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Digital twin for sustainable manufacturing supply chains: Current trends, future perspectives, and an implementation framework

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A R T I C L E I N F O

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A B S T R A C T

A digital twin is an integration of virtual and physical systems using disruptive technologies. More precisely, it is a method of developing sustainable, intelligent manufacturing systems for attaining robust quality, reducing time, and customized products using real-time information throughout the product life cycle. This paper presents a systematic literature review of 98 research papers on various digital supply chain twin dimensions with sustainable performance objectives. The selected papers were reviewed and classified into three broad categories: components of the digital twin, applications in the manufacturing supply chain, and sustainability. Based on the review and future perspectives from the study, we suggest that advancements in technologies such as IoT, cloud computing, and blockchain have increased the potential of digital twin applications in the supply chain. The results indicate that a digital supply chain twin should include the *things* and *humans* from the entire supply chain and not be restricted to the local manufacturing systems. Based on our review findings, we present a sustainable digital twin implementation framework for supply chains. The proposed framework will guide future practitioners and researchers.

1. Introduction

Digitalization in manufacturing offers an opportunity for organizations to achieve increased productivity and efficiency (Uhlemann et al., 2017). Digitization enables efficient integration of the present interconnected intelligent systems on the shop floor and in the workspace area (Negri et al., 2017). Intelligent technological systems promise a strategic and sustainable development that combines humans and information technology (Mandola et al., 2019). Smart manufacturing frameworks are composed of materials; data; predictive sciences; and sustainability, resource sharing, networking, and manufacturing processes (Kamble et al., 2020; Kusiak, 2018). An important feature of smart manufacturing is the use of data acquired throughout the product life cycle to design effective and efficient manufacturing systems (Tao et al., 2018). Industry 4.0 technologies, such as the IoT, cloud computing, and augmented and virtual reality systems, enable the remote sensing and monitoring of real-time systems, allow effective control of devices, and create a cyberphysical environment, offering direct interaction, integration, and synchronization between the virtual and the real world (Kamble et al., 2018, 2020).

A digital twin is a virtual model and comprehensive depiction of the system used to understand the performance parameters, ameliorate processes, and effectively enhance value-added activities (Park et al., 2019; Rezaei et al., 2019).

A digital twin is a digital counterpart of the physical systems based on a simulation that deals with design systems and optimizes them for improved efficiency (Guo et al., 2019). Digital twin development has considerable potential in sustainable manufacturing operations because of its data-rich environment that facilitate real-time monitoring, simulation, and prediction of manufacturing processes (Cheng et al., 2018;

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Ding et al., 2019). Many manufacturing organizations have automated their production lines using robotic systems and IoT-based technologies, generating digital information (Goasduff, 2018; Tao et al., 2017). Digital information acts as an asset for optimizing production performance, and any minor improvement in the throughput, product quality, or equipment reliability in a high-productivity manufacturing environment adds a considerable value (Kamble et al., 2018). The digital twin simulates the manufacturing environment based on the collected information and helps the owner decide between the available actions for increased efficiency, better accuracy, and economies of scale (Negri et al., 2017; Rosen et al., 2015; Uhlemann et al., 2017). Cyberphysical systems have played an essential role in many upcoming technologies with the development of real-time sensing, advanced control, artificial intelligence, and service-oriented manufacturing (Luo et al., 2019). Smart manufacturing, combined with cyberphysical system development, has paved the road for digital twin technology to provide enough resolution to coordinate between the physical world and the virtual world (Alam and El Saddik, 2017). The interoperability between these emerging technologies results in significant potential for the development of effective platforms and applications to monitor and control the manufacturing systems, transforming them into sustainable manufacturing systems (Cai et al., 2017; He and Bai, 2019).

The existing literature indicated that organizations are considered successful if they can produce high-quality products meeting customer needs and expectations with low manufacturing and supply chain costs (Bao et al., 2019; Liu et al., 2019; Lu and Xu, 2019). A digital twin can control production processes in response to the changing market needs with high accuracy and agility. Digital twin frameworks have considered one or more manufacturing facilities with the focus of developing independent customized applications, but they lack a focus on developing a digital twin as a core technological element of the entire system (Park et al., 2020). Although many review studies have been conducted in the past, their focus was on understanding the digital twin concept, the enabling technologies, and industrial applications (Table 1 provides a summary of comprehensive list of review studies in this domain). The digital transformation agenda of many organizations necessitates upgrades in existing manufacturing systems to smart and intelligent sustainable manufacturing systems (He et al., 2021). The literature reviews are mainly skewed towards understanding the applications of digital twins from the perspectives of the manufacturing environment and are restricted to production applications (Kritzinger et al., 2018; Negri et al., 2017; Oyekan et al., 2019). Recent studies have called for the development of a digital supply chain twin that digitally depicts the organization's actual supply chain (Simchenko et al., 2020). A digital supply chain twin is used for advanced supply chain modeling based on prescriptive analytics that works in real-time and can determine the proper corrective action supporting supply chain optimization. The potential of the digital twin in the supply chains and recent developments in emerging technologies, such as additive manufacturing, BDA, and IoT, demand a review of existing literature to understand digital twin components, applications, and challenges.

Further, technological innovations and digital transformations are changing our economy, ecology, and society as never before (Kutzschenbach & Daub, 2021). It is a matter of concern to practitioners on how digital supply chain twin development can support sustainability challenges. Therefore, we undertook this review to address the following research questions:

What are the applications of digital twins in the manufacturing supply chain environments?

Which Industry 4.0 technologies are significant for the development of digital supply chain twins?

Can digital supply chain twins lead to the attainment of sustainable objectives?

We conducted a systematic literature review (SLR) to answer the above research questions. A total of 98 research papers were selected from the SCOPUS database. The review discussions are focused on

Table 1
Recent literature review studies on digital twin.

Author	Review objectives
Kritzinger et al. (2018)	A systematic literature review provides an overview of critical enabling technologies and areas of application of digital twin. Key areas identified are production planning and control, maintenance management, and layout planning. The enabling technologies included simulation, big data, IoT, and cloud computing.
Holler et al. (2018)	A literature review based on 38 papers was conducted to identify relevant concepts and conceptualizations for digital twins in manufacturing industries. It discusses the evolution of digital twin and presents a lifecycle-based application of digital twin in manufacturing industries.
Jones et al. (2020)	A systematic literature review and a thematic analysis of 92 Digital Twin articles to provide a characterization of the Digital Twin. Physical entity; Virtual entity; Physical environment; Virtual environment; State; realization; metrology; twinning; twinning rate; physical-to-virtual connection; virtual-to-physical connection; physical processes; and virtual processes identified as the critical characteristics of the digital twin.
Tao et al. (2020)	A review of literature based on 50 research articles to study the industrial applications of digital twin in manufacturing. Discusses the evolution of digital twin and presents a lifecycle-based application of digital twin in manufacturing industries.
Negri et al. (2020)	A review to understand the role of digital twin and its relationship with the industry 4.0 technologies. The study findings reveal that the relevance of digital twins in the manufacturing industry lies in their definition as virtual counterparts of physical devices.
Melesse et al. (2020)	A systematic literature review based on 41 papers. The findings reveal that digital twin has advanced industrial operations in the field of production and predictive maintenance. However, its potential in after-sales services remains highly restricted.
Golovina et al. (2020)	The study compiles the literature on digital transformation from the perspective of the digital twin. The results identify that digital twins have a huge potential for production organizations. The digital twin provides the benefit of increased productivity, resource efficiency, energy efficiency, and cost reduction in all the stages of the product life cycle.
Liu et al. (2020)	Based on the 240 research papers, the study analyzes digital twin from concepts, technologies, and industrial applications over the entire product life cycle.
He et al. (2021)	The study reviews the literature on the digital twin and related technologies to understand the sustainability of intelligent manufacturing.

digital twins with the objectives of identifying the current state of the literature on digital twins, with specific reference to the use of various technology components in developing digital twin frameworks and applications of the digital twin in the manufacturing supply chain, and identifying future challenges for digital supply chain twin development.

The remainder of the paper is organized as follows: In the next section, we present the SLR methodology. Then we discuss the findings of the SLR and offer a digital supply chain twin framework. Future perspectives and challenges are presented in the subsequent section. The last section presents the conclusions and limitations of the study.

2. Review methodology

In this study, we used an SLR to focus on studies related to digital twins in the manufacturing supply chain. Kitchenham (2004) reported that SLR is a secondary research method originating from medical science that has gained much attention from researchers working in the areas of social science, engineering, and other disciplines. Generally, SLR is a methodological approach for reviewing, identifying, and for synthesizing the complete research available on a research topic. An SLR should include all the details necessary to carry out future studies that can replicate or extend the study (Navimipour and Charband, 2016). A typical SLR follows a protocol for identifying and assessing the studies that are to be included and reported (Afrooz & Navimipour, 2017; Boell and Cecez-Kecmanovic, 2015). Thus, a literature review forms the core of a research study as the review helps provide valuable insights for investigating research in emerging fields and supports to frame directions for research in the future (Govindan et al., 2015). Despite different presentations by different researchers, all SLRs have a thread of commonality. This thread of commonality comprises three phases: review planning, review execution, and reporting of the review. In this review on digital twins, we adhered to the phases and guidelines determined by Tranfield et al. (2003; see Fig. 1).

2.1. Planning the review

The review-planning phase includes electronic database selection, development of inclusion and exclusion criteria for the studies, and definition of the review protocol. The review process flowchart is elaborated in Fig. 2.

2.2. Review objective articulation

This review aims to conduct an SLR that highlights the state-of-the-art literature on the digital supply chain twin.

2.3. Defining the exclusion and inclusion criteria

To systemize the review process, we identified clear inclusion and exclusion criteria.

2.4. Inclusion criteria

- Include studies found using keyword combinations as listed in Fig. 2.
- Include only journal articles published in the English language.
- Include only journal articles in the subject categories Business and Economics, Decision Sciences, and Computers.
- Include studies by applying a funneling process of selection based on title, abstract, and keywords.
- Include studies by doing a content analysis of the full text.
- Include studies based on citation chaining search.

2.5. Exclusion criteria

- Exclude studies that are not relevant.
- Exclude papers with duplicate or matching digital object identifiers.
- Exclude industry reports, white papers, dissertations, and theses (Lamba and Singh, 2017).

2.6. Review protocol specification

We carried out a literature search of the SCOPUS database because it is the most reliable and one of the most popular databases (Geraldi et al., 2011). To ensure extensive and thorough coverage of papers, we performed a citation-chaining search on the downloaded papers using a backward and forward approach.

2.7. Executing the review

Search Syntax Specifications. To ensure the selection of a comprehensive and high-quality collection of papers for the review, we used specific keyword combinations in the selected database. This enabled the identification of articles that exclusively focused on topics relevant to the research. The search keywords used were combinations of “digital twin” OR “digital mirror” OR “digital shadow” AND “operations” OR “manufacturing” OR “supply chain” OR “machine” OR “product” AND “sustainable” OR “sustainability” OR “economic” OR “environment” OR “ecological” OR “social.”

Selection of Papers Using Metasynthesis. As a protocol for methodological qualitative metasynthesis technique, we used a linear and citation-chaining procedure by specifying the syntax in the preceding subsection in the selected electronic databases. The initial search resulted in 483 articles. To ensure that only articles relevant to the chosen area of focus were included, we analyzed the articles by thoroughly reading the abstracts. This was done to cross-check that all identified articles fit the purpose of the review. As a result of this screening process, we identified 232 articles as relevant to the digital supply chain twin theme. We then applied the exclusion criteria to the remaining articles, which left 140 articles. We then performed a complete reading of the abstracts and titles, arriving at a final count of 98

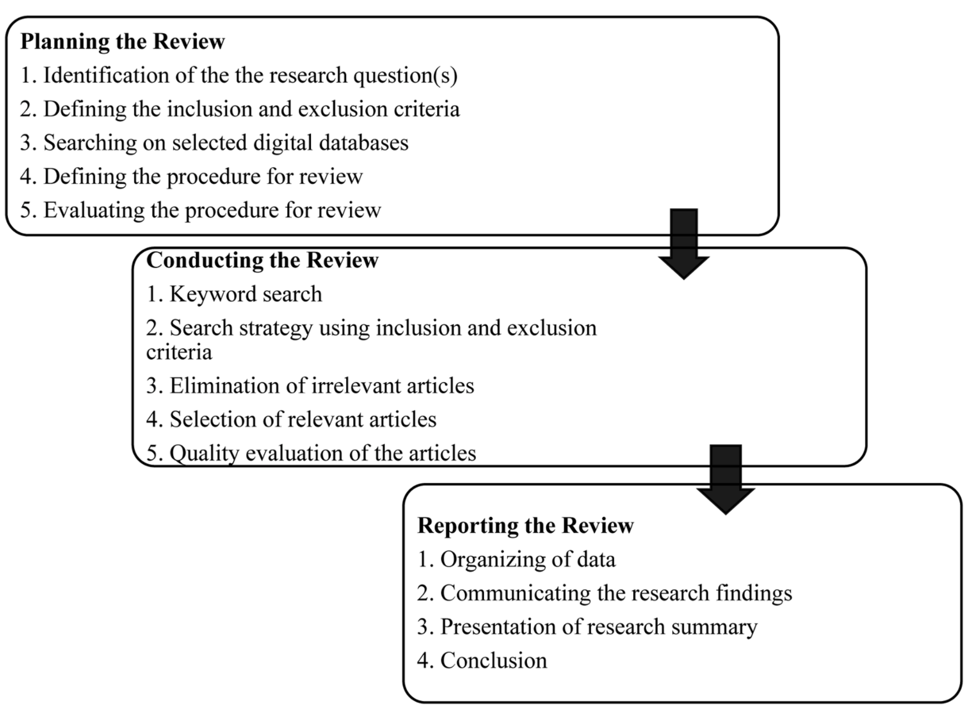

Fig. 1. Steps in the SLR on Digital Twins, *Note.* SLR = systematic literature review.

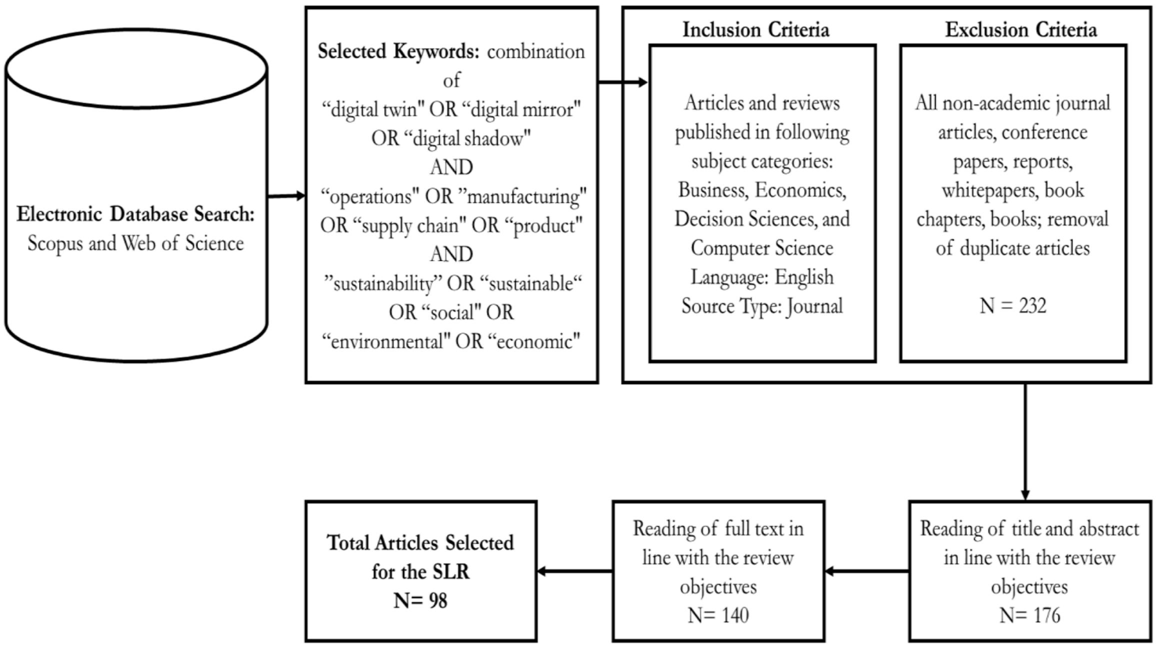

Fig. 2. SLR Process Flow Chart, *Note*. SLR = systematic literature review.

articles. These 98 articles represented 36 journals, as shown in Table 2.

Of the 98 papers selected for the SLR, 68% were published in 2019 or later. The interest in and attention on the growth of this technology have been rapidly increasing since 2017, with 96% of the selected articles published after 2017. The trend shows exponential growth in intellectual contributions (see Fig. 3), and the increase in the number of publications can be attributed to the growing understanding of digital twin potential and feasibility in different manufacturing services and operations.

The International Journal of Production Research and IEEE Access were the most significant contributors to the literature on digital twins, followed by the International Journal of Computer Integrated Manufacturing and IFAC Paper Online. The selected papers focused on various aspects of digital twins, which are reviewed in the following section.

Table 2
Journal Representation of Selected Articles.

Journal Name	No of Articles
International Journal of Production Research	9
IEEE Access	9
International Journal of Computer Integrated Manufacturing	8
Sustainability	7
IFAC PapersOnline	7
Journal of Cleaner Production	7
Resources, Conservation and Recycling	6
Robotics and Integrated Manufacturing	6
International Journal of Advanced Manufacturing Technology	6
Computer Integrated Manufacturing	6
Proceedia Manufacturing	4
Journal of Ambient Intelligence and Humanized Computing	3
Journal of Manufacturing Systems	3
Computers in Industry	3
Journal of Machine Engineering	2
Acta Materialia	2
Enterprise Information Systems	1
Sustainability	1
Proceedia Engineering	1
Journal of Manufacturing Science and Engineering	1
Int. Journal of Design and Natural Eco-dynamics	1
Computers and Operations Research	1
Int. Journal of Information Management	1
Int. Journal of Interactive Design & Mfg.	1
Information Systems & E-Business Management	1
IEEE Transaction in Industrial Information	1
International Journal of Precision Engineering and Manufacturing - Green Technology	1
International Journal of Critical Infrastructure Protection	1
CIRP Annals	1
Int. Journal of Simulation Modeling	1
IEEE Communications Standards Magazine	1
Management Systems in Production Engineering	1
Int. Journal ff Aerospace Engineering	1
Knowledge Based Systems	1
Int. Journal of Advanced Robotic Systems	1
Total	**98**

2.7.1. Findings and discussions

Physical equipment or a product can be associated with its digital twin using the asset ID or equipment number. The digital information about the specific asset is integrated with the live streaming of the operational data with the help of a digital twin (Park et al., 2019). The concept of a digital factory is linked with the aggregation of all the equipment and processes in a factory into a digital twin. The digital twin, combined with the power of big data analytics, artificial intelligence, and interconnected IoT systems, has the potential to unlock hidden value for organizational decision-making (Lu and Xu, 2019; Schroeder et al., 2016). Digital twin owners can predict operational failures, improve product quality, and reduce downtime (Tao et al., 2018a). The technology actively uses continuous optimization systems, which supports incorporating the system and process parameters during the production cycle (Min et al., 2019).

Digital twin technology offers three significant advantages. First, it allows existing production systems, processes, and mechanisms to be integrated and made compatible using small devices like sensors and application software. Second, it helps increase productivity by decreasing errors and applying predictive maintenance to reduce malfunctioning (Sujova et al., 2019). Finally, the production data of digital twins are stored in the system and are used for process optimizations (Rosen et al., 2015).

Simchenko et al. (2020) recommended using digital twins to map activities across the entire supply chain. As soon as customer orders are entered into the system, the order details and associated transactions can be captured by the digital supply chain twin, enabling real-time

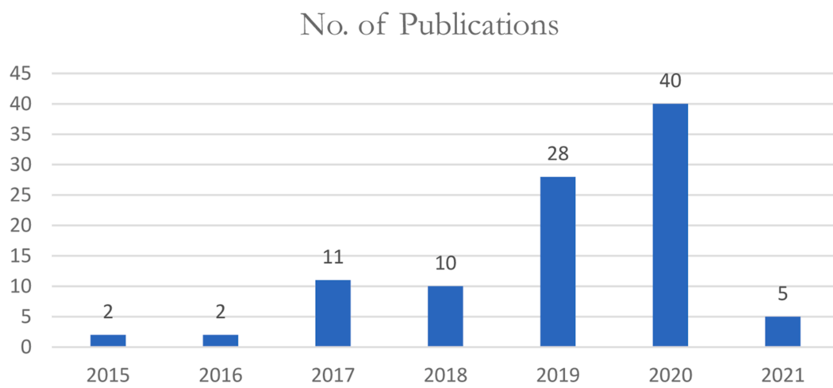

Fig. 3. Year-Wise Publications.

simulation and decision-making. For example, if any delays occur in the supply chain due to machine breakdown or supply delays, this information can be sent to the digital supply chain twin using emerging technologies such as industrial IoT (IIoT) devices, cloud computing, and big data analytics. Therefore, it is essential to review how different Industry 4.0 technologies can meet supply chain needs when considering the deployment of digital supply chain twin.

The literature revealed the use of various Industry 4.0 technologies that are used in the digital supply chain twin architecture. We identified IIoT, simulation modeling, cyberphysical systems, machine learning, and artificial intelligence as up-and-coming technologies that can play a significant role in developing digital supply chain twins.

3. Components of digital supply chain twin architecture

3.1. Industrial Internet of Things

The high adoption rate of digital twins in manufacturing organizations is driven by the extensive use of IoT for interconnected systems. Advancements in IoT technologies have made high volume data collection technically and economically feasible compared to traditional manufacturing systems that require massive efforts (Lu et al., 2019). Using digital twins allows organizations to structure, access, and analyze complex unstructured data, which otherwise would have been less exploited. Kamble et al. (2018) defined the IIoT as an interoperable information infrastructure interconnecting physical and virtual things to provide advanced services through physical entities with engineering services. The IIoT enables smart integration by avoiding complex manufacturing applications and is utilized in industries for the entire product life cycle (Lu et al., 2019). Multilayered reference architecture with interfacing between the various layers used for designing the IIoT systems, dependent on business needs, preferred technology, and technicalities, is the most efficient carrier of the digital twin platform (Cheng et al., 2020).

3.2. Modeling and simulation

In the past, organizations used closed, proprietary-by-design simulation tools and factory automation platforms for product and process developments to protect their data models and maintain secrecy. However, these are typically no longer used, and organizations currently use APIs and open sources to avoid the intensive efforts required for software development and to build infrastructure for new product development. A digital twin architecture that consists of five layers—a device layer, a web service layer, a user interface layer, a data repository layer, and a web service layer—is efficient in managing the digital twin database (Schroeder et al., 2016). Several architectures have been proposed to validate and implement digital twins (Alam and El Saddik, 2017; Angrish et al., 2017), including, for example, the digital twin model that uses Automation ML to design industrial valves using a communication method for data exchange (Schroeder et al., 2016). Workflow for building digital twins is the other aspect that has been extensively explored in the literature. Angrish et al. (2017) presented an architecture for integrating third-party software with virtual twin systems. Moreno et al. (2017) proposed a five-step process for structuring a digital twin, which included 3D modeling, behavior extraction, operation designing, simulation, and designing the communication between the machine and virtual elements. Researchers have studied diverse applications like heat transfer modeling, property prediction, distortion, and residual stress modeling using physical entity, digital entity, and interface connections (Zhuang et al., 2018). The primary consideration in building a simulation model is defining behavior logic for physical objects, which covers entity status, activities, and events (Zheng et al., 2019).

3.3. Cyberphysical systems

Cyberphysical systems (CPSs) are defined as advanced systems developed using the IoT to incorporate hidden knowledge of manufacturing systems, which subsequently helps bridge the gap between the physical and virtual worlds (Kamble et al., 2018). Leng et al. (2019a; J. 2019b) described CPSs as having the ability to bring out mass individualization in smart manufacturing by predicting operational decisions without the requirement of physical setup. The twinning of CPSs (real-time synchronization of heterogeneous systems) and self-organization in a CPS environment (dynamic decision-making) are considered as the two underlying challenges of CPS implementation (Alam and El Saddik, 2017).

To overcome the first challenge, the digital twin model can be used to provide controlled action using advanced automation and sensing technology. The second challenge can be addressed through the deployment of a decentralized, self-organizing strategy that enables dynamic processes and control (Leng et al., 2019a; Liu et al., 2020). Several CPS frameworks have been proposed and built for diverse applications. Liu et al. (2020) developed a web-based framework to connect resources and jobs using a distributed system to increase productivity. Likewise, Terkaj et al. (2015) developed a distributed production framework for adapting to the dynamic environment using smart devices to manage and incorporate local decision-making. Others showcased the ability to establish real-time control in decision-making using a stochastic manufacturing system (Zhang et al., 2017). The literature identified digital twins as the technical core for developing CPSs in the context of Industry 4.0 (Liu et al., 2020).

3.4. Artificial intelligence and machine learning

This review demonstrates that the latest advancements in data analytics have transformed the quality of insights extracted from complex collected data sets (Luo et al., 2019). Various machine learning algorithms help digital twins predict the future state of equipment conditions and make autonomous decisions. The integration of artificial intelligence and advanced manufacturing technology can help designers create a knowledge-driven decision-making framework for a digital twin (Min et al., 2019). This review also acknowledges the contribution of cloud manufacturing (Corondo et al., 2018) and smart manufacturing systems (Kusiak, 2018) in developing digital twin frameworks.

3.5. Blockchain and smart contracting

Blockchain technology offers distributed consensus and tamper resistance, potentially useful in manufacturing processes, making it collaborative and decentralized. The digital twin is a centralized system and lacks trusted data provenance, audit, and traceability (Hasan et al., 2020). Integration of IIoT and blockchain technology can help create a digital twin that enables an online decentralized social manufacturing network (Tao et al., 2018a, 2018b). A social manufacturing, cyber credit-based system that was developed using blockchain technology and smart contracts helped to overcome two critical challenges in the traditional manufacturing systems related to the physical verification and mapping of manufacturer relationships (Leng et al., 2019a). Mandolla et al. (2019) proposed a theoretical digital twin framework for application in additive manufacturing using blockchain technology. Smart contracts are expected to monitor and track the transactions performed by the stakeholders involved in creating digital twins, providing improved data security and data sharing efficiency (Hasan et al., 2020; Huang et al., 2020).

3.6. Cloud computing

Cloud computing was found to improve efficiency and productivity by encapsulating manufacturing resources into an open network. Its applicability spreads across various domains, and it is quite popular among researchers for developing architectures, designing business models, and enabling technologies (Lu and Xu, 2019). The development, maintenance, and use of a digital twin is a data-intensive activity that requires significant computing and storage facilities. The integration of the cloud into traditional systems and requirements for high-performance systems for real-time data capturing are the two critical challenges for implementing digital twin systems (Lu and Xu, 2018, 2019). High-performance data analytics is required to analyze real-time data transferred to cyberspace, creating a digital twin. The digital model depicts the physical structure, also ensuring that critical components are in logical relation (Olivotti et al., 2019).

3.7. Augmented reality and virtual reality

The review illustrates that digital twins have a stronger impact when the insights obtained from them are rendered in 3D. However, this requires moving away from conventional 2D display systems (laptops, computers, screens, etc.) to high-end technologies with the ability to display 3D systems such as augmented reality (Park et al., 2019). The latest digital twin frameworks incorporate mixed reality to allow interaction between the digital content and the actual physical environment. The use of virtual reality in the digital twin provides a high level of a new immersive environment, providing productive interaction with the available information (Mallik et al., 2020). Kuts et al. (2019) proposed using virtual reality and computer simulations to design a digital twin, improving the workspace awareness of a robot without any physical entity (Kuts et al., 2019). However, augmented reality and virtual reality are undoubtedly prone to specific challenges, including the lack of training, knowledge about potential, complex system integrations, and time consumed by development (Kamble et al., 2018).

3.8. Applications of the digital supply chain twin

The above discussion reveals that the real-time data availability supported by Industry 4.0 technologies is a critical competitive advantage for supply chains and is the essential component of a digital supply chain twin framework. The digital supply chain twin is essentially a virtual supply chain mirror that consists of hundreds of physical assets, warehouses, logistics, and inventory positions. Improvements in the technical and analytical capabilities and developments in manufacturing technologies provide immense potential for digital supply chain applications. In this section, we review the various uses of digital twins in the supply chain.

3.9. Sustainable product and process design

Digital twins can be used for industrial product development, making it more effective, efficient, and receptive (Tao et al., 2018a). Many studies in the literature focused on digital twin-based design decisions with real-time feedback, conceptual designing, product planning, and evaluation of the product quality using virtual assistance (Cai et al., 2017; Zhang et al., 2017). Digital twins integrate the physical product data, virtual product data, and connected data to support product design, manufacturing, and service more efficiently and increase sustainability (Tao et al., 2018a; Tao and Zhang, 2017). Apart from the development phase of manufacturing, digital twin applications gained popularity in industrial processes using predictive analysis, agility, and more adaptability (Liu et al., 2019a; Polini and Corrado, 2020). Their ability to monitor industrial processes in real-time and advances in simulation give them a cardinal role in the development of CPSs (Weyer et al., 2016). Several researchers have stated that digital twins can improve complex processes and optimize operations based on realistic situations and simulations. Digital twins can integrate various data (environmental data, process, and operations data), thus enabling the production system to change state even during ongoing operations (Tao et al., 2018a, 2018b). The job scheduling problem is a classic optimization that can be better understood using virtual plant setting and digital twin technology (Zhang et al., 2019). Liu et al. (2019a; J. 2019b) proposed an evaluation methodology based on the digital twin to design machining processes with less time and lower cost by reusing the existing process framework. The framework provides real-time status, thereby meeting the process requirement precisely (Liu et al., 2019a; J. 2019b). Berefi et al. (2018) found that digital twins can detect errors in the manufacturing process using simulations. The digital twin framework proposed by Bevilacqua et al. (2020) allowed the identification of problems and the development of corrective actions, leading to increased safety of the operators, reduced maintenance, and operating costs.

3.10. Prognostic and health management for smart manufacturing

Prognostics and health management have been considered the most potential digital twin application, given its popularity among researchers. The first application came about in the aviation domain, where the structural life of aircraft was predicted using a multiphysics model, structural FEM analysis, damage models, and other high-resolution fundamental analyses (Tuegel et al., 2011). The digital twin is also used to predict the behavior of CPS based on the machine environment, physical necessity, and reactions. Various parameters in additive manufacturing processes such as cooling rate, temperature, velocity distribution, solidification, and hardness can be predicted using digital twin frameworks (Knapp et al., 2017). Digital twin seems to be more advantageous than traditional methods that had previous empirical data because of its quick ability to uncertainty arising in real-time situations. Prognosis and health monitoring can predict fault detection without damage initiation, and crack pathways can be predictively detected, enabling systems to improve, wishing to replace or redesign components making the manufacturing process more sustainable. However, proper design and adaptability of the digital twin remain a challenge (Wang et al., 2019).

3.11. Factory layout and design

Factory layout and planning are extensively studied, which proves to increase productivity and utilization of resources. Guo et al. (2019) proposed using the digital twin to perform simulation using different designs that help for ramifications and save time. Although digital factory technology has been promising in factory layout and planning, it is sparsely supported with architecture and algorithms using a simulation approach. Zhang et al. (2019) developed a simulation-based architecture that combines algorithms and heuristics to optimize cost, improve design and production planning, and is supported with a case study.

3.12. Manufacturing operations and services

Product manufacturing and services have much potential for improvement with digital twin technology because it will allow management to meet demand throughout the product life cycle (Tao et al., 2018). The real-time synchronization between physical and virtual entities helps improve competitiveness and agility among manufacturing systems (Zheng et al., 2019). Traditionally using existing data from information systems to create a virtual copy and integrating it with real-time data has been a challenge, especially for value networks (Olivotti et al., 2019). Using base management, analytics can be smooth for service applications, and the system should react to customer requirements. For base management, data storage and information are the essential components and should be integrated when creating a digital twin (Olivotti et al., 2019). Digital twin acts as an enabler or direct support in achieving on-demand manufacturing services that include smart factories, smart manufacturing, job shop scheduling, and human–robot collaboration (Cimino et al., 2019). The capability of a digital twin to instantly share data is used as the basis for developing the system architecture. The data-driven cyberphysical fusion is done at the operational, sensor, and service levels. Digital twin further defines performance metrics to support manufacturing services and provide a knowledge-driven approach that enables continuous improvement and strategic adaptability to autonomous manufacturing (Zhou et al., 2020).

The digital twin is used to optimizing machine design processes by determining locator position, welding order, clamping strategies, and tolerances yielding high-quality products (Soderberg et al., 2017). Deep transfer learning was utilized to predict future degradation, fault diagnosis, and expected machine service life (Xu et al., 2019). The technology has promising applications with real-time (dynamic) modeling and can exhibit interoperability with a physical system (Zheng et al., 2019). Apart from the dynamic process application, smart decision-making is enabled with iterative and regulatory data interaction between physical and virtual space. Machine optimization of diverse applications has been proposed and articulated in the literature (Qi and Tao, 2018; Rauch and Pietrzyk, 2019; Ulhemann et al., 2017).

The literature reports the applications of a digital twin for achieving high levels of human–robot collaboration (Mallik et al., 2020). With the changing and expanding customer needs and demands, there has been an exponential rise in the expansion of warehouses and the need for the processes to be made as automated as possible with less human intervention, thereby minimizing the error due to human factors. Analyzing humans and their minds and behavior in real-time through theoretical aspects has been made possible due to digital twins (Ardanza et al., 2019). The use of robots in automation is essential, but the test of human and robot interaction and collaboration could be dangerous (Kamble et al., 2018). The use of digital twin in human–machine partnership can lead to the safe exchange of humans and machines (Ardanza et al., 2019).

3.13. Predictive maintenance for intelligent manufacturing

Predictive maintenance is a precautionary or preventive technique to predict machine component failure well before the inability to avoid unexpected circumstances. It is generally complemented with the use of IoT technology, which enables real-time tracking. Using the aerospace industry an example, Zheng et al. (2019) combined the IIOT with digital twin using data fusion technique to increases the extent of useful life, efficacy, and operation capability (Liu et al., 2019a). Digital twin technology shows promising results in reducing unplanned maintenance and reducing high costs due to its dynamics tracking. Predictive maintenance using digital twin is not restricted to aerospace applications; health care applications such as biophysical systems show promising usage with the development of molecular biomarkers, which are a predictor of incoming disease (Liu et al., 2019). The digital twin for predictive maintenance is built on the outcome of the simulation results, which evaluates the remaining useful life of the machine and allows for noninvasive techniques (Aivaliotis et al., 2019).

3.14. Resource planning

Smart resource planning is defined as designating tasks to be human and nonhuman resources with the help of future technology to maximize operational efficiency. Zhuang et al. (2018) proposed a smart manufacturing architecture for sophisticated assembly shop floors using four layers. The four components included conducting real-time data synchronization and management, building an assembly floor digital twin, performing predictive analysis using big data, and utilizing the digital twin to check services. Implementing a digital twin in manufacturing systems has been found to improve energy and resource efficiency (Kannan and Arunachalam, 2019).

3.15. Logistics management

A combination of logistics resources and real-time virtual counterparts that permit real-time control and monitoring can help plan a logistical system. Furmann et al. (2017) proposed a genetic algorithm to enable the design of a production layout with dynamic updating of the requirements using a digital twin. Similarly, other studies have used a simulation hierarchy structure to create a digital twin to be utilized for designing large-scale logistical systems (Straka et al., 2018). Logistics decision-making has been a vital process for optimizing operations using the IoT. Kuehn (2018) argued that the optimization of modern logistical systems is a complex problem and demands a data-driven multicriteria decision approach. Technical challenges between humans and machines in intralogistics are identified and use real-time data to build virtual systems, and material handling efficiency is improved. Herein, the author also described interoperability due to the use of multiple data as a challenge. The digital twin shows considerable potential to track and trace the products for better quality and improved productivity. However, several problems, including a long idle time and energy waste, need to be overcome (Wang et al., 2020; Wang and Wang, 2019).

Through this review, we identified the digital twin as an effective platform for connecting the physical devices and the network to collect, transfer, and integrate the fragmented knowledge in a manufacturing system (Vrabic et al., 2018). The literature has acknowledged the importance of digital platforms such as the digital twin in the digital transformation of traditional manufacturing systems, enabling a high level of customization and operational efficiency through front- and back-end integration (Cenamor et al., 2017; Eloranta et al., 2016). In the next section, we propose an integrated digital platform to incorporate the various aspects of equipment asset management, product life cycle management, and manufacturing process management to develop a sustainable manufacturing system.

3.16. Digital twin and sustainable objectives

Economic benefits drive many initiatives in an industry. However, the growth prospects of the businesses promote resource consumption and cause social impacts (Bartie et al., 2021). A process simulation-based digital twin supports sustainable development and circularity by quantifying the resource efficiency and recovery of high-quality secondary resources (Bartie et al., 2021) and the energy savings (Leiden et al., 2021). Zhao et al. (2021) developed an IoT- and digital-twin-enabled tracking system for enhanced safety by recognizing an abnormal condition and using real-time location tracking. Such systems can be highly useful for efficiently managing warehouse operations. The digital twin has the potential to provide greater intelligence and autonomy in industrial manufacturing transportation processes.

Vehicular digital twins that facilitate data collection, data processing, and analytics can offer the advantages of reduced accidents and the development of a secure environment in the workplace (Almeaibed et al., 2021). Digital twins based on data fusion principles can be highly useful for minimizing the ambiguity and uncertainty associated with evaluating sustainable designs. He et al. (2021) developed a quantitative model for sustainable designs based on data collected by robots. The quantitative indicators are reflected in a digital twin data flow system and improved all-around performance. Similar frameworks using IoT and digital twin approaches are used to sustain buildings by providing real-time evaluation and control (Tagliabue et al., 2021).

Similarly, digital twin models are used to perform environmental risk and pollution assessments. Zheng et al. (2020) developed a digital twin model of a pipeline to simulate and generate leakage data to offer improved safety, cost savings, and environmental protection. Rocca et al. (2020) successfully demonstrated the use of augmented reality to support circular economy practices by virtually testing the waste from electric and electronic equipment using simulation tools. Moreover, such systems reduce the injury risk for operators, providing improved production sustainability (Damiani et al., 2020). The use of a digital twin across the entire life cycle benefits information sharing, eases technical communication, improves design quality, reduces design errors, increases energy intensity and efficiency, assists fast-paced implementation, and reduces carbon footprints (Golovina et al., 2019; Kaewunruen and Lian, 2019).

3.17. Proposed sustainable digital supply chain twin framework

Based on our review findings and future perspectives on digital twins, we propose a sustainable digital twin framework for supply chