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Significance of Industry 4.0 technologies in major work functions of manufacturing for sustainable development of small and medium-sized enterprises

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Abstract

Industry 4.0 (I4.0) has brought transformative changes in the manufacturing sector. This paper aims to provide a comprehensive analysis of the applications of I4.0 technologies in major work functions of small and medium-sized enterprises (SMEs). Specifically, this review focuses on the suitability of I4.0 technologies in areas such as New Product Development, Supply Chain Management, Internal Logistics Management, Production Planning Execution and Control, Quality Management, and Maintenance Management. This study employs a systematic literature review (SLR) methodology to comprehensively analyze relevant sources to present valuable perspectives and practical suggestions customized to the requirements of different essential work functions within manufacturing SMEs. The findings of SLR indicate that Big Data Analytics (BDA), Robotics, and Automation are perceived as highly sustainable, on the other hand, blockchain and cloud technology are viewed as having lower sustainability from SMEs' point of view. The findings presented in this article have several theoretical and practical implications including technology selection and integration, and considering sustainability and ethics. This will allow SMEs to seamlessly integrate distinct I4.0 technologies along three dimensions: vertical, horizontal, and end-to-end digital integration. This article intends to provide an unbiased assessment to ascertain the landscape occupied by I4.0 in the context of SMEs. This article highlights the connection and synergy between I4.0 and SMEs as well as the pertinence of how advanced technologies of I4.0 can influence the business processes in manufacturing SMEs.

KEYWORDS
big data analytics, Industry 4.0, robotics and automation, small and medium-sized enterprises, sustainability

1 | INTRODUCTION

The pursuit of advanced technology has consistently been the driving force behind global developments and the manufacturing sector has always been at the heart of such developments, eager to experiment with new concepts and adopt next-generation technologies (Nunes et al., 2017). These developments are what caused the journey of industrial revolutions from Industry 1.0 to Industry 4.0 (I4.0). I4.0 encompasses a wide range of digital and a few other enabling technologies that have a profound impact on manufacturing processes (Cioffi et al., 2020; Ghobakhloo, 2020; Liu & Xu, 2017). Enabling technologies of I4.0 refers to a set of advanced digital systems and tools that are transforming traditional industries by enabling automation, connectivity, and data exchange (Pozzi et al., 2023). These technologies include the Internet of Things (IoT), Artificial Intelligence (AI), Big Data Analytics (BDA), Cyber-Physical-Systems (CPS), Blockchain, Modeling and Simulation, Robotics and Automation, and Additive Manufacturing (AM) (Nascimento et al., 2019; Thoben et al., 2017). The integration of these technologies seamlessly integrates manufacturing processes and transforms the manufacturing sector. Smart manufacturing is the result of I4.0, which integrates intelligent systems and data analytics into manufacturing processes, paving the way for more socially and environmentally responsible industrial practices (Chiarini, 2021; Evjemo et al., 2020). Smart manufacturing processes enable real-time monitoring, data-driven decision-making, and predictive maintenance, leading to decreased downtime and increased productivity (Ghobakhloo, 2020). Additionally, I4.0 fosters agile production, customization, and sustainable practices, making the manufacturing sector more competitive and innovative (Hariyani & Mishra, 2022; Sartal et al., 2020).

Large enterprises (LEs) already have started implementing I4.0 practices in their operations, whereas SMEs lag due to limited resources, lack of knowledge, unwillingness to take risks, and short-term operational goals (Kumar et al., 2020; Masood & Sonntag, 2020; Narkhede & Rajhans, 2022). I4.0 initiatives in SMEs have been limited to monitoring manufacturing operations, lacking significant applications in other work functions manufacturing (Moeuf et al., 2018). SMEs provide substantial employment opportunities, contribute significantly to the GDP, and their geographic distribution aids in balanced regional development in growing economies like India (Chandra et al., 2020). The impetus driving this research stems from the insufficient knowledge of the important role of I4.0 technologies in the sustainable development of SMEs. The motivation of the study lies in bridging this gap by examining the applicability and potential benefits of I4.0 technologies within critical functional areas of SMEs to improve their work efficiency. Therefore, due to the growing interest in examining the suitability of I4.0 technologies, the objective of this literature review is to investigate the applicability and potential benefits of I4.0 technologies in key areas such as New Product Development (NPD), Supply Chain Management (SCM), Internal Logistics Management (ILM), Production Planning Execution and Control (PPEC), Quality Management (QM), and Maintenance Management (MM). By exploring these specific domains, this research aims to gain a comprehensive understanding of how I4.0 technologies can revolutionize different facets of manufacturing SMEs. In the current dynamic and technologically driven market, it becomes crucial to conduct sustainability measurements to fully understand the impact of I4.0 technologies across various manufacturing work functions from the SME's perspective. Sustainability measurement also known as sustainable measurement, is the process of evaluating and quantifying the economic, social, and environmental impact of an organization's activities, products, or services (Scoones & Scoones, 2010).

By harnessing the power of I4.0 technologies, SMEs can streamline processes, optimize resource allocation, improve product quality, enhance customer satisfaction, and ultimately drive sustainable growth (Moeuf et al., 2019). This study employs an inductive-deductive approach developed by (Seuring & Gold, 2012) for preparing a conceptual framework as shown in Figure 1. Each intersection within the framework signifies the impact of implementing the I4.0 technologies on each of the above-mentioned mechanical processes.

Through an extensive review of relevant literature, this study delves into the existing research and insights on the adoption and implementation of I4.0 technologies within the mentioned functional areas. By examining the potential opportunities associated with I4.0 technologies, this article provides valuable insights into the intersection of these concepts and recommendations for SMEs to implement these technologies in their manufacturing operations. Overall, this literature review contributes to the subject domain by shedding light on the suitability and potential benefits of I4.0 technologies in

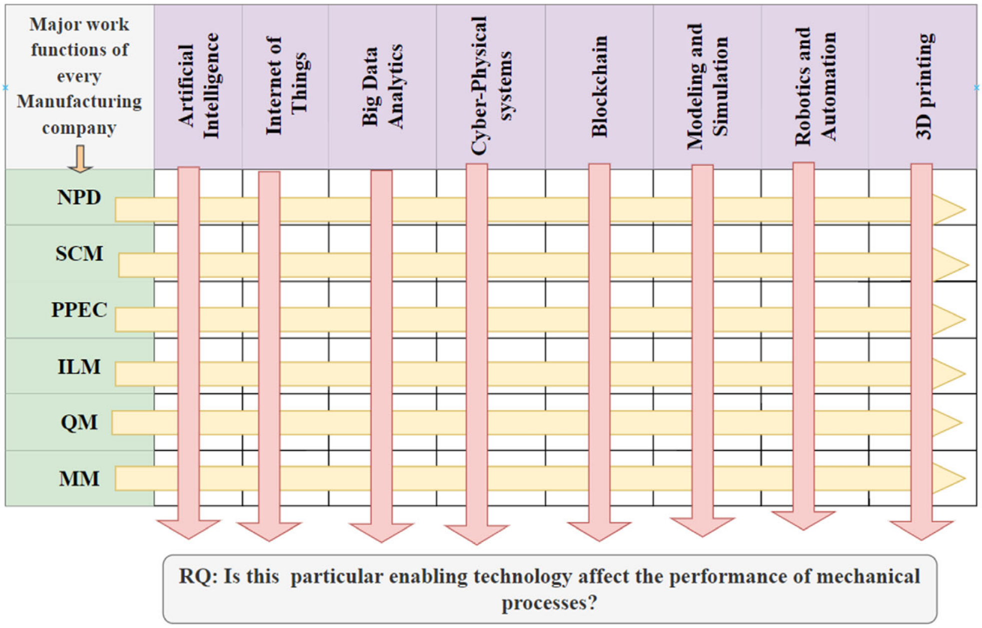


FIGURE 1 Conceptual framework for measuring the impact of I4.0 technologies.

various critical work functions of manufacturing SMEs. The findings and insights obtained from this study will serve as a valuable resource for decision-makers of SMEs to drive the successful adoption of I4.0 technologies. In this view, this article aims to address the following research objectives (ROs) concerning I4.0 and its implications in different domains of manufacturing SMEs:

- RO1: How I4.0 can contribute to manufacturing SMEs to become technologically advanced?
- RO2: To measure the level of impact of each technology in different work domains.
- RO3: To propose a framework to implement I4.0 technologies effectively in the manufacturing SMEs.

