

A comprehensive and consistent evaluation of the effects of solutions enabled by digital technologies is crucial for validating, disseminating, and optimizing their intended impacts. Such evaluation can significantly contribute to advancing a sustainable and just transition. This chapter explores how increasing digitalization affects the environment while enabling innovative, sustainable solutions across industrial and manufacturing sectors. It also examines both the positive and negative environmental impacts of ICT in digitalization (Section 24.2). Section 24.3 discusses the existing methods for evaluating the environmental impacts of ICT solutions based on the LCA framework. Additionally, Section 24.4 presents mitigation strategies and sustainable practices related to digitalization and Industry 4.0. Lastly, this chapter provides conclusions and a future outlook.

24.2 Digitalization and its environmental footprint

In the context of digital transformation, terms like “digitization” and “digitalization” are often used interchangeably, though they have distinct meanings (Bumann & Peter, 2019). “Digitization” involves converting analogue data into digital form, while “digitalization” refers to the application of digital technology and its impacts on processes. The environmental repercussions of digitalization have been studied for a long time; however, the current technological advancements have broadened the domain of digitalization.

A previous review has discussed various environmental benefits of digitalization in manufacturing (Chen et al., 2020). For instance, cyber-physical systems (CPS) and IoT could allow transparency in manufacturing by enabling real-time monitoring of resource consumption, which enhances production management responsiveness (Oláh et al., 2020). Additive Manufacturing (AM) enhances resource efficiency through just-in-time production closer to the end-user, minimizing waste by allowing for customized production (Ford & Despeisse, 2016). Intelligent robotics boosts productivity and stabilizes quality, leading to higher resource efficiency and reduced waste (Ghobakhloo, 2020). Virtual reality (VR) and augmented reality (AR) platforms can assist in the design stage by enabling virtual prototyping, thereby saving the resources and energy typically used for physical prototypes (Chang et al., 2017). Additionally, integrating AI, cloud computing, and big data can be used to minimize downtime, “just in time” provision of spare parts, and energy and resource distribution optimization (Gobbo et al., 2018).

The current era’s critical dependence on ICT has significantly diverted attention to the negative environmental effects arising from digitalization. Despite being an important factor in the economic and social welfare of a society, this sector has been criticized for its environmental degradation due to the extensive use of resources and materials for hardware manufacturing and processing, excessive energy consumption, toxic or hazardous waste disposal, and significant emissions.

Most of the environmental assessments primarily focus on the carbon footprint, neglecting the other major effects on the environment, such as pollution, water deprivation (Mir et al., 2024), and resource depletion. Environmental footprint is not only limited to carbon footprint but also includes various other effects on the environment which can

emerge from the different stages of a product's life cycle, such as raw material acquisition phase, transportation, manufacturing and processing, use, and the disposal phase. Each phase can have different effects, depending on requirements such as energy consumption, material use, waste generation, and water consumption.

The following subsection outlines the components that enable digitalization and highlights the key environmental concerns associated with these technologies.

24.2.1 Overview of the digital ecosystem

For properly comprehending digitalization, it is important to understand its components. Based on prominent research, ICT equipment can be divided into three main categories: data centers, telecommunication networks, and end-user devices.

Data centers are specialized buildings designed to house computer systems and associated components, such as supply infrastructure and IT components. They are critical for storing, managing, and processing data. They are characterized by the operator, their deployment model, or by the capacity/size of the data center. They play a crucial role in the functioning of the internet, cloud computing, and various digital services we rely on daily. Due to an increase in data traffic, data centers are expected to consume more electricity, thereby amplifying their environmental footprint (Roussilhe et al., 2023).

Telecommunication networks communicate the data from the data centers to the end-user devices. They manage data transmission through various infrastructures, including the internet (5G, LTE), intranets, and other communication networks. These systems vary in scale, purpose, and complexity; however, all serve the same purpose, that is, to facilitate data transfer. Similar to data centers, the studies on the network systems also focus largely on the electricity consumption. The use phase of the network system represents 80% of the total carbon footprint (Malmodin & Lundén, 2018). On the other hand, the manufacturing phase is out of scope and will increase the impacts further when included.

End-user devices are microelectronic tools or gadgets used to collect, process, transmit, or store data, serving as interfaces between users and the digital world. These devices enable various tasks, from simple communication to complex data analysis. Common end-user devices include personal computers, laptops, smartphones, smartwatches, and tablets, while in public spaces, devices used are ticket machines, security cameras, etc. Additionally, IoT devices connect the digital virtual world with the physical world, allowing for a digital transformation in various sectors such as home, industry, automotive, energy, or healthcare. Specifically, integrated circuits (ICs) used in these devices have a substantial environmental impact due to its advanced technological manufacturing and fabrication (Clément et al., 2020).

24.2.2 Energy consumption and efficiency in digital systems

The energy consumption of digital technologies throughout their life cycle is roughly equal to 8%–10% of the global electricity consumption (Freitag et al., 2021). This is expected to rise further because of the huge demand for ICT. The emissions from this sector are in the range of 2.1%–3.9% of the global GHG emissions, which also include their embodied emissions. The more the demand for ICT, the more energy consumption, hence more emissions (Freitag et al., 2021).

The projected increase in the data traffic, network, and the user devices leading to an increase in energy consumption and associated emissions would depend on the five modeling assumptions stated next:

- Rising use of digital systems is surpassing the energy efficiency gains.
- Approaches for modeling the energy intensity of data traffic per user or per gigabyte.
- Future balance between data center capacity expansion and the energy efficiency of IT equipment and utility infrastructure, including power usage effectiveness (PUE).
- Projections and trends in future data volumes against the transmission efficiency of communication networks.
- Anticipated trends and demand in electricity consumption by key digital technologies.

The energy consumption of the subsectors, such as data centers, networks, and end-user devices, is projected to increase along with the energy efficiency and performance. For data centers, there is an exclusive demand for capacity building to store, process, and transmit more data. The anticipated net growth in electricity consumption due to digitalization significantly exceeds the efficiency gains. The enormous load from data volumes, computation and transmission expects the net growth in electricity consumption 2.5 times in 2030 with respect to 2020 (Pohl & Hinterholzer, 2023) while another study projects that energy demand will grow annually by 6% in the best-case scenario and by 13% in the expected scenario through 2030 (Andrae, 2020).

Communication networks have significantly increased in energy efficiency by employing energy-efficient technologies for data transmission, which includes a shift from older technologies to new ones like 5G. Despite decent improvement in efficiency, the fast-paced data traffic surpasses the improved energy efficiency. The projected increase in the network electricity consumption is expected to be threefold between 2020 and 2030 (Andrae, 2020). Some studies have shown a decrease in network electricity consumption, but the representativeness of this data is specific to a country's communication network system.

The end-user devices subsector is characterized by intense energy consumption during the production phase, with a predominant proportion of fossil fuel in the electricity mix (Manhart et al., 2016). For common devices such as laptops, phones, and tablets, around 50%–60% of the energy demand and emissions occur in the production stage (Hischier et al., 2015). The advancement in the development of digital devices producing bigger and better performing devices is associated with increased energy consumption during the production as well as the operation phase due to increased computing power and functionalities (Proske et al., 2020). The number of devices is expected to increase drastically, but at the same time, the efficiency of the devices has increased tremendously both from a performance perspective and the use of device types. Therefore, a slight electricity consumption of 3% is anticipated in annual electricity demand to 2030 (Schneider Electric, 2021).

24.2.3 Resource extraction and material use in manufacturing digital devices

The majority of the research on digital technologies focuses on the energy consumption and the corresponding emissions without accounting for other direct environmental effects.

Beyond carbon footprint, digital systems cause damage to the environment, particularly due to resource (abiotic and biotic) consumption, water consumption, land use, and thereby causing biodiversity loss.

Data centers encompass two main components: ICT equipment (servers, networking devices, and storage systems) and infrastructure equipment (e.g., heating, ventilation, air conditioning, lighting, and backup power supply). From a resource consumption perspective, support systems are heavier due to metals like steel, copper, and aluminum, whereas ICT equipment is lighter, comprising semiconductors, precious metals, and rare earth elements. ICT equipment has a shorter service life than support systems, prompting earlier replacement. Therefore ICT components in data centers contribute more significantly to natural resource depletion. A study on data centers shows that the production phase of both ICT equipment and support systems accounts for 45% to 60% of the abiotic depletion impact category over the whole life cycle (Liu, Gailhofer, Köhler, et al., 2019). Components with high abiotic depletion potential in their production phase include integrated circuits, hard disk drives (HDDs), solid-state drives, printed wiring boards, large lithium-ion batteries, and chassis.

The data transmission network require various hardware devices for its operation. Networks can be fixed or mobile, utilizing hardware such as copper cables, optical network units, cooling systems, power units, routers, switches, and undersea cables. These systems require significant amounts of metal and mineral raw materials during production. For mobile telecommunication networks, raw material acquisition accounts for 95% of the abiotic resource depletion impact, with silver contributing 54%, followed by gold and antimony at 18% and 17%, respectively. Approximately 1,207,005 km of undersea cables are already connected across continents, highlighting their material consumption and resource use (Pino, 2017).

End-user devices are electronic devices containing a mix of critical elemental substances mined in small quantities. They are resource-intensive due to parts and components with high environmental impact during production, such as ICs, displays, printed wiring boards, batteries, and power supplies. Studies indicate that the production phase of electronic devices, such as smartphones, tablets, and laptops, including raw material acquisition, accounts for 85% of the resource depletion impact throughout the product's life cycle. However, for long-life products, the use phase dominates the resource depletion category due to electricity consumption (Andrae & Vajja, 2017). Smartphones and tablets are particularly resource-intensive because they contain a high share of rare materials, have short lifespans necessitating frequent replacement, and are shipped globally in large quantities. These devices significantly drive the demand for cobalt, palladium, silver, gold, indium, tantalum, and magnesium (Liu, Gailhofer, Köhler, et al., 2019).

24.2.4 E-waste generation and management challenges

E-waste, or electronic waste or the waste from electrical and electronic equipment (WEEE), consists of discarded ICT products from consumers, including phones, tablets, laptops, desktops, and HDDs. This waste is a complex mixture of diverse materials, comprising various organic and inorganic substances whose composition varies by type, age, and manufacturer. Classified as hazardous waste, WEEE contains harmful

substances such as heavy metals (e.g., mercury and lead in fluorescent lamps and batteries) and flame retardants (e.g., brominated flame retardants, BFRs). Improper management of this waste stream can pose significant threats to human health and the environment. However, WEEE also contains valuable materials, making it an important source for recovering plastics, glass, precious metals, and rare earth metals. E-waste is a critical waste stream due to its rapid growth and associated pollution problems worldwide (Cui & Zhang, 2008).

E-waste has been produced two to three times in excess of other waste streams globally, mainly due to their wider distribution and consumption. According to the Global E-Waste Monitor 2020 (Forti et al., 2020), a record 53.6 million metric tons (Mt) of electronic waste was generated worldwide in 2019, up 21% in just five years. The prediction of this report says that global e-waste will reach 74 Mt by 2030—almost a doubling of e-waste tonnage in just 16 years. Only 17.4% of 2019's e-waste was collected and recycled. According to UNEP (United Nations Environment Program), around 90% of the electronic waste worth US\$19 billion is illegally dumped or traded each year (Mihai et al., 2019). Recycling only a small amount of e-waste implies that all the precious items, such as gold, silver, copper, platinum, and other high-value, recoverable items (materials conservatively valued at US\$57 billion) were mostly dumped or burned rather than being collected for treatment and reuse. This signifies the essence of recycling e-waste; otherwise, loss of valuable materials is evident (Balde et al., 2015).

Over time, the toxic chemicals of the different components of e-waste, such as metals, plastics, heavy metals, and flame retardants, penetrate the soil or are emitted to the atmosphere if managed inappropriately, thus affecting the neighborhood communities, society, and the environment. Improper management of WEEE is a cause for environmental pollution. The practices of open dumping and open burning are the worst options that many underdeveloped countries have adopted due to a lack of proper legislation, infrastructure, and waste management planning. Proper directives must be followed for the e-waste, which sets collection, recycling, and recovery targets for all types of ICT devices and digital technologies. The European waste management hierarchy could provide the most desired solutions, starting with waste prevention and reuse, followed by recycling (including composting), then energy recovery, and last, waste disposal in landfills (Kiddee et al., 2013).

24.3 Quantifying the impacts of digital technologies and solutions

Building upon the previous section, it is clear that evaluating the impact of digital solutions requires consideration of various ICT components, life cycle stages, and functionalities. These factors are crucial in assessing the overall performance and eco-effectiveness of the solutions. Therefore a robust, objective, and science-based methodology and calculation of the environmental impacts of digital technologies, relying on LCA, is important to provide holistic solutions. This section summarises LCA in general, its application to digital technologies and services, established methodologies, and illustrative case studies, as well as the key methodological challenges involved.

24.3.1 General principles and methodological approach of life cycle assessment

LCA evaluates the environmental impact of a product, process, or service across its entire life cycle (raw material extraction, production, use, and postuse). It provides insights for improving product development, strategic planning, environmental communication, and evidence-based decision-making (Nurdiawati et al., 2025).

LCA follows a standardized methodology, ensuring its reliability and transparency. The International Organization for Standardization (ISO) outlines the LCA process in standards ISO 14040 and 14044 (ISO, 2006a, 2006b), detailing its four interrelated phases (see Fig. 24.1):

1. **Goal and scope definition:** Establishes the study's purpose, intended audiences, system boundaries, and the functional unit, which is the "quantified performance of a product system for use as a reference unit" (ISO, 2006a, 2006b).
2. **Inventory analysis:** Quantify the relevant inputs (raw materials, energy) and outputs (emissions, waste) of the system under study. In reality, most industrial processes yield multiple products and/or intermediate products, with some waste being recycled. Therefore, allocation criteria must be applied to assign the environmental load to each product.
3. **Impact assessment:** Evaluates the potential environmental impacts identified in the inventory analysis. This process involves selecting impact categories (e.g., climate change) and linking inventory data to impact category indicators (e.g., climate change in 100 years using the IPCC 2021 model) through a characterization factor. The numerical results of the indicators can be sorted, standardized, grouped, and weighted as needed. This phase provides information for the interpretation phase.
4. **Interpretation:** Reviews and validates conclusions to ensure reliability and transparency. This stage forms the basis for making recommendations and guiding decision-making in line with the established objectives and scope. Sensitivity and uncertainty analyses are necessary to assess the extent of result variations caused by data uncertainty. LCA is an iterative process, allowing continuous refinement and improvement.

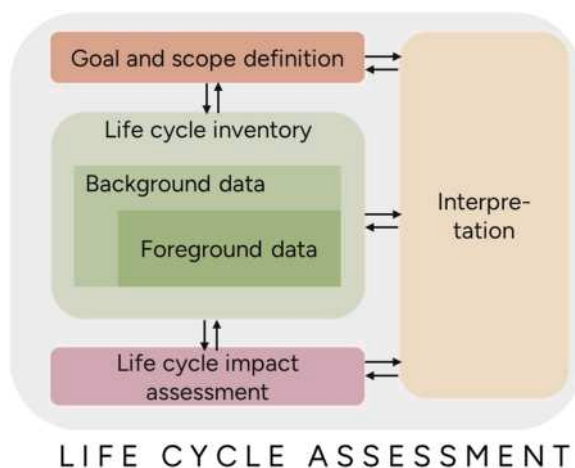


FIGURE 24.1 Life cycle assessment framework (ISO, 2006a, 2006b).

24.3.2 Methodology for assessing the environmental impact of digital technologies based on life cycle assessment

In its early years, LCA primarily focused on the direct impacts of ICT physical infrastructure. A comprehensive LCA of digital transformation, however, involves evaluating ICT with its diverse multifunctional devices, along with the substitution and cumulative effects resulting from new services enabled by modern ICT. The fast-paced growth of the digital sector underscores the need to streamline LCA methods for ICT applications and draw generalizations from previous case studies. The development of specific methodologies for ICT applications has been ongoing, as demonstrated in [Table 24.1](#).

Overview of key concepts related to the LCA of digital solutions ([European Green Digital Coalition, 2024](#)):

- Reference scenario: The baseline situation without the ICT solution, including activities delivering the same service as the ICT solution. It shall be determined as the most likely alternative scenario in the event the solution is not implemented.
- ICT solution scenario: The scenario with the ICT solution, modifying or replacing some reference activities while potentially leaving others unaffected.
- Functional unit: The quantified performance of the system, used to describe GHG impacts and allow comparison between reference and ICT solution scenarios.
- Implementation context: The context in which the solution is implemented, common to both scenarios.

The differences between reference and ICT Solution scenarios are classified into three different effects that are defined in the following ([ITU, 2022](#)):

- First-order effects: Direct environmental impact linked with the physical existence of an ICT solution, that is, the raw materials acquisition, manufacturing, use, and end-of-life treatment stages, and generic processes supporting those, including the use of energy and transportation.
- Second-order effects: The indirect impact resulting from the use and application of ICTs, which includes changes of environmental load due to the use of ICTs that could be positive (i.e., an emissions reduction) or negative (i.e., where additional activities occur, or existing activities are modified to increase GHG emissions).
- Higher order effects: The indirect effects, beyond first and second-order effects, include but are not limited to rebound effects (e.g., efficiency gains tend to be counteracted by increased consumption).

A net carbon impact assessment measures the potential GHG impacts resulting from the implementation of a solution compared to a reference scenario. According to the methodology developed by [European Green Digital Coalition \(2024\)](#), the framework is summarized in [Fig. 24.2](#).

Before beginning the calculation, it is necessary to fully define the solution, assessment criteria, and context. This is followed by the identification of all effects resulting from the implementation of the ICT solution. First-, second-, higher-order effects and GHG impacts are mapped out analytically in a consequence tree. Estimating the relative magnitude of

TABLE 24.1 Existing methodologies that address the environmental impacts of information and communications technology (ICT) solutions.

Existing methodologies	Summary
L.1410—Methodology for environmental life cycle assessments of information and communication technology goods, networks, and services (ITU, 2014)	Addresses environmental LCAs of ICT goods, networks, and services. It consists of: Framework and guidance for ICT LCA methodology Framework and guidance for comparative analysis between ICT and reference product systems (baseline scenario).
ITU-T L.1480—Enabling the Net Zero transition: Assessing how the use of information and communication technology solutions impact greenhouse gas emissions of other sectors (ITU, 2022)	A methodology for assessing how ICT solutions impact GHG emissions of other sectors. It covers the net second-order effect (after accounting for emissions due to the first-order effects of the ICT solution) and higher order effects like rebound. Guidance is provided for assessing these effects in various contexts: specific user implementations, different scales (organizational, city, country, or global), and from the perspective of ICT organizations providing the solutions.
Net Carbon Impact Assessment Methodology for ICT Solutions (European Green Digital Coalition, 2024)	The net carbon impact of a solution is determined by comparing its carbon impacts to a reference scenario without the solution, both within the same boundary. This comparison includes all direct and indirect effects, considering both positive and negative impacts. This methodology focuses exclusively on quantifying the impact of greenhouse gas emissions, measured in kg CO2e. Net carbon impact assessments should assess the full ICT solution that delivers a specific service to the user.

GHG, Greenhouse gas; LCAs, life cycle assessments.

these impacts helps determine data requirements and justify excluding certain effects based on cut-off criteria, allowing organizations to focus resources on the most significant elements of the analysis.

Following the calculation of the GHG impacts of the first-, second-, and higher-order effects, the net carbon impact of the ICT solution is determined according to the selected functional unit, as follows:

$$\text{Net Carbon Impact}_{\text{FU}} = \sum \text{1stOrderEffects} + \sum \text{2ndOrderEffects} + \sum \text{HigherOrderEffects}$$

The impact of GHG emissions on climate change is the main subject of the net carbon impact assessment. Nonetheless, it’s also critical to consider an ICT solution’s other environmental impacts. According to the methodology by the European Green Digital Coalition (EGDC), a qualitative assessment proving the ICT solution produces no significant harm is required.

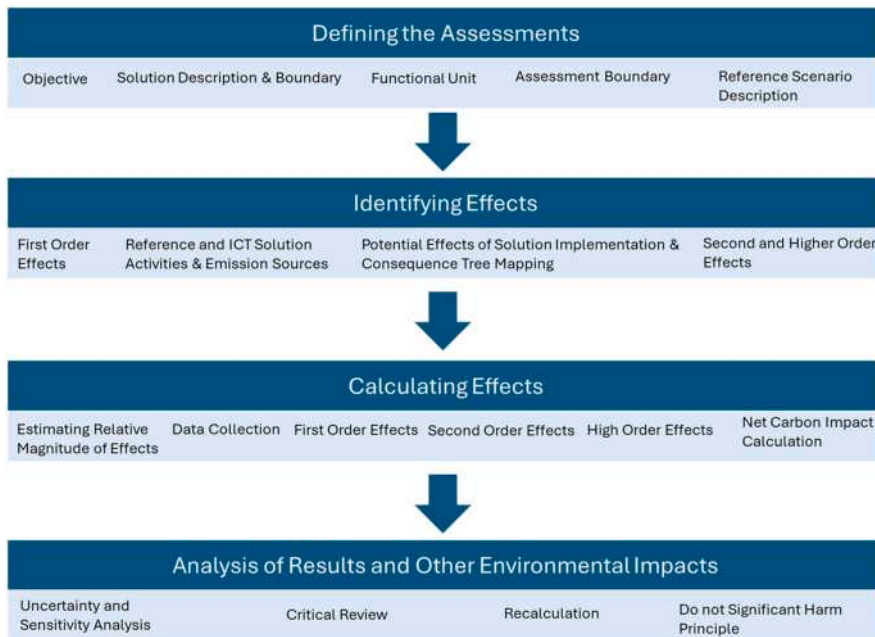


FIGURE 24.2 Assessment steps in Net Carbon Impact Assessment Methodology for ICT Solutions. Source: Adapted from European Green Digital Coalition. (2024). Net carbon impact assessment methodology for ICT solutions. European Green Digital Coalition.

24.3.2.1 Quantifying direct impacts (first order)

First-order effects are calculated according to an existing LCA standard (Section 24.3.1) and within the boundary of the defined ICT solution. Within the scope, it is crucial to have clear technological boundaries, what should be included and what can be excluded, in relation to the study objective. Direct effect is not limited to the hardware and software components but must include any supporting infrastructure and technologies. Allocation and end-of-life scenarios should be well-defined, as they can significantly impact results. For example, recycling and recovering materials at the end of their life cycle are considered crucial. Moreover, the lifetimes of components should be considered, as different components may have varying lifespans. In the net impact calculation, components already existing within the solution boundary before implementing the ICT solution should be excluded from the assessment of first-order effects.

While LCI databases are still lacking, the Négaoctet consortium has developed the first database for assessing the environmental impacts of digital services using LCA. As presented in Section 24.2.1, digital service consists of three parts: data centers, networks, and end-user terminals.

24.3.2.2 Quantifying indirect impacts (second and higher order)

Higher order effects occur due to shifts in consumption patterns, lifestyles, and value systems. It can be difficult to pinpoint higher order effects from applying the solution,

particularly if they take a long time to manifest. Higher order effects, for instance, rebound effects, lock-in effects, and cumulative ICT growth impacts ([European Green Digital Coalition, 2024](#)). One should evaluate potential rebound effects by considering if the digital solution generates savings, how these might be redirected, potential behavioral impacts, and any immediate or long-term rebound effects from increased adoption. In terms of the solution's overall net carbon impact, evaluation of the projected size of higher order impacts can take the form of qualitative such as low, medium, or high, depending on the effect's understanding and the data's accessibility.

Usually, gathering primary data for the reference and ICT solution scenarios is the most precise way to estimate the influence of a second-order effect. The calculating approach evaluates the distinction between the two scenarios when this strategy is used. When the primary data is not available, several approaches can be undertaken as guided in the methodological framework by EGDC ([European Green Digital Coalition, 2024](#)).

24.3.3 Selected life cycle assessment studies and associated methodological challenges

There is a rapidly increasing trend in research connecting digital technologies with environmental sustainability, highlighting the escalating importance and urgency of tackling environmental issues ([Chen et al., 2020](#)). However, the majority of studies focus predominantly on the operational or use phase (i.e., energy use), lacking a comprehensive whole life cycle perspective.

[Arushanyan et al. \(2014\)](#) conducted a comprehensive review of LCA studies on ICT products and services. According to the study, the environmental impact of ICT products is dominated by their production and usage stages, with the use phase being primarily responsible for energy consumption and global warming for many ICT products ([Arushanyan et al., 2014](#)). However, the production process might have a more significant impact on lightweight and energy-efficient products. At the national level, a study by [Malmmodin et al. \(2014\)](#) evaluated the life cycle carbon footprint (CF) and operating electricity consumption of ICT in Sweden ([Malmmodin et al., 2014](#)). The study included operations that are frequently disregarded, like data centers, shared data transport networks, and network infrastructure manufacturing. The results showed that the majority of the carbon footprint of the ICT network was caused by end-user equipment, mostly personal PCs, followed by enterprise networks and data centers. At the regional level, the ICT's environmental impacts have been assessed in the EU to provide policymakers and the public with updated environmental impact data and a robust, science-based methodology using LCA ([Benqassem et al., 2021](#)). It focuses on end-user equipment, networks, and data centers, considering only direct impacts (indirect impacts, whether positive or negative such as rebound effects are not taken into account). "Resource use, minerals and metals" is the most critical environmental indicator, emphasizing the need for multicriteria assessments to avoid burden shifting. The manufacturing phase has the greatest impact on resource use, while end-user devices contribute significantly to overall impacts. Data centers also play a significant role in ICT's environmental impact.

In the manufacturing sector, a previous study investigated the environmental benefits of digital fabrication methods in construction, particularly for complex concrete geometries (Agustí-Juan et al., 2017). Their case study on robotic additive processes applied to wall structures showed that digital fabrication provides environmental benefits without additional costs, supporting its potential to drive innovation in the construction industry. Shou and Domenech (2022) explored the potential integration of LCA and blockchain technology in the fashion sector. They proposed using LCA to measure the impact reduction potential of circular strategies and developed a protocol for integrating LCA and blockchain to assess circular practices accurately (Shou & Domenech, 2022). In a study by Ballarino et al. (2017), the integration of cyber-physical systems (CPS) with LCA was evaluated to improve environmental performance (Ballarino et al., 2017). Their findings indicated that CPS and IoT-enabled platforms could enhance sustainability by minimizing energy consumption, reducing transportation impacts, and supporting closed-loop manufacturing processes.

Favi et al. (2022) presented a framework based on the plant metabolism concept, integrating Energy Material Flow Analysis (EMFA) and LCA tools for assessing the economic and sustainability aspects of production plants using Industry 4.0 technologies (Favi et al., 2022). Their multicriteria decision-making (MCDM) method aims to optimize production processes by reducing energy and material flows. Using the net carbon impact assessment methodology for digital solutions from the EGDC, the case study of Nokia Smart Cities-Smart Waste Management demonstrates the methodology's practical application. While case studies offer valuable insights into calculating the net carbon impact of digital solutions, caution is necessary when interpreting results due to variations in data quality and the evolving methodology (European Green Digital Coalition, 2024).

A previous study has reviewed the implications of digitalization on environmental sustainability through a literature study of 93 articles within the manufacturing sector (Chen et al., 2020). The study highlighted the environmental benefits and challenges associated with digitalization across product design, production, transportation, and customer service. Within the product life cycle, digital technologies primarily reduce environmental impacts through high material efficiency and enhanced information support during production. Conversely, the technology life cycle is characterized by substantial energy and resource consumption and increased emissions, particularly during production and end-of-life stages. This perspective can assist practitioners in reevaluating their roles as producers and/or consumers, enabling them to account for both the positive and negative environmental impacts of digitalization across different stages of these lifecycles.

Conducting LCA of digital solutions presents significant challenges and limitations, primarily due to issues such as data availability, accounting methodologies, quantification of indirect effects, the problem of multifunctionality, and the incorporation of social aspects like user behavior and patterns. The methodological challenges and limitations observed in the several reviewed studies are summarized in Table 24.2.

These challenges and limitations need to be addressed in LCA studies and development efforts to improve the reliability and robustness of LCAs for digital solutions.

24.4 Mitigation strategies and sustainable practices

Mitigation strategies and sustainable practices in digitalization refer to the systematic approaches and procedures used to decrease the environmental impact of digital technologies throughout their life cycle (Mondejar et al., 2021; Munang et al., 2013). These measures include increasing energy efficiency, reducing e-waste, using environmentally friendly materials, and implementing green computing practices. Addressing environmental externalities with these methods is critical to mitigating the huge ecological disturbances produced by the rapid growth of digital infrastructure and device usage (Mondejar et al., 2021). By incorporating sustainable practices into the design, manufacture, and operation of digital technologies, we can reduce resource consumption and GHG emissions by promoting a circular economy, ensuring a balance between technological advancement and environmental stewardship (Kanwal et al., 2022).

The massive infrastructure of cloud computing, which includes large data centers with thousands of computers, consumes 1.1%–1.5% of worldwide electricity and is anticipated to grow further (Mastelic et al., 2015). However, energy efficiency techniques must be tailored or redesigned for cloud computing due to its intricate infrastructure. While optimizing individual systems improves energy efficiency, greater gains can be achieved by implementing shared techniques that account for interactions and dependencies among

TABLE 24.2 Methodological challenges in life cycle assessment (LCA) of digital solutions/information and communications technology (ICT).

Challenges/limitations	Brief description
Data availability	Difficulty in obtaining freely accessible and high-quality LCI data for digital services, e.g., networks, data centers, IT components Difficulties in estimating the quantity of equipment or infrastructure items in the inventory. Lack of data related to the effective end-of-life of devices, primarily due to the lack of tracking of e-waste. Difficulty in estimating the use phase
Data maturity	Recognition of varying levels of maturity in data and approaches, in which continuous improvement in quality over time is needed Rapid technological development as a source of variability in results
Accounting method	The likelihood of double/multiple counting of positive impacts along the chain of actors, necessitating caution in interpreting net carbon impact claims of the ICT sector using this methodology.
Multifunctionality	A single product can be involved in multiple functions, thus a wide variety of possibilities complicate the assessment
Indirect effects assessment	Consideration of only direct impacts, with indirect impacts (positive and negative) such as rebound effects, substitution, potentially significant macroeconomic effects of ICT services, and structural changes, not included.
Types of impacts	Much of the available LCI and LCA data focuses on the carbon footprint only
User behavior	Lack of incorporation of user behavior in a realistic way

components (Liu, Gailhofer, Gensch, et al., 2019; Mastelic et al., 2015). This holistic approach underscores the need for comprehensive strategies to enhance energy efficiency in data center hardware and infrastructure.

Cloud computing can improve energy efficiency in ICT by improving data center resource use and emphasizing energy-efficient hardware and network operations. However, significant research obstacles exist in completely applying these energy-saving approaches to cloud computing systems.

Greening data operations includes encouraging and promoting waste heat utilization from data centers by transforming it into a useful energy source. Furthermore, data center operators should be required to report on their water usage and disposal methods for obsolete technology and to reduce the impact over time. Promoting comparably sustainable software (for example, the voluntary implementation of the German Blue Angel label's standards for resource-efficient software could be a first step but should become mandatory in the medium term). Software-induced hardware obsolescence should be avoided through product laws (Chidolue et al., 2024; Liu, Gailhofer, Gensch, et al., 2019).

Integrating renewable energy into data centers and network operations is critical to reducing reliance on traditional power grids and lowering carbon emissions (Liu, 2024). Data centers can achieve a more sustainable and ecologically friendly energy supply by using renewable energy sources like solar and wind. This change not only reduces the overall energy consumption connected with cloud services but also addresses the issue of heat generation, resulting in lower cooling requirements and increased system reliability (Buyya et al., 2024). Integrating renewable energy is critical for building energy-efficient and environmentally friendly cloud computing infrastructures (Birch, 2012).

The exponential growth of digitalization has resulted in a boom in electronic device manufacturing and use, posing substantial environmental difficulties, particularly in the management of electronic waste. E-waste is made up of abandoned electronic items such as computers, smartphones, and televisions that contain toxic elements such as lead, mercury, and cadmium, which can pose environmental and health problems if not responsibly managed.

Recycling e-waste is a critical part of mitigating these environmental impacts. The process involves recovering valuable materials, including gold, silver, copper, and rare earth elements, which can be reused in the manufacturing of new electronic products. Effective recycling not only reduces the environmental impact by decreasing the need for raw material extraction but also lowers energy consumption and GHG emissions associated with new product production (Kiddee et al., 2013; Parajuly & Wenzel, 2017).

However, recycling alone cannot adequately address the growing e-waste problem. Implementing circular economy principles provides a more sustainable solution. These principles focus on extending the life cycle of electronic products through design for durability, ease of repair, and upgradability (Bakker et al., 2014). By creating products that are more durable and modular, manufacturers can ensure prolonged use, thus reducing the frequency of e-waste generation.

Furthermore, circular economy strategies include the development of take-back programs and reverse logistics systems, enabling consumers to return old electronics for refurbishment, reuse, or proper recycling. Companies such as Apple and Dell have implemented such programs, offering incentives for consumers to return their old devices. These initiatives

facilitate the appropriate disposal and recycling of e-waste while allowing companies to recover valuable components and materials for new products (Wilts et al., 2016).

Regulatory frameworks also play a pivotal role in promoting e-waste recycling and circular economy practices. Legislation like the European Union's WEEE Directive mandates the responsible collection, recycling, and recovery of e-waste, setting a precedent for other regions (European Commission, 2012).

Integrating e-waste recycling and circular economy approaches within the tech industry is crucial for mitigating the environmental impacts of digitalization. Embracing these strategies can significantly reduce the industry's ecological footprint, conserve natural resources, and contribute to a more sustainable future (Bressanelli et al., 2019).

24.4.1 Design for Environment

Design for Environment (DfE) in digital devices optimizes the life cycle environmental impact through strategies like LCA, end-of-life planning, and design for disassembly (Lagerstedt et al., 2003). Engineers integrate environmental considerations early in the design process to create sustainable products. By focusing on material and energy flow optimization, DfE seeks to balance ecological responsibility with financial success (Goldstein & Rasmussen, 2017). Efforts over the past three decades have been dedicated to developing tools and methodologies for DfE principles. Despite progress, their widespread adoption remains challenging. There is a pressing need for a paradigm shift in the structure and functionality of DfE tools to overcome barriers to utilization.

This chapter briefly discusses mechanisms within DfE tools, emphasizing strategy-specific and product-specific outputs. While strategy-focused mechanisms are common and helpful, product-specific mechanisms offer greater customization potential, leading to more effective guidance for designers.

Early consideration of environmental factors during the design phase holds immense potential for minimizing the ecological footprint of products and systems. Effective tools offering structured assistance to designers in identifying and addressing environmental issues early in the design process are crucial (Birch, 2012; Boothroyd et al., 2010). This underscores the importance of effective tools that offer structured assistance to designers in identifying and addressing environmental issues early in the design process. Such tools play a pivotal role in curbing the accumulation of adverse environmental impacts "locked-in" to products and systems, thereby contributing to sustainable development objectives (Chen, 2001).

Researchers have highlighted various barriers hindering the uptake of DfE tools, including issues related to their structure and presentation. One common challenge is the lack of comprehensive support and guidance provided by these tools when addressing environmental design issues. Often, designers are confronted with a plethora of information, much of which may not be directly relevant to their specific project needs. This inundation of irrelevant data can overwhelm designers and deter them from utilizing DfE tools effectively.

The ability of such tools to deliver tailored guidance and output mechanisms that align with the unique requirements of individual design projects is paramount. By providing

targeted and relevant information, DfE tools can enhance their usability and effectiveness, thereby fostering greater adoption and integration within industry practices.

Despite the proliferation of DfE tools and methodologies, challenges persist in their widespread adoption and utilization within industry. Addressing these challenges necessitates a paradigm shift in the structure and functionality of DfE tools (Boothroyd et al., 2010; Luttrupp & Lagerstedt, 2006). By providing targeted and relevant information, DfE tools can enhance their usability and effectiveness, thereby fostering greater adoption and integration within industry practices.

Briefly, DfE represents a vital approach in advancing sustainability objectives within design and development processes. Addressing challenges requires refining the structure and functionality of DfE tools to provide tailored guidance and support for design practitioners. Future trends in DfE emphasize the incorporation of societal models and advanced tools to enhance collaboration among stakeholders and promote industry-wide sustainability.

24.4.2 Policy implications and regulatory frameworks

The rapid advancement of digitalization necessitates a thorough examination of its environmental impacts through LCA to inform policy and regulatory frameworks. Digital technologies, from their production to disposal, contribute significantly to environmental degradation, including e-waste generation, high energy consumption, and carbon emissions from data centers (Mondejar et al., 2021). Policymakers must establish stringent regulations to mitigate these effects. Effective policies should encompass e-waste management, energy efficiency, and sustainable digital infrastructure (Wilts et al., 2016). Regulatory frameworks must incentivize responsible disposal, promote renewable energy, and support the development of green technologies. These measures will help balance digital innovation with environmental sustainability (Table 24.3).

24.5 Conclusion and outlook

This chapter explores the environmental impacts of digitalization, underpinned by an LCA methodology, and provides insights into how digital technologies intersect with ecological concerns. While digital solutions are driving innovation and efficiency across various sectors, they also contribute to increased energy consumption, GHG emissions, and electronic waste, presenting complex challenges to environmental sustainability.

The dual nature of digitalization's impact requires a nuanced understanding of its benefits and drawbacks. On one hand, digital technologies like AI, big data analytics, and blockchain offer transformative potential for optimizing resource use and reducing waste. On the other hand, the energy-intensive nature of emerging technologies such as quantum computing and advanced blockchain applications exacerbates environmental burdens. Our findings resonate with the growing body of research suggesting that without reliable assessment and strategic interventions, the environmental costs of these technologies may offset their benefits.

TABLE 24.3 Policy implications and regulatory frameworks for digitalization.

Policy	Area implications	Regulatory frameworks	References
E-waste Management	Exponential increase in electronic waste poses environmental and health risks	Mandate responsible disposal, promote extended producer responsibility, and encourage product design for longevity and recyclability	Robinson (2009), Zeng et al. (2017)
Energy Consumption	High energy use by data centers and digital devices contributes to carbon emissions	Incentivize renewable energy use, enforce energy efficiency standards, and support green data center development	Baliga et al. (2011), Cosar (2019)
Network Infrastructure	Environmental costs of expanding digital networks and infrastructure	Promote energy-efficient network technologies, encourage sustainable data storage and processing practices	Coroama et al. (2012), Hinton et al. (2011)

A significant gap in current research is the comprehensive assessment of the indirect effects of digital technologies. Most studies have focused on direct impacts such as energy consumption and CO₂ emissions. However, the broader environmental implications, such as the impact on ecosystem biodiversity, water usage, and full life cycle impacts of hardware, remain under-explored. Reliable assessment of the environmental impacts of digitalization is also hindered by significant challenges, including limited data availability, inconsistent data maturity, and the complexity of accounting methods. These issues highlight the need for robust frameworks that incorporate both direct and indirect effects, ensure accurate data interpretation, and reflect the multifunctionality and dynamic nature of digital technologies. Future research should aim to fill these gaps, developing and employing innovative LCA methodologies that capture both the immediate and long-term environmental effects of digitalization.

The principles of the circular economy emerge as pivotal in mitigating the negative impacts observed. By designing products and systems with longevity, reparability, and upgradability in mind, the tech industry can reduce the life cycle environmental impacts significantly.

Reflecting on the balance between digitalization's benefits and its environmental toll, it is clear that the path forward must involve a concerted effort from stakeholders across all sectors to forge a sustainable digital future. This includes policymakers, industry leaders, and academia, all of whom must collaborate to integrate sustainability into the core of digital transformation strategies. Sustainable digital transformation will require innovative digital design, a reliable and consistent benchmarking and accounting impact assessment method, and policies that promote circular economy approaches.

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Blockchain in supply chains: a promise still unfolding

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25.1 Introduction

Blockchain technology has long been indicated as a pivotal digital innovation, capturing the attention of entrepreneurs, technologists, and policymakers alike. Its central promise lies in decentralization, transparency, immutability, and enhanced security; qualities that, in principle, could eliminate many trust deficits and inefficiencies in both public and private sectors. When blockchain first gained popularity through Bitcoin and similar cryptocurrencies, observers envisioned that comparable distributed ledgers would profoundly reshape how organizations record ownership, execute transactions, and validate data. Within the expanding stream of digital technologies, blockchain stood out as an apparatus for bypassing conventional intermediaries. Early discourses brimmed with optimism that a decentralized ledger might democratize industries by dispensing with expensive third parties (Mubarik & Shahbaz, 2023). This conviction was grounded in the belief that once data were entered in a decentralized ledger, trust in their accuracy and security would be all but guaranteed.

However, more than 15 years after blockchain's conceptual origin, there is growing concern that the technology has not fulfilled its highest aspirations. Proponents who once peddled blockchain as a universal solution now encounter a more complex reality characterized by scepticism and even frustration in some circles. Although theoretical arguments for blockchain's effectiveness, in areas such as supply chain traceability, secure financial operations, and robust governance, may remain cogent, tangible implementations often reveal shortfalls. Critics (e.g., Lustenberger & Spychiger, 2025) suggest that blockchain's anticipated advantages were not as transformative as initially portrayed, while others (Jovanovic et al., 2022; Xu et al., 2020) maintain that the technology's strengths persist but have been obstructed by practical barriers. Indeed, real-world projects expose a gulf between blockchain's expected potential and its tangible outcomes, prompting questions regarding whether obstacles arise from technical complexities, organizational constraints, or more systemic factors.

This debate is shaped significantly by a series of emblematic disappointments in high-profile blockchain endeavors. IBM, for instance, committed considerable resources to blockchain-driven supply chain solutions, notably in collaboration with Walmart for food traceability (Sristy, 2021). In theory, a decentralized ledger that monitors food production end-to-end could create a nearly foolproof mechanism for quality control and rapid recalls. Yet, despite ample funding and media excitement, such projects have struggled to expand meaningfully, hindered by complications in onboarding smaller suppliers and inconsistencies in data input. Similarly, the Australian Securities Exchange aimed to replace its longstanding CHES platform with a blockchain-based clearing and settlement system (The Fintech Times, 2024), purportedly to modernize financial transactions and reduce operational risks. Instead, that initiative was bogged down by repeated delays and technical setbacks, exacerbating doubts over blockchain's readiness for mission-critical activities. Another frequently cited example is Kodak's blockchain-oriented photography platform, KodakOne, intended to safeguard photographers' intellectual property rights more transparently. Despite Kodak's brand recognition, the platform failed to generate market enthusiasm, plagued by vague demand, suboptimal execution, and skepticism about blockchain's added value (Munster, 2019). These and similar instances have led some researchers to conclude that blockchain has fallen short of the revolutionary breakthroughs once anticipated.

Lustenberger and Spsychiger (2025) echo such sentiments by arguing that blockchain's pledges of trust, transparency, and immutability have not materialized at scale, undermining its prospective contributions to sustainability and efficiency. This disconnect between theoretical promise and operational realities fuels broader questions about the technology's structural soundness. Is the perceived mismatch a result of inherent design flaws, or does it reflect institutional and market dynamics that block effective deployment?

Within this context, this chapter aims to chart a balanced course between outright dismissal of blockchain and uncritical endorsement. If the technology indeed underperforms, what are the key drivers? Are they rooted in the technical underpinnings of the ledger itself, or might external conditions be stifling its potential? While certain critiques highlight fundamental issues in blockchain's design, others emphasize misguided interpretations, organizational unpreparedness, and regulatory incongruities. Accordingly, the subsequent discussion investigates whether blockchain is a broken promise or a latent opportunity pending the correct convergence of expertise, regulations, and market demand. The chapter begins by outlining the theoretical foundations that initially fostered confidence in blockchain. It then reviews real-world adoption outcomes, illustrating both notable successes and conspicuous failures. The final segments examine factors underlying blockchain's perceived shortcomings, exploring whether they stem from technical limitations, managerial complexities, or broader societal challenges. Throughout, this chapter adopts a descriptive perspective, allowing readers to assess whether blockchain is inherently flawed or simply underutilized. This approach ensures that while the analysis draws upon relevant literature and case studies, it does not deliver a definitive judgment on blockchain's destiny. Rather, the goal is to illuminate the multidimensional character of its evolution, recognizing that technology rarely progresses linearly from hype to large-scale implementation. Often, what seems to be a "failure" may reflect a mismatch between business strategies and organizational objectives, insufficient stakeholder alignment, or unfortunate timing.

In the following section, the chapter transitions to a discussion of the theories that have sustained blockchain's appeal, focusing on how these frameworks connect to sustainability and supply chain optimization.

25.2 Theoretical underpinnings and anticipated advantages

Blockchain has been able to captivate support from various economic, organizational, and strategic theories. Understanding these theoretical roots clarifies both the anticipation surrounding blockchain and the disappointment encountered when its actual deployments fail to fulfil expectations.

Principal-agent theory, based on the work of [Jensen and Meckling \(1976\)](#), is frequently invoked in this context. The theory dissects the relationship between an agent (e.g., a supplier) and a principal (e.g., a manufacturer or retailer) who delegates responsibilities yet faces challenges in monitoring compliance and aligning incentives. Traditional supply chains often struggle with information asymmetry, incomplete contracting, or opportunistic behaviours by the party controlling crucial data. Owing to its decentralized ledger and cryptographic processes, blockchain appeared ideally equipped to mitigate these vulnerabilities. In principle, each node in the supply chain would have access to an unfalsifiable record of every transaction, thus impeding agent misconduct. The ledger's transparency would mitigate moral hazard and reduce dependence on surveillance-based enforcement. Moreover, through smart contracts, companies could automate routine tasks—such as triggering payments or validating product quality—in a manner consistent with shared objectives among all participants.

Transaction cost theory—*based on the work of* [\(Coase, 1937; O'Brien & Williamson, 1976; 1985\)](#)—furnishes a second cornerstone of support for blockchain's potential worth. This framework posits that firms consistently weigh the relative costs of market transactions and hierarchical controls. In complex supply chains, uncertainties, search and negotiation processes, and coordination overhead can substantially inflate transaction costs. Advocates of blockchain argue that shared decentralized ledgers curtail these expenses by furnishing a unified "source of truth," thereby reducing both data redundancies and the necessity for intermediary verification. In an ideal scenario, participants utilize a standardized environment for transaction logging, streamlining conflict resolution, and diminishing the need for multiple reconciliations. Because all stakeholders can observe real-time ledger entries, trust shifts from hierarchical oversight or specialized third parties to a technologically assured platform.

Beyond these two initial theories, other theories such as the resource-based view [\(Wernerfelt, 1984\)](#) are used to draw theoretical support for blockchain adoption. Proponents of blockchain, drawing on the RBV, argue that it enables firms to leverage their unique resources and capabilities as drivers of competitive advantage. Within a high-velocity market, a company that successfully integrates blockchain may acquire unique proficiencies in transparency, speed, and reliability—traits that could differentiate it from competitors. Enhanced auditing processes, rapid product recalls, and robust traceability could become key selling points in industries especially sensitive to compliance and reputational factors, such as pharmaceuticals or organic foods.

Institutional theory, based on the works of DiMaggio and Powell (1983), Meyer and Rowan (1977), and Selznick (1949), underscores norms, legitimacy, and collective expectations as critical elements in organizational conduct. As sustainability gains traction as both a business and societal imperative, blockchain-based systems have been promoted as a credible vehicle for meeting environmental, social, and governance (ESG) criteria. In principle, designing supply chain processes around a decentralized and immutable ledger offers a clear demonstration of compliance to regulators, investors, and end consumers. This alignment with institutional pressures for transparency can, in turn, incentivize additional businesses to adopt blockchain—especially if being part of a recognized, verified network enhances legitimacy or reputation.

25.2.1 The potential gains for supply chain sustainability

Theories discussed in the previous section highlight several interlinked advantages that blockchain could deliver, particularly in sustainable supply chain operations. First, transparency confers an all-encompassing view of product origins, processes, and distribution channels, thereby aiding the verification of ethical labour standards, environmental impact, and raw material authenticity. Second, traceability stands as an adjacent benefit, vital in sectors such as food and pharmaceuticals where the authenticity and safety of products are paramount. For instance, a blockchain-driven ledger could trace a batch of produce to its originating farm, enabling swift identification and handling of contamination sources. Third, lowered costs might arise from reducing the duplication of data entries and reliance on centralized databases, freeing organizational resources for further innovation. Fourth, trust is reinforced by a system in which records are resistant to subsequent modification, potentially easing adversarial relationships among supply chain participants. Finally, collaboration may deepen, as a transparent, tamper-proof ledger counters suspicions of opportunism or hidden practices. Should these benefits be realized in practice, they could substantially reshape supply chain structures, advancing ethical sourcing, mitigating ecological harm, and optimizing logistics. Blockchain's compatibility with principal-agent theory, transaction cost theory, RBV, and institutional theory is thus construed by supporters as more than incremental enhancement—representing a profound reenvisioning of cross-regional and cross-cultural coordination. Yet caution arises from the mismatch between these theoretical possibilities and observed industry outcomes. Although select pilot programs have demonstrated some of the improvements, very few can claim comprehensive adoption across large networks. Whether these limitations stem from technological infancy, flawed alignment with actual business needs, or deeper systemic issues remains an active topic of inquiry.

Nevertheless, the theoretical basis remains sufficiently robust to validate continued interest in blockchain. These frameworks also guide the design of new blockchain initiatives, with hopes that improved protocols or narrower use cases might more effectively capitalize on the technology's strengths. The crucial question, which unfolds in the next section, is how well these theoretical advantages hold up under the realities of organizational adoption and market-level constraints. By exploring both successes and disappointments, we gain deeper insights into blockchain's progress and the structural hurdles it faces.

25.3 Current adoption landscape: successes, challenges, and outcomes

A review of blockchain's use in contemporary business environments reveals a diverse panorama; some organizations have utilized the technology for data sharing and transaction verification, whereas others remain reluctant or have terminated pilot efforts. The adoption rate, if measured by actual operational footprint, is often more modest than headlines suggest. Numerous startups promoting blockchain-based approaches have emerged over the past decade, yet many either ceased operations or pivoted after failing to secure sustained market demand (Khan et al., 2025; Gobakhloo et al., 2023). Meanwhile, large-scale consortia across logistics, energy, and healthcare have attempted to standardize blockchain protocols, occasionally showing promise but frequently encountering limited success. Precise quantification of adoption is elusive, as media announcements can distort the genuine extent of usage and the degree to which blockchain has integrated into everyday processes. However, many analysts observe that although blockchain-related enthusiasm reached a zenith in 2017–2018, real-world implementations largely remain confined to pilot projects rather than fully integrated enterprise solutions.

Instances of partial success do exist in specialized contexts. Maersk's TradeLens, developed with IBM, initially garnered significant publicity for uniting shipping lines, port authorities, and customs agencies on a decentralized platform to manage maritime documentation (Jensen et al., 2019). Early data suggested gains in cargo visibility and operational speed. Yet, over time, multiple shipping majors either chose not to join or participated selectively, restricting the network effect essential for widespread blockchain success. Similar patterns appear in supply chain finance, where pilot projects have shown that small suppliers in emerging markets can secure more favourable credit terms once their blockchain-recorded transactions reduce perceived risks. Pharmaceutical companies, too, have experimented with blockchain systems to authenticate drug origins and combat counterfeit products. While some results were encouraging, these initiatives remain exceptions rather than norms.

Contrastingly, the technology has also frequently failed to yield notable benefits or culminated in project closures. One recurring issue is that blockchain infrastructure may duplicate functionalities already available through established databases, but at a higher complexity. Enterprises sometimes discover that existing solutions—often supplemented with simpler cryptographic methods—offer similar value at a lower cost. Moreover, the hype surrounding blockchain has fuelled scenarios in which businesses adopt it more for publicity than for concrete operational gains, leading to disappointment when the costs outweigh the benefits, or when employees find the system more cumbersome than prior tools. Even successes at a limited scale can unravel under broader implementation, as blockchain networks that function adequately for a small user set might experience performance lags or synchronization difficulties when expanded.

These mixed outcomes are particularly notable in sectors like agriculture, textiles, and minerals, where a transparent supply chain would seem naturally advantageous for asserting ethical sourcing. Yet achieving comprehensive adoption has been elusive, largely because smaller producers lack digital infrastructure or see few incentives to display their production processes. Simultaneously, multinational corporations can be reluctant to shoulder the expense of integrating large, varied supplier networks. Thus, only portions

of a supply chain may operate on a blockchain, undermining the fully transparent “end-to-end” model. The immutable nature of blockchain also fails to address the “garbage in, garbage out” dilemma; if data entry is flawed from the outset, having an incorruptible ledger merely preserves inaccurate information.

Overall, the evidence reveals that it is misguided to label blockchain unequivocally as either a monumental breakthrough or a debacle. The actual record is a mosaic of moderate triumphs, unremarkable outcomes, and outright failures. Some observers argue that these results are typical for an emergent technology with disruptive aspirations. Others suggest that the technology’s decentralized ethos clashes with entrenched organizational hierarchies and market structures. Looking forward, certain analysts perceive blockchain’s history of stumbles and limited uptake as indicative of an overhyped concept. Yet others maintain a cautious optimism, believing that ongoing protocol improvements, regulatory clarity, and well-crafted incentives could eventually enable blockchain to realize its potential.

In essence, the field is at an inflection point. The technology has shown both enough promise to attract dedicated adherents and enough vulnerabilities to prompt widespread skepticism. Understanding why blockchain often struggles in real-world applications is thus essential for determining if its challenges reflect normal technology adoption curves or if they signal more profound structural hindrances. The next section addresses these core issues, exploring how both technological and organizational factors can shape blockchain’s trajectory in ways that either stifle or unlock its purported benefits.

25.4 Analyzing blockchain’s underperformance

25.4.1 Technology-driven causes

Insights from the preceding discussion underscore the importance of dissecting the technical root causes of blockchain’s uneven outcomes. While the concept of a decentralized ledger with cryptographic security holds substantial allure, practical implementations encounter challenges such as limited scalability, high energy usage, and complex data handling. For example, public blockchain networks often rely on consensus algorithms, notably Proof of Work, that necessitate resource-intensive computations and constrain transaction throughput. Such mechanisms may also undermine blockchain’s sustainability credentials, given their high carbon footprint. Even private or permissioned blockchains that adopt more efficient consensus protocols can struggle to handle the complexities of global supply chains, particularly when scaling beyond carefully managed test environments. Data immutability, typically touted as a core virtue, can transform into a liability when errors need correction or regulations demand data removal. Certain developers attempt to alleviate this tension by storing only hashed references on-chain, with actual data stored off-chain, but this tactic can dilute the blockchain’s inherent advantages and raise questions about whether a decentralized structure is genuinely necessary (Dujak & Sajter, 2019; Liu & Wang, 2025; Queiroz et al., 2020). Another pivotal technical consideration is the fragmented nature of the blockchain ecosystem, marked by competing platforms such as Ethereum, Hyperledger Fabric, and Corda, alongside various proprietary protocols. This lack of

interoperability forces organizations to either confine themselves to a specific platform or invest in bridging solutions that may introduce additional complexity. Furthermore, security challenges persist beyond the ledger's core cryptographic safeguards. Vulnerabilities in smart contract code, wallet storage, and the external "oracle" systems that feed data to the blockchain can all imperil the network's reliability. High-profile breaches or misuses of smart contracts have eroded trust among stakeholders with little tolerance for system malfunctions. Consequently, an array of large organizations, initially drawn by blockchain's promise, have paused or scaled back their ambitions once confronted with these realities (Henrichs et al., 2025; Longo et al., 2019).

25.4.2 Organizational and external issues

Technological limitations alone do not explain why blockchain often fails to meet expectations. Equally significant are the cultural, structural, and regulatory elements that influence adoption. Transitioning from conventional, centralized data repositories to decentralized governance models entails fundamental organizational shifts. Many firms are ill-prepared or unwilling to embrace the transparency and collaborative ethos required (Ali et al., 2025). Internal stakeholders, anxious about losing control or exposing trade secrets, may balk at the open data-sharing frameworks that blockchain necessitates. Beyond internal misgivings, a shortage of skilled blockchain professionals adds another layer of complexity, as these specialists command premium compensation and can be challenging to integrate into existing teams (Moraes et al., 2025). Regulatory and legal uncertainties amplify these organizational dilemmas. Because blockchain networks may extend across national borders, companies must reconcile varied and often inconsistent legislation related to data sovereignty, encryption standards, and digital asset categorization. Some governments and regulatory agencies remain reticent about blockchain, citing concerns over illicit uses or threats to market stability. This environment of uncertainty can dampen the enthusiasm of potential adopters, who weigh the risk of regulatory penalties against the uncertain benefits of implementing an unproven system. Meanwhile, misalignment with actual business needs frequently arises when organizations adopt blockchain without a clear rationale or feasible use case (Ali & Maheshwari, 2025). This scenario can lead to pilot projects that lack stakeholder buy-in or fail to reach critical mass, ultimately stunting the network effects essential for realizing blockchain's potential.

These considerations reflect the multifaceted nature of blockchain's adoption hurdles. Simply attributing the technology's shortcomings to immaturity or overpromising neglects the complex interplay of corporate culture, market incentives, and legal frameworks. By acknowledging how the internal and external environment intertwines with technological design, one can develop a more sophisticated view of why blockchain can falter. Such understanding may guide strategies to mitigate these problems—from refining protocol architecture to restructuring corporate practices, advocating for clearer regulations, and ensuring that all relevant stakeholders perceive tangible value in a blockchain-based approach. Rather than categorizing blockchain as definitively successful or failed, a more measured perspective recognizes that technology adoption, particularly one with blockchain's disruptive ambitions, involves negotiation among diverse and often conflicting forces.

25.5 Conclusion: toward a pragmatic future for blockchain

Declaring blockchain a failure simply because it has not achieved the meteoric scaling once anticipated would be shortsighted. Like prior transformative technologies, blockchain must traverse a winding path from conceptual emergence to full-fledged commercialization. The dissonance between the early hype and the current reality has proven especially glaring in blockchain's case. Yet such tensions may typify how an innovation challenging existing data governance norms evolves. As technological breakthroughs, institutional learning, and regulatory guidance gradually reduce the gap between theoretical promise and practical utility, blockchain may yet prove its worth in select domains or perhaps even achieve broader relevance. Realistic expectations are vital, as transformative impacts rarely occur overnight.

A key imperative moving forward is to pivot from theoretical speculation to grounded application. Blockchain's foundational principles have been extensively examined, with multiple proofs of concept demonstrating that certain use cases are technically viable—albeit under circumscribed conditions. The crucial task is to identify and refine these viable scenarios, rather than attempting to overhaul entire industries in one sweep. Incremental improvements in consensus algorithms, governance models, and standardization efforts could foster a stronger environment for blockchain experimentation. In tandem, robust communication between technology developers and enterprises is necessary to align solutions with concrete operational challenges. Research and development should continue targeting known technical constraints—scalability, interoperability, and energy consumption—to move beyond small-scale pilots.

Regulatory clarity stands out as another cornerstone for blockchain's future. Clear, well-calibrated rules regarding data privacy, smart contracts, and transnational data exchange can reduce uncertainties and lower the risk premium associated with adopting emerging technologies. Regulatory sandboxes, which allow organizations to test blockchain solutions under supervised yet flexible conditions, may bolster confidence and facilitate early-stage learning. Moreover, reconciling blockchain's ideal of decentralization with the realities of organizational hierarchies will likely require hybrid structures that retain certain centralized elements while leveraging specific blockchain attributes for transparency and trust enhancement. From a sustainability viewpoint—a prominent rationale for blockchain's use in supply chain contexts—an integrated approach is critical. Aligning blockchain with ESG frameworks and orchestrating cross-industry alliances for tracking carbon footprints and labor standards could yield a credible demonstration of blockchain's real-world applicability. This would demand substantial interfirm coordination, reliable data input at every stage, and a robust incentive system to ensure compliance. Although the technical concept of an immutable, transparent ledger for supply chain verification remains compelling, converting it into tangible gains demands more than technology alone; it necessitates shared objectives and collaborative commitment.

Further strategic considerations include sector-focused research initiatives, user-centric interface design, and recalibrating funding models away from inflated valuations toward methodical, measurable experiments. Industry consortia that integrate academic expertise, industry knowledge, and regulatory oversight can accelerate the establishment of standards and the exchange of best practices. Emphasizing user-friendly interfaces—for both

organizational administrators and end users—will be vital in lowering barriers to adoption. Finally, transparency in project scope, expected deliverables, and progress assessments can mitigate overhyped discourse and cultivate a more authentic evaluation of blockchain's contributions.

Ultimately, any assessment of blockchain's viability must be contextualized within broader discussions of digital transformation, trust-building, and changing socio-economic conditions. Even if blockchain's track record appears inconsistent, the technology retains significant potential, contingent on the synchronization of protocol enhancements, business alignment, and supportive regulatory ecosystems. Declaring its definitive failure ignores the iterative processes through which new technologies often mature. However, proponents of blockchain would do well to heed the lessons of overinflated assurances. A measured, incremental path—featuring stakeholder engagement and multiparty cooperation—offers the most promising route toward mainstream adoption.

In closing, although it is essential not to overlook the numerous hurdles and misconceptions that have hindered blockchain's impact, one need not dismiss its underlying value proposition. Blockchain's key features, transparent record-keeping, cryptographically secured data, and distributed governance, represent genuine differentiators if leveraged appropriately and realistically. The initial wave of excitement may have subsided, but this transition could mark the advent of a more focused, less sensationalized phase of development. For supply chain sustainability, financial inclusion, and other critical concerns, the coming years may determine whether blockchain evolves into a durable fixture in organizational strategies or remains confined to niche applications. The deciding factor will likely hinge on collaborative problem-solving, technical fine-tuning, and a willingness among participants across the value chain to adopt and adapt the technology's core principles in harmony with real-world needs.

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INDUSTRY 4.0 AND SUSTAINABILITY

Integrating Digital Technologies and Circular Models for a Sustainable Future

Edited by M. Imran Khan, Sami G. Al-Ghamdi, and Mushtaq Khan

The Fourth Industrial Revolution, commonly termed Industry 4.0, is transforming production and manufacturing through the integration of advanced digital technologies such as artificial intelligence (AI), Industrial Internet of Things (IIoT), big data analytics, additive manufacturing, and advanced robotics. While much discussion has centered on potential economic impacts, Industry 4.0 holds significant implications for sustainability across environmental, social, and economic dimensions. However, simply adopting a given technology does not guarantee sustainability benefits, and improperly managed, they pose risks related to job losses, inequality, and rebound effects that must be addressed through integrative frameworks.

Industry 4.0 And Sustainability provides the first comprehensive, evidence-based perspective unifying technological, organizational, policy, and social considerations to strategically direct Industry 4.0 innovations toward improved sustainability across the economy, society and the environment. With applied case studies and integrated roadmaps spanning engineering, management, and policy, it offers guidance on how to deploy Industry 4.0 to accelerate progress on sustainable development goals.

Key Features

- Understand capabilities of Industry 4.0 technologies to transform manufacturing, operations, and business models toward sustainability
- Develop interdisciplinary literacy at the nexus of digital technologies and sustainability
- Apply findings through recommendations and guidelines for research and practice

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