The subsequent sections of this article are organized as follows: Section 2 outlines the methodology employed for sourcing relevant research articles. Section 3 presents an extensive literature review. Section 4 focuses on a comprehensive discussion of the obtained results. Finally, Section 5 concludes the article, explores potential avenues for future research, and acknowledges the study's limitations.

2 | LITERATURE SEARCH METHODOLOGY

To accomplish the objective of this research, a systematic literature survey (SLR) approach is used with various combinations of keywords such as Industry 4.0; Enabling technologies; Sustainable development; and sustainability. The importance of the SLR approach lies within its systematic and rigorous approach, which ensures a thorough analysis of existing research conducted in a specific field. SLR systematically identifies, assesses, and synthesizes the research studies, which offers a strong basis for decision-making and scientific progress. The structured process of SLR minimizes bias and enables researchers to identify research gaps in the literature, trends, and potential directions for further research. In essence, this approach offers a strong basis for evidence-based research, making SLR a preferred choice for knowledge synthesis. This is carried out in seven stages, which include formulating the research objective (RO) and developing research questions (RQs); defining the literature search strings (LSS); identifying inclusion criteria (ICs) and exclusion criteria (ECs); performing initial screening and full-text review; completing both forward and backward reviews; extracting data and content analysis; and, at last presenting the SLR findings in a structured manner in this study. Additionally, the VOS viewer tool is used for bibliographic analysis that provides insights including identifying highly researched I4.0 technologies and their diverse applications across work functions. Figure 2 outlines a systematic approach for collecting, summarizing, and synthesizing current research on the significance of I4.0 technologies in different work functions.

Initially, the articles were retrieved from databases, including Scopus, Web of Science, Research Gate, and Google Scholar. The search for LSS was conducted using Boolean syntaxes (AND/OR) to refine the results. The research publications were obtained by applying the search strings as shown in step 2. The formulation of inclusion and exclusion criteria ensures the reliability of identified research articles and enables researchers to preserve their relevance and integrity, enhancing the reliability of the findings. Subsequently, 21 articles were excluded according to exclusion criteria, yielding 33 eligible papers after conducting an initial screening and conducting a thorough review of the full-text articles. Next, the authors examined the references cited in the eligible pool of research papers and conducted a forward search to identify new research papers. Following this forward review, the total number of eligible research papers increased to 65. Eventually, the included articles were analyzed to categorize them according to their respective theoretical perspectives and empirical findings. This categorization approach facilitates summarizing accurately and cites the identified articles throughout the research paper.

3 | LITERATURE REVIEW

I4.0 aims to address sustainability aspects, including economic, social, and environmental dimensions, to ensure the sustainable development of manufacturing enterprises (Ahmad et al., 2019). Nevertheless, a decade after the advent of I4.0, most SMEs still work in conventional ways for various reasons, and this reluctance to embrace I4.0 technologies impedes their progress toward achieving sustainable development. Sustainable development of SMEs refers to the strategic approach that integrates economic, social, and environmental aspects in their business operations (Malik & Jasińska-Biliczak, 2018). It encourages long-term profitability and growth while minimizing adverse impacts on the environment and society (Lopes de Sousa Jabbour et al., 2020).

A survey conducted in Japan, the USA, and Germany revealed that merely 15% of enterprises have already developed or actively striving to implement I4.0 in their operations (Strandhagen et al., 2017; Yin et al., 2018). It is reasonable to infer that the situation is even more challenging in developing countries like India. Hence it becomes imperative to assess the impact of each technology on different work functions of the manufacturing industry. The primary objective of this research is to assist decision-makers of SMEs in implementing I4.0 enabling technologies based on their specific requirements for their business operations. The following subsections provide a detailed overview of I4, enabling technologies, manufacturing work functions, and the impact of enabling technologies on mentioned work functions.

3.1 | I4.0: An overview

I4.0 refers to the integration of digital technologies, automation, and data exchange in the manufacturing sector (Thoben et al., 2017). It represents a significant shift in how industries operate and is characterized by the use of technologies such as IoT, AI, BDA, CPS, Modeling and Simulation, Robotics and Automation, and 3D printing (Narkhede et al., 2023; Nascimento et al., 2019; Thoben et al., 2017).

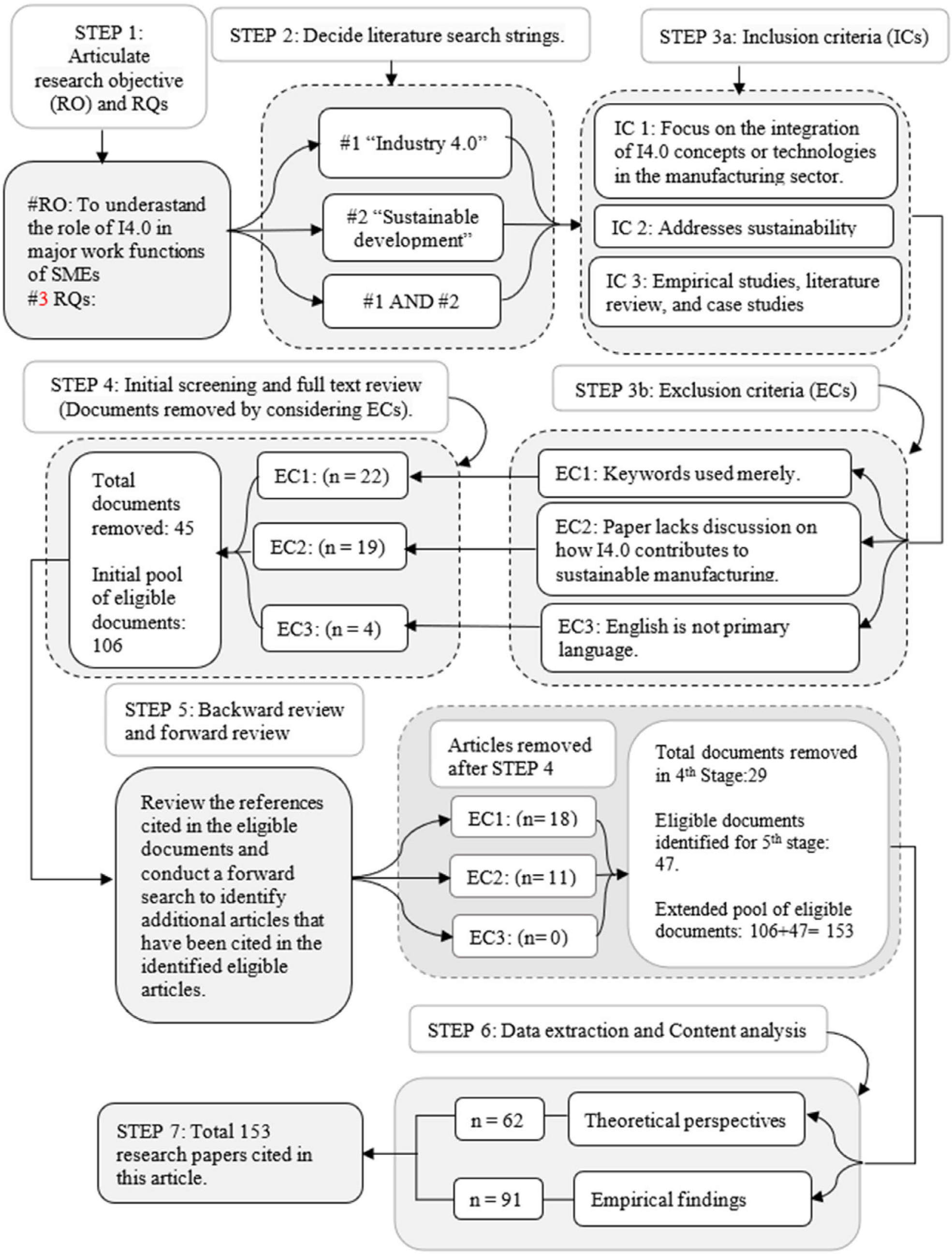


FIGURE 2 Research articles search methodology.

Ultimately, the I4.0 technologies offer unprecedented benefits by increasing operational efficiency, providing safe working conditions, minimizing resource consumption, and reducing environmental impact, all of which contribute to the sustainability of industrial operations (Tabim et al., 2021). "Sustainability is the development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Scoones & Scoones, 2010).

A bibliographic analysis was conducted using the VOSviewer tool to identify the most researched enabling technologies of I4.0, as illustrated in Figure 3.

This bibliographic analysis revealed that AI, IoT, BDA, CPS, Blockchain, Modeling and simulation, Robotics and Automation, and 3D printing are the most researched I4.0 technologies and therefore further evaluated their significance for the sustainable development of SMEs. I4.0 enabling technologies aim to create smart factories that are highly connected, flexible, and efficient (Elvis Hozdić, 2015). However, it becomes important to conduct thorough preliminary research before integrating I4.0 technologies into the business operations of SMEs, aligning them with the specific requirements of each business.

I4.0 is characterized by its integration along three dimensions: vertical integration, involving networked manufacturing systems; horizontal integration, achieved through value networks; and end-to-end digital integration of engineering across a product's lifecycle value chain (Liu & Xu, 2017). I4.0 entails the digitization and interconnection of diverse components and processes within the value chain, consisting of design, production, supply chain, and customer interaction. At

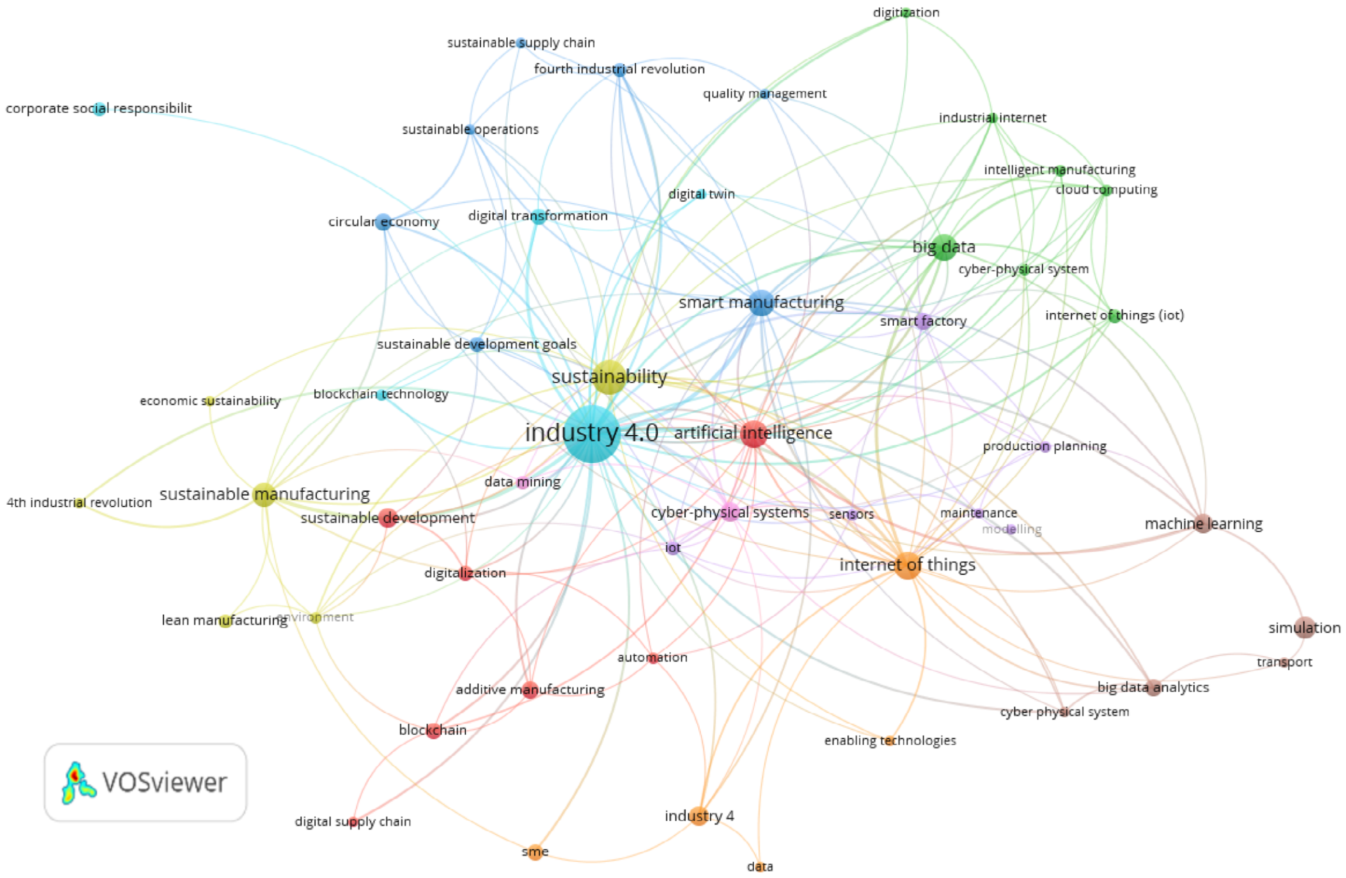


FIGURE 3 Most researched keywords related to I4.0.

its core, the smart factory represents a fundamental concept and a key element of I4.0, serving as the platform for vertical integration (Tabim et al., 2021). Horizontal integration, on the other hand, involves linking multiple smart factories through value networks, both within individual facilities and across different ones (Pérez-Lara et al., 2020). The synergy of vertical and horizontal integration facilitates seamless end-to-end integration throughout the entire value chain (Zhou et al., 2016). Another critical aspect of I4.0 is the concept of smart products (Nunes et al., 2017). In a smart factory, products, and machines communicate collaboratively, driving the production process and these smart products can encompass objects, devices, and machines equipped with sensors, controlled by software, and connected to the internet, enabling advanced capabilities and interactions within the manufacturing ecosystem (Elvis Hozdić, 2015). Figure 4 shows the integration of I4.0 along three dimensions as mentioned above.

By leveraging these advanced technologies, I4.0 enables real-time data collection, analysis, and decision-making, leading to improved productivity, quality, and customization (Lasi et al., 2014). The following section highlights the importance of core technologies of I4.0.

3.2 | Core technologies of I4.0

I4.0 is driven by a set of enabling technologies that are transforming the modern manufacturing world. These technologies form the foundation for the seamless integration of digital and physical systems, enabling intelligent, autonomous, and data-driven manufacturing processes (Pasi et al., 2020). Table 1 provides an overview of I4.0 core enabling technologies, highlighting their potential to revolutionize manufacturing processes.

3.3 | Significance of I4.0 enabling technologies for key work functions of every manufacturing firm

Manufacturing companies perform essential functions to produce goods efficiently. The scientific literature offers different frameworks and models outlining standard work functions in manufacturing companies. These frameworks or models help in comparing the performances of alternative processes, potentially uncovering the best practices to improve productivity. Value Chain analysis is the most widely used model and a strategic management tool that includes several activities to manufacture products or provide services (Knez et al., 2021). These activities are divided into primary (inbound logistics, operations, marketing) and support activities (procurement, technology, HR), and aim to optimize processes and improve productivity (Knez et al., 2021). Supply Chain Operations Reference Model (SCOR) is another framework used to improve supply chain performance and it outlines best practices, and processes for planning, sourcing, making, delivering, and returning products (Kirikova et al., 2012;

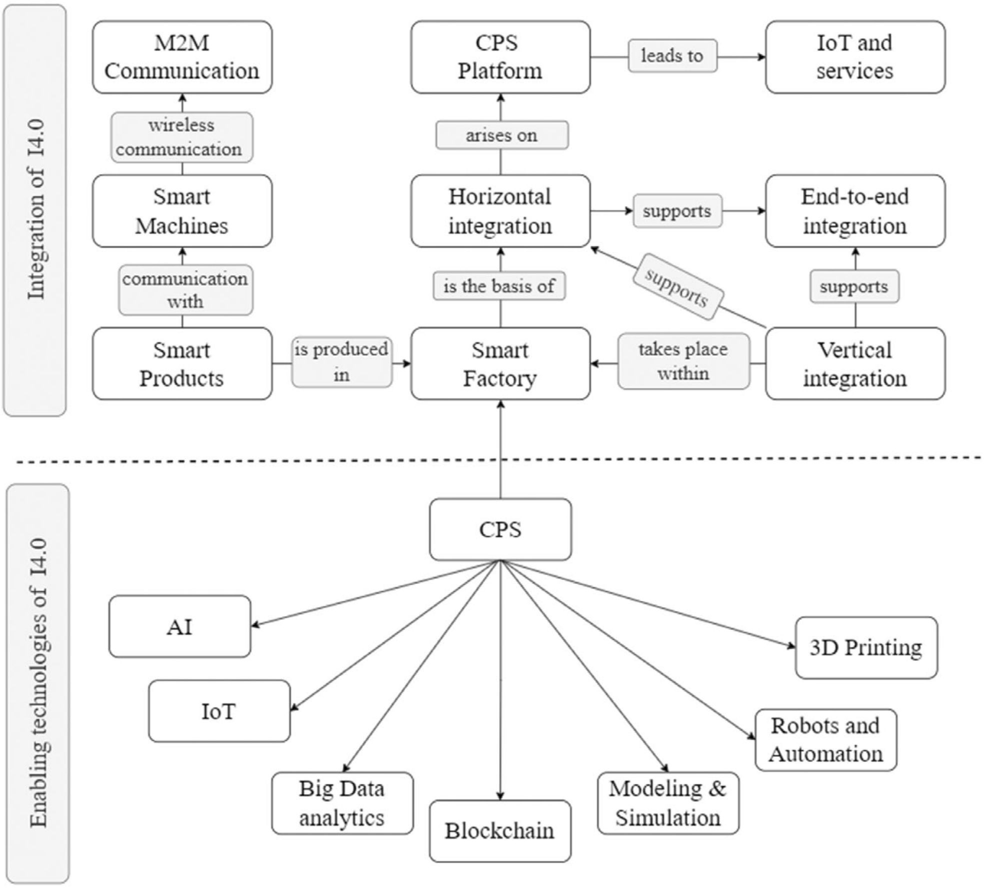


FIGURE 4 Integration of I4.0 along three dimensions (*Data source*: Liu & Xu, 2017).

TABLE 1 I4.0 enabling technologies.

I4.0 technologies	Description	References
AI	Simulates human intelligence in machines, enabling them to learn, reason, and perform tasks autonomously	(Kok et al., 2009; Maddikunta et al., 2022; Monostori, 2003)
IoT	Connects devices to the internet, enabling data exchange and communication for smarter interactions	(Atzori et al., 2010; Oztemel & Gursev, 2020; Trappey et al., 2016)
BDA	Involves extracting valuable insights from diverse datasets using advanced algorithms, enabling data-driven decision-making processes and uncovering patterns and trends.	(Buhl et al., 2013; Fosso Wamba et al., 2015; Vera-Baquero et al., 2014)
CPS	CPS are interconnected devices integrating the physical world with digital intelligence for advanced automation and control.	(Al-Salman & Salih, 2019; Lee et al., 2015; Trappey et al., 2016)
Blockchain	Decentralized, immutable ledger technology that ensures secure, transparent, and tamper-resistant data storage.	(Belotti et al., 2019; Chen et al., 2018; Xu et al., 2019)
Modeling and simulation	Virtual representations of real-world systems to analyze, predict, and optimize their behavior, enabling better decision-making and understanding the complex processes.	(Ghobakhloo, 2018; Kocian et al., 2012)
Robots and Automation	Use of machines and intelligent systems to perform hazardous and repetitive tasks autonomously or semi-autonomously to enhance productivity, and transform manufacturing industries.	(Aghimien et al., 2020; Ribeiro et al., 2021)
3D printing	3D printing, or Additive Manufacturing, constructs objects layer by layer from digital models, revolutionizing industries by enabling rapid prototyping, customization, and cost-effective production of complex designs with various materials	(Durão et al., 2017; Ramya & Vanapalli, 2016)

Stephens, 2001). Value Reference Model (VRM) is another important model used in the field of enterprise architecture. VRM encompasses three levels: governance for strategic processes; planning for tactical processes; and execution for operational processes (Kirikova et al., 2012). All these mentioned models facilitate aligning activities, optimizing resources, and improving overall business performance. From the models discussed, the authors have compiled a list of major business functions that characterize typical manufacturing SMEs. The list includes NPD, SCM, IL, PPEC, QM, and MM.

3.3.1 | New product development

NPD is the process of developing new products or services to the market and it is an important aspect of business growth and innovation since it enables organizations to stay competitive and capitalize on emerging market trends (Bessant & Francis, 1997). NPD involves various stages, starting from idea generation and concept development to design, prototyping, testing, and commercialization (Ernst, 2002). The literature offers some insights into how digital technologies can facilitate and enhance the process of NPD.

Tao and Qi (2019) developed an innovative framework Service-oriented Smart Network (SoSM), wherein IoT is used to interconnect all stakeholders engaged in the design phase which facilitates to develop the product information model. Chen (2017) highlighted that the IoT-based receiver and feedback mechanism improves the efficiency of data source collection in the NPD process. Furthermore, Bressanelli et al. (2018) emphasized the potential of IoT and BDA in improving product design from the context of the Circular Economy (CE) approach. Miranda et al. (2019) conducted a study on the theme of smart product development, emphasizing the utilization of a reference framework that incorporates CPS to design sensing, smart, and sustainable (S^3) products. Certainly, IoT enables direct data collection from the product itself, identifying potential design improvements during the development phase.

Moreover, beyond simply gathering the data, it is imperative to process the collected data to identify and highlight any potential improvement trends. Numerous studies in the literature have demonstrated the effectiveness of BDA technology in performing this crucial phase of data processing. According to the findings of Dalenogare et al. (2018), there is concrete evidence indicating that operational big data, obtained from sensors, impacts positively on product design within Computer-Aided Design systems. This is further supported by (Chen, 2017), who asserted that BDA can empower decision-makers to convert data into valuable insights. Additionally, Ang et al. (2017) emphasized that when BDA is combined with machine learning, the information gathered from the product lifecycle can be utilized to optimize product design effectively.

Cloud technology presents another captivating avenue for NPD. It offers a platform wherein data and functionalities are seamlessly deployed. This enables the transmission of specific customer requirements across the global network to the cloud, facilitating storage, computing, and analysis. As a result, distributed and collaborative product design is promoted, allowing teams to work together efficiently and effectively in the NPD process (Ang et al., 2017; Rao & Prasad, 2018).

3D printing enables to manufacture the complex geometries that are difficult to manufacture by other traditional manufacturing processes (Ang et al., 2017). This technology guarantees rapid prototyping for subsequent testing which expedites the NPD process (Ghobakhloo, 2018). Robotics and automation expedite NPD by streamlining production processes, reducing errors, and enabling rapid prototyping and testing, leading to quicker time-to-market and improved productivity and quality (Evjemo et al., 2020). Table 2 highlights the significant impact of I4.0 technologies on NPD.

A consumer electronics company (SmartTech Innovations), used IoT sensors for collecting user data, which enabled continuous feedback for new product developments or further improvements in existing products. Furthermore, this data-driven approach reduced time-to-market.

3.3.2 | Supply chain management

SCM is a comprehensive process that involves planning, coordination, and control of the flow of goods or services, information, and finances across the entire supply chain, from the raw material stage to the end consumer (Felea & Albăstroiu, 2013; Mentzer et al., 2001). The primary objective of SCM is to optimize efficiency, reduce costs, improve product quality, and enhance customer satisfaction (Lambert & Cooper, 2000). It encompasses various key components, such as sourcing, procurement, production, inventory management, logistics, and distribution, all of which work together to create a seamless and responsive supply chain network (Houlihan, 1985).

I4.0 technologies have emerged as a driving force, bringing unprecedented advancements and opportunities in SCM and these technologies leverage the power of digitalization, automation, and data-driven insights to revolutionize traditional SCM practices (Hofmann et al., 2019). One of the most significant contributions of I4.0 to SCM is IoT, where sensors and connected devices enable real-time tracking and monitoring of goods, enabling supply chain stakeholders to have greater visibility and control over their operations (Ben-Daya et al., 2019; Srai & Lorentz, 2019).

Additionally, BDA and AI play an important role in SCM by processing a huge amount of data to identify patterns, forecast demand, streamline logistics and transportation, and optimize inventory levels (Chehbi-Gamoura et al., 2020; Min, 2010; Pournader et al., 2021; Tiwari et al., 2018). Predictive analysis helps to anticipate SCM disruptions and improve risk management (Hendricks & Singhal, 2005), while AI-enabled automation avoids manual errors and enhances process efficiency (Helo & Hao, 2022).

By offering real-time visibility, predictive analytics, effective inventory management, quality control, an optimized supply chain, accurate forecasting, collaboration, risk management, and resource optimization, CPS improves SCM performance in the manufacturing sector, resulting in increased efficiency, lower costs, and better ability

TABLE 2 Significance of I4.0 technologies for NPD.

I4.0 technologies	Applications	References
IoT	Data collection to improve product design	(Ang et al., 2017; Bressanelli et al., 2018; Chen, 2017; Tao & Qi, 2019)
BDA	Processing and analyzing collected data for further product design improvements.	(Ang et al., 2017; Belhadi et al., 2019; Bressanelli et al., 2018; Chen, 2017; Dalenogare et al., 2018; Tao & Qi, 2019)
CPS	Distribution of the production process	(Durão et al., 2017; Miranda et al., 2019)
Cloud technology	Design the NPD process in a distributed and collaborative way	(Ang et al., 2017; Rao & Prasad, 2018)
AI	Enhancing innovation and efficiency in product development processes with AI.	(Ang et al., 2017; Ghobakhloo et al., 2023; Zheng et al., 2018)
Simulation and modeling	Improving product design accuracy through virtual prototyping and technical assessment of product design	(Ang et al., 2017; Bai et al., 2020; Kusiak, 2018; Pasi et al., 2020; Smith & Srinivas, 2019)
Blockchain	Security in the product development process of critical parts using blockchain	(Khanfar et al., 2021)
Robots and automation	Hazardous or repetitive tasks of the NPD process	(Doyle-Kent & Kopacek, 2021; Evjemo et al., 2020; Thoben et al., 2017)
3D printing	Rapid prototyping, customized production in NPD	(Ang et al., 2017; Dilberoglu et al., 2017; Nascimento et al., 2019; Oztemel & Gursev, 2020; Pasi et al., 2020; Ramya & Vanapalli, 2016; Yin et al., 2018)

to respond to market demands (Matana et al., 2020). Simulation and modeling benefit manufacturing SCM by mitigating risks, optimizing manufacturing processes, reducing costs, aiding the decision-making process, enhancing collaboration, and improving overall performance through data-driven insights and efficient resource allocation (Abukhousa et al., 2014).

Incorporating blockchain technology into SCM improves transparency and traceability to the supply chain (Queiroz et al., 2020). Smart contracts in blockchain facilitate secure and automated transactions between parties, further streamlining processes (Kamble et al., 2019; Saberi et al., 2019). Additionally, additive manufacturing also referred to as 3D printing, which enables decentralized production and reduces lead times, has made a significant impact on SCM (Oettmeier & Hofmann, 2016). Companies can manufacture spare parts on demand, eliminating the need for extensive inventories and minimizing supply chain disruptions (Handal, 2017).

Automation and robots improve manufacturing SCM by improving productivity, and efficiency. They make the supply chain more responsive and agile by streamlining processes, enhancing quality control, providing data-driven insights, and ensuring a safe working environment (Demir et al., 2019; Maddikunta et al., 2022).

Overall, I4.0 technologies empower SCM managers with real-time insights, quick decision-making capabilities, and more efficient operations, ultimately driving competitiveness, sustainability, and customer satisfaction in today's fast-paced and dynamic business landscape. The significant effect of I4.0 technologies on SCM is summarized in Table 3.

An automobile manufacturer (AutoTech Solutions), used blockchain technology to improve supply chain transparency and traceability. This streamlined communication between distributors, suppliers, and manufacturers which further reduced delays, and resulted in timely deliveries.

3.3.3 | Internal logistics

IL refers to the movement of materials and resources within the premises of the company and it entails the planning, execution, and control of numerous activities, including inventory management, warehousing, order fulfillment, transportation, and distribution, to ensure the smooth flow of goods and materials throughout the internal supply chain (Granlund & Wiktorsson, 2014).

AI optimizes route planning, resource allocation, and demand forecasting, leading to efficient material flow and reduced lead times (Foster & Rhoden, 2020; Lee et al., 2018; Olessków-Szłapka et al., 2019). IoT enables real-time tracking of inventory and assets enables better visibility and enhances inventory management and asset utilization (Tadejko, 2015). Wang et al. (2016) emphasized the use of RFID for material identification and recording manufacturing information. CPS integration allows seamless coordination between physical and digital systems, enabling automated workflows and better decision-making (Matana et al., 2020).

BDA in IL optimizes operations by extracting valuable insights from huge datasets. It marks key performance indicators, such as inventory turnover, order processing time, and transportation costs, to identify inefficiencies and bottlenecks (Hopkins & Hawking, 2018; Nimtrakoon, 2015). Data-driven decision-making improves route planning, reducing delivery times. Real-time monitoring enhances visibility and enables agile responses to changes in demand or disruptions

TABLE 3 Significance of I4.0 technologies for SCM.

I4.0 technologies	Applications	References
IoT	Enables SCM managers to have greater visibility and control over their operations.	(Ben-Daya et al., 2019; Srai & Lorentz, 2019).
BDA	Identify patterns, forecast demand, streamline logistics and transportation, and optimize inventory levels	(Bressanelli et al., 2018; Chehbi-Gamoura et al., 2020; Kamble et al., 2018; Maheshwari et al., 2021; Tiwari et al., 2018)
CPS	Offers real-time visibility, predictive analytics, an optimized supply chain, accurate forecasting, collaboration, and risk management.	(Matana et al., 2020; Muhuri et al., 2019; Pasi et al., 2020; Shiroishi et al., 2018)
Cloud technology	—	—
AI	Identify patterns, forecast demand, streamline logistics and transportation, and optimize inventory levels	(Helo & Hao, 2022; Min, 2010; Pournader et al., 2021)
Simulation and modeling	Mitigate risks, optimize manufacturing processes, reduce costs, and aid the decision-making process	(Abukhousa et al., 2014)
Blockchain	Improves transparency and traceability to the supply chain	(Kamble et al., 2019; Queiroz et al., 2020)
Robots and automation	More responsive and agile supply chain, Safe working environment	(Demir et al., 2019; Maddikunta et al., 2022)
3D printing	Decentralized production and reduced lead times	(Handal, 2017; Oettmeier & Hofmann, 2016)

TABLE 4 Significance of I4.0 technologies for IL.

I4.0 technologies	Applications	References
IoT	Enables real-time tracking of inventory and enhances asset utilization	(Hofmann et al., 2019; Lee et al., 2018; Tadejko, 2015)
BDA	Route planning and reducing total delivery times	(Hopkins & Hawking, 2018; Nimtrakoon, 2015)
CPS	—	—
Cloud technology	—	—
AI	Optimizes route planning, resource allocation, and demand forecasting	(Foster & Rhoden, 2020)
Simulation and modeling	Digital models enable refining IL processes, predicting outcomes, and identifying areas for improvement before implementation.	(Hofmann et al., 2019; Karkula, 2014; Pasi et al., 2020; Smith & Srinivas, 2019)
Blockchain	Secure and transparent tracking of goods and transactions	(Khanfar et al., 2021; Raja Santhi & Muthuswamy, 2022)
Robots and automation	Seamless technology integration	(Novais et al., 2019; Strandhagen et al., 2017; Tang & Veelenturf, 2019; Yang et al., 2019)
3D printing	—	—

(Yudhistyra et al., 2020). By leveraging BDA, businesses can streamline IL, enhance productivity, and ultimately enhance services to customers (Yang et al., 2019).

Blockchain technology enhances internal logistics through improved security, traceability, and transparency (Rejeb et al., 2021). It reduces the possibility of data manipulation and fraud by creating a decentralized record of every transaction (Khanfar et al., 2021). Secure and transparent tracking of goods and transactions enhances supply chain visibility and ensures data integrity and trust (Raja Santhi & Muthuswamy, 2022).

Simulation and modeling optimize IL by analyzing performance, finding obstacles, improving capacity planning, creating layouts, allocating resources, analyzing hazardous tasks, and driving process improvements (Hofmann et al., 2019). This results in decreased cost, improved efficiency and productivity, and enhanced customer satisfaction (Karkula, 2014; Smith & Srinivas, 2019). Digital models developed by modeling and simulation allow for refining IL processes, predicting outcomes, and identifying areas for improvement before implementation.

Robots and automation boost IL with seamless technology integration, around-the-clock operations, faster order processing, and most important improved safety (Novais et al., 2019; Strandhagen et al., 2017; Tang & Veelenturf, 2019). Table 4 highlights the significance of I4.0 technologies for IL.

A logistics company (Efficient Logistics Solutions), implemented automation and robotics for automating warehouse activities, including order picking, inventory management, space optimization, error reduction, and speed efficiency.

3.3.4 | Production planning execution and control

PPEC is a crucial process in manufacturing and production industries that involves the planning, organizing, execution, and monitoring of all activities necessary to manufacture products or services efficiently (Bueno et al., 2020). The key components of PPEC include forecasting, master production scheduling, material requirement planning, capacity planning, and manufacturing. Its main objective is to ensure that the production process runs smoothly, resources are used effectively, and products are delivered on time, meeting quality standards and customer demands. The potential of real-time data monitoring, data analytics, and adaptive production systems is examined to optimize production processes, reduce downtime, and increase productivity.

Connected sensors and IoT devices provide real-time data on machine performance, production status, and inventory levels, enabling agile decision-making and proactive issue resolution (Bueno et al., 2020; Tsai & Lu, 2018). AI and machine learning algorithms can predict production obstacles, and demand fluctuations, optimizing resource allocation and minimizing machine downtime (Shang & You, 2019; Usuga Cadavid et al., 2019).

CPS plays a crucial role in PPEC by integrating physical manufacturing systems with digital technology. CPS enables real-time data collection, analysis, and communication between machines and systems (Alexopoulos et al., 2016). This facilitates enhanced visibility and decision-making in the production process (Lu & Xu, 2018). CPS allows for predictive maintenance, optimizing production schedules, and improving resource utilization (Lalanda et al., 2017). By leveraging BDA and automation, CPS can identify bottlenecks, streamline workflows, and minimize downtime (Shafiq et al., 2016). The seamless interaction between physical processes and digital intelligence in CPS empowers manufacturers to achieve higher efficiency, flexibility, and responsiveness in their production processes, leading to cost savings and better overall production outcomes (Bueno et al., 2020).

Cloud technology solutions enable real-time collaboration, data sharing, and remote access to production-related information (Erol & Sihn, 2017). This connectivity facilitates better communication between different departments involved in PPEC. The use of robots and autonomous vehicles on the shop floor can streamline production activities, reduce lead times, and improve overall productivity (Anzolin & Andreoni, 2023; Syed et al., 2020). These systems can be integrated into the PPEC process to optimize material flow, reduce human intervention, and promote reliable, effective production methods in smart manufacturing systems (Bueno et al., 2020). 3D printing technology enables on-demand production, reducing lead times, inventory costs, and waste, while enabling customization (Bueno et al., 2020). Table 5 highlights the significance of I4.0 technologies for PPEC.

Precision Manufacturing Ltd. employed CPS for predictive maintenance to monitor the condition of their machinery to enhance operational efficiency, reduce downtime, and maximize production schedules.

TABLE 5 Significance of I4.0 technologies for PPEC.

I4.0 technologies	Applications	References
IoT	Provide real-time data on machine performance, production status, and inventory levels	(Bueno et al., 2020; Tsai & Lu, 2018)
BDA	Predict maintenance schedules, production obstacles, and fluctuations; optimize resource allocation; and minimize machine downtime.	(Bueno et al., 2020; Shang & You, 2019; Usuga Cadavid et al., 2019)
CPS	Integrate physical manufacturing systems with digital technology	(Alexopoulos et al., 2016; Bueno et al., 2020; Lalanda et al., 2017; Lu & Xu, 2018; Shafiq et al., 2015, 2016)
Cloud technology	Data sharing, remote access to production-related information	(Bueno et al., 2020; Erol & Sihn, 2017; Jeon & Kim, 2016)
AI	Predict maintenance schedules, production obstacles, and demand fluctuations	(Shang & You, 2019; Usuga Cadavid et al., 2019).
Simulation and modeling	—	—
Blockchain	—	—
Robots and automation	Streamline production activities, reduce lead times, and improve overall productivity	(Anzolin & Andreoni, 2023; Bueno et al., 2020; Krzywdzinski & Jo, 2022; Mortimer, 2006; Syed et al., 2020; Wilson, 2010)
3D printing	Enables on-demand production, reducing lead times, inventory costs, and waste	(Bueno et al., 2020; Chi et al., 2022; Dilberoglu et al., 2017; Ferreira et al., 2023; Savsani et al., 2023)

3.3.5 | Quality management

QM refers to the process of ensuring the quality of products or services provided by the company and the process of QM consists of systematic planning, implementation, and monitoring of all activities to improve product quality or services, thereby enhancing customer satisfaction (Claver et al., 2003). I4.0 technologies can enhance customer satisfaction when integrated with QM principles such as Total Quality Management (TQM), Six Sigma, Lean Manufacturing, and ISO Standards (Chiarini, 2020; Nicholas, 2016; Patyal & Maddulety, 2015). I4.0 technologies play a major role in improving QM in various ways.

IoT improves QM by monitoring real-time data and data collection across production processes (Hyun Park et al., 2017; Khalili et al., 2018). Connected sensors and devices track process parameters, detect defects, and measure performance (Illa & Padhi, 2018). This data-driven approach enables proactive issue identification and timely maintenance (Hyun Park et al., 2017). IoT-based predictive analytics helps in decision-making, minimizes downtime of machines, and improves product quality, steering overall efficiency and customer satisfaction (Illa & Padhi, 2018). BDA in QM leverages huge data sets from diverse sources to identify patterns or irregularities and detect quality issues, identify root causes, and further scope for improvement (Tao & Qi, 2019). Kucukoglu et al. (2018) studied the combined utilization of artificial neural networks and digital wearable gloves to identify wrong assembly operations during connector assembly with the analysis of feedback signals related to finger vibrations and force. Carvajal Soto et al. (2019) developed discrete event simulation to evaluate various techniques for product failure inspection. Their approach involved testing various machine learning methods on physical production processes without causing a disturbance to the production line. Robotics and automation ensure precise and consistent production processes, reduce human error, and enable real-time quality measurements and monitoring (El Hachem et al., 2021; Navon, 2000). Table 6 highlights the significance of I4.0 technologies for QM.

TABLE 6 Significance of I4.0 technologies for QM.

I4.0 technologies	Applications	References
IoT	Monitors real-time data and data collection	(Hyun Park et al., 2017; Illa & Padhi, 2018)
BDA	Identify patterns or irregularities and detect quality issues, identify root causes	(Pasi et al., 2020; Tao & Qi, 2019)
CPS	—	—
Cloud technology	—	—
AI	Identify wrong assembly operations	(Kucukoglu et al., 2018)
Blockchain	Product failure inspection	(Carvajal Soto et al., 2019)
Simulation and modeling	—	—
Robots and automation	Reduce human error, and enable real-time monitoring	(El Hachem et al., 2021; Navon, 2000; Pasi et al., 2020)
3D printing	—	—

PharmaX Inc., a pharmaceutical firm, integrated BDA for QM. By analyzing real-time production data, they identified patterns that led to defects, enabled to take immediate corrective action and improved the overall quality of the product.

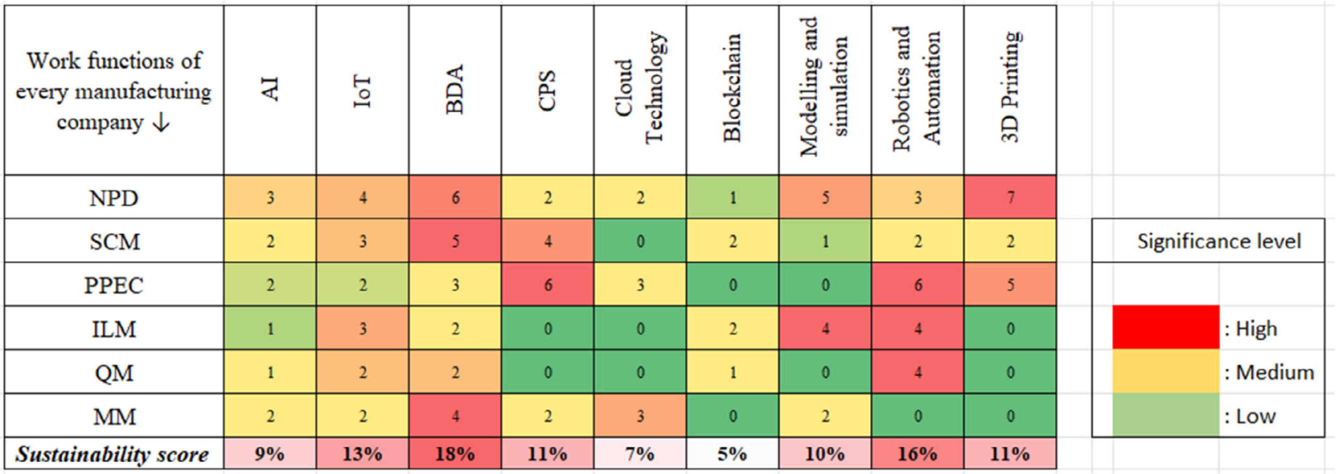
3.3.6 | Maintenance management

MM includes planning and execution of maintenance activities within an organization to ensure the reliability, availability, and performance of machines and facilities (Márquez et al., 2009). It aims to minimize machine downtime and improve operational efficiency while controlling costs.

IoT mechanisms, equipped with sensors, ensure continuous monitoring of the machine's health and performance metrics (Ang et al., 2017) and then collect data analyzed using AI and ML algorithms to identify potential failures and recommend proactive maintenance actions (Ansari et al., 2019). Augmented reality and virtual reality assist in remote diagnostics, repairs, and reducing downtime. Furthermore, BDA insights help to plan maintenance schedules, allocate resources effectively, and improve decision-making (Li et al., 2017). Table 7 focuses on the importance of I4.0 technologies for MM.

TABLE 7 Significance of I4.0 technologies for MM.

I4.0 technologies	Applications	References
IoT	Data collection for maintenance analytics	(Ansari et al., 2019; Shamayleh et al., 2020)
BDA	Data analysis for scheduling predictive maintenance	(De Tre et al., 2014; Hoyer, 2023; Li et al., 2017; Lopes de Sousa Jabbour et al., 2018)
CPS	Industrial data collection and structuring maintenance analytics	(Ansari et al., 2019; Li et al., 2017)
Cloud technology	Storage and computing resources for maintenance analytics	(Caggiano, 2018; Diez-Olivan et al., 2019; Liu & Xu, 2017)
AI	Diagnosis and predictive maintenance	(Ansari et al., 2019; Diez-Olivan et al., 2019)
Blockchain	—	—
Simulation and modeling	Machines and equipment health monitoring	(De Tre et al., 2014; Tao & Qi, 2019)
Robots and automation	—	—
3D printing	—	—



Work functions of every manufacturing company ↓	AI	IoT	BDA	CPS	Cloud Technology	Blockchain	Modelling and simulation	Robotics and Automation	3D Printing
NPD	3	4	6	2	2	1	5	3	7
SCM	2	3	5	4	0	2	1	2	2
PPEC	2	2	3	6	3	0	0	6	5
ILM	1	3	2	0	0	2	4	4	0
QM	1	2	2	0	0	1	0	4	0
MM	2	2	4	2	3	0	2	0	0
Sustainability score	**9%**	**13%**	**18%**	**11%**	**7%**	**5%**	**10%**	**16%**	**11%**

Significance level

🟥 : High
🟨 : Medium
🟩 : Low

FIGURE 5 Heatmap showing the significance of I4.0 technologies for different work functions.

TABLE 8 A concise summary of the significance of I4.0 technologies and associated risks.

Work functions	I4.0 technologies	Applications in different work functions	Risks	References
NPD	BDA, Modeling and Simulation, and 3D printing	BDA: analyzes past data; Modeling and Simulation: optimize designs; 3D printing: prototypes.	Technology advancements, data security issues, and market uncertainty.	(Ang et al., 2017; Chen, 2017; Nascimento et al., 2019; Pasi et al., 2020; Tao & Qi, 2019)
SCM	BDA and CPS	BDA: Forecast demand, streamline logistics, and transportation, and optimize inventory levels; CPS: real-time visibility, predictive analytics, an optimized supply chain, and risk management.	Market uncertainty, cybersecurity threats, data integrity concerns	(Belhadi et al., 2019; Fosso Wamba et al., 2015; Maheshwari et al., 2021; Miranda et al., 2019)
PPEC	Robotics and automation, CPS, and 3D printing.	Robotics and Automation: Streamline production activities, reduce lead times, and avoid human errors; CPS: To integrate physical manufacturing systems with digital technology; 3D printing: Complex parts manufacturing, reduce lead times.	Technology advancements, real-time data accuracy, skill gaps	(Anzolin & Andreoni, 2023; Bueno et al., 2020; Ejsmont et al., 2020; Lu & Xu, 2018; Shafique et al., 2017)
ILM	Robotics and automation, modeling and simulation, IoT	Robotics and Automation: Smart transportation, Modeling and Simulation, and IoT: Optimize transportation lines, reducing lead times, inventory costs, and waste.	System integration, Technology advancements	(Hofmann et al., 2019; Karkula, 2014; Novais et al., 2019; Tang & Veelenturf, 2019; Yang et al., 2019)
QM	Robotics and automation, BDA, IoT	Robotics and Automation: Automated inspection systems, and avoiding human errors. BDA and IoT: Collecting, analyzing, and acting upon real-time data to minimize inaccuracies.	Technology advancements, real-time data accuracy	(El Hachem et al., 2021; Hyun Park et al., 2017; Illa & Padhi, 2018; Navon, 2000; Pasi et al., 2020; Tao & Qi, 2019)
MM	BDA and cloud technology	BDA: Predictive maintenance; Cloud Technology: Minimizing unplanned downtime, optimizing maintenance schedules.	Technology advancements, skill gaps	(Caggiano, 2018; De Tre et al., 2014; Diez-Olivan et al., 2019; Hoyer, 2023; Liu & Xu, 2017)

SteelTech Industries used AI algorithms to predict machine failure patterns. AI effectively predicted maintenance needs by analyzing historical data, minimizing unplanned breakdowns, and ensuring uninterrupted production.

4 | RESULTS AND DISCUSSION

As discussed in the preceding sections, SLR includes numerous studies digging into the significance of I4.0 technologies and their potential applications in various business processes. Additionally, not all the I4.0 technologies might be equally important for all manufacturing companies. Nevertheless, certain technologies have garnered more attention than others, for various reasons. The following section aims to measure the sustainability of discussed I4.0 technologies.

4.1 | Sustainability measurement of I4.0 technologies for different work functions

The sustainability of the mentioned I4.0 enabling technologies is assessed by the volume of research articles that focused on their application within specific work functions. Figure 5 illustrates a heatmap representing the sustainability measurements of each I4.0 technology for each work function.

This heatmap highlights BDA as the most important technology among I4.0 technologies, with the highest sustainability score of 18%, and showcases its pivotal role in driving sustainable development across SCM, NPD, and MM. BDA is followed by Robotics and Automation with a score of 16%, showing future avenues in PPEC, ILM, and QM. IoT is third with a score of 13%, highlighting the significance to NPD, SCM, and ILM. Other than these three technologies 3D printing has gathered considerable attention in NPD and PPEC with a score of 11%. Similarly, CPS has attracted much attention due to its importance in PPEC with a score of 11%. Whereas, Blockchain, Cloud technology, and AI have low manufacturing sustainability. Based on the findings of SLR and sustainability measurement, Table 8 concisely summarizes the significance of I4.0 technologies along with their key applications for different work functions.

In the end, Table 9 shows the significance of important I4.0 technologies resulting from sustainability measurement in achieving integration along three dimensions.

4.2 | Roadmap for I4.0 adoption and sustainability

The synergy of I4.0 enabling technologies occupies the significant potential to improve manufacturing SMEs' performance (Kumar et al., 2020). By integrating discussed technologies, SMEs can streamline their manufacturing operations and maximize efficiency (Masood & Sonntag, 2020; Moeuf et al., 2018). Insights gained from SLR underscore the necessity of a roadmap to guide the implementation and long-term viability of I4.0 practices in SMEs. This roadmap is divided into four stages as shown in Figure 6.

As all the I4.0 technologies might not be equally important to all SMEs (Masood & Sonntag, 2020), at the first stage, firms need to identify their business requirements based on the type of production types they are engaged in. Step 2 deals with the selection of I4.0 technologies suitable for their business needs. Table 8 will enable decision-makers of SMEs to select appropriate I4.0 technologies. This step deals with the vertical integration of AI, IoT-based, and real-time data-driven manufacturing systems. Furthermore, this second stage encompasses the seamless integration of vendors, transporters, and customers into the production system. Such integration enables the alignment of the manufacturer's value chain with all stakeholders. This level of integration empowers manufacturers to improve quality, decrease operational expenses, and minimize rejection rates. Step

TABLE 9 Significance of important I4.0 technologies in achieving integration along three dimensions.

I4.0 technologies	Integration along vertical, horizontal, or end-to-end digital dimensions	Author(s)
BDA	BDA serves as a crucial technology that underpins the integration of data, processes, and systems along all three dimensions. SMEs can use BDA to harness the power of data to build a unified and integrated framework that crosses many organizational levels, a wide range of processes, and the whole value chain.	(Buhl et al., 2013; Fosso Wamba et al., 2015; Vera-Baquero et al., 2014)
Robotics and automation	In the context of I4.0, robotics, and automation enables smart production system and mostly contribute to the horizontal integration dimension. This technology enables the seamless collaboration of various components of the production process, leads to accurate process coordination, increased productivity, and no human errors.	(Aghimien et al., 2020; Ribeiro et al., 2021)
IoT	Enables vertical integration by interconnecting different echelons of hierarchy, from the shop floor to the management level.	(Atzori et al., 2010; Oztemel & Gursev, 2020; Trappey et al., 2016)
3D printing	Primarily contributes to the horizontal integration dimension by enhancing the flexibility and efficiency to manufacture complex or customized products. Additionally, it provides advantages for both vertical integration and end-to-end digital integration. The technology supports the objectives of I4.0's smart factory by enabling decentralized manufacturing, reducing lead times, and creating customized products.	(Durão et al., 2017; Oettmeier & Hofmann, 2016; Pasi et al., 2020)

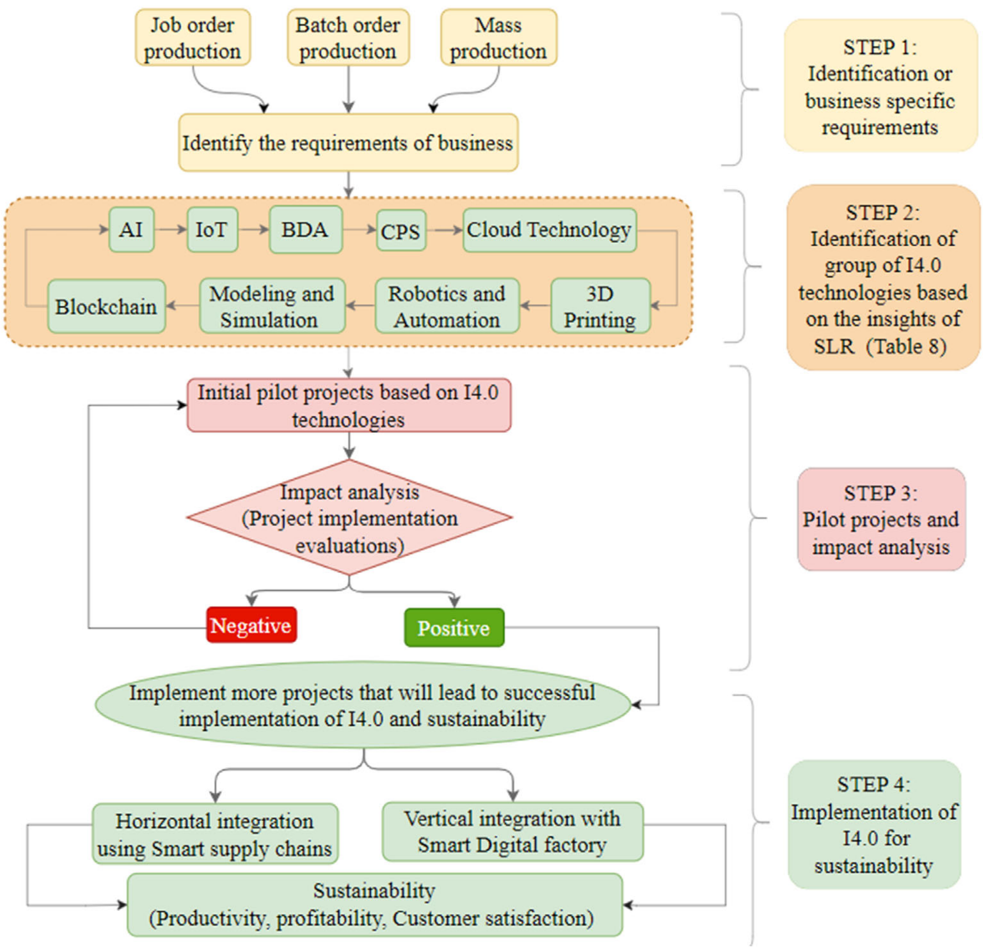


FIGURE 6 Roadmap for I4.0 implementation and sustainability.

3 deals with the initiation of pilot projects and their impact analysis. Based on the impact analysis, step 4 deals with the implementation of I4.0 for sustainability. Successful implementation of I4.0 technologies will enable horizontal and vertical integration at different stages, which will further result in smart factories and smart supply chains.

5 | CONCLUSION

This SLR thoroughly explored the potential opportunities of I4.0 technologies. It presents valuable insights and practical recommendations tailored to the requirements across various critical work functions of the manufacturing SMEs, which will enable SMEs to effectively integrate specific technologies into their manufacturing operations based on their business requirements. The findings of this study underscore BDA as the most crucial I4.0 technology for driving sustainable development in NPD, SCM, and MM. Following closely, robotics and automation show a huge potential in PPEC. IoT ranks third, significant for NPD, SCM, and ILM. Additionally, 3D printing and CPS, draw attention in NPD and PPEC respectively. On the other hand, blockchain, cloud technology, and AI exhibit comparatively lower sustainability impacts in manufacturing work functions. The knowledge gained from this study will serve as a valuable resource for decision-makers within manufacturing SMEs to drive the successful adoption of I4.0 technologies. Finally, a road map is presented to implement I4.0 technologies and improve the sustainability of manufacturing companies.

5.1 | Implications for theory and practice

The integration of I4.0 technologies holds substantial implications for both theory and practice in the context of SMEs engaged in manufacturing. Theoretical implications stem from a paradigm shift toward a smart production system. This challenges traditional manufacturing theories, necessitating the development of new theories that consider the interconnectedness of machines, big data sets, and manufacturing processes. This SLR and proposed framework will increase the knowledge and awareness about I4.0 implementation and sustainability, which will further assist decision-makers of SMEs while adopting I4.0 culture in their operations.

The second implication pertains to practical implication. I4.0 technologies profoundly impact key work functions across manufacturing SMEs. In production, BDA, Robotics and Automation, and 3D printing enhance operational efficiency and minimize downtime. Supply chain benefited from improved visibility and traceability. IoT-based manufacturing systems, collaborative robots, and 3D printing aids optimize labor-intensive tasks. However, the initial costs of I4.0 technology adoption might deter SMEs, and require partnership models. Data security and privacy concerns necessitate robust cybersecurity measures. Overall, integrating I4.0 in manufacturing operations requires a holistic approach to set strategic targets for horizontal and vertical system integration, bridging theory and practice to navigate these transformative changes effectively.

5.2 | Limitations of the study

This SLR provides valuable insights into the integration of I4.0 technologies within SMEs who are engaged in manufacturing. However, it becomes important to recognize some limitations that could affect the scope of the findings. First, the rapid evolution of I4.0 technologies means that some current developments and practical implications might not be underrepresented in the reviewed literature. Furthermore, the generalizability of the findings is restricted to SMEs within the manufacturing sector. The specific context, resources, and challenges faced by other sectors differ significantly from SMEs within the manufacturing sector, potentially restricting the applicability of the conclusions to broader manufacturing industrial settings.

5.3 | Future research directions

This work opens the door for some exciting new research avenues. In-depth case studies and examining the long-term impact of I4.0 on overall performance can give SMEs richer insights. Examining the challenges associated with implementing I4.0, as well as the cost-effectiveness and scalability of I4.0 technologies within diverse SME contexts, may provide practical implementation strategies. Additionally, exploring the importance of human factors and workforce upskilling can address critical socio-technical aspects.

AUTHOR CONTRIBUTIONS

Authors contributed equally in conception, research design, manuscript writing, critical revisions, and final approval of the submitted manuscript.

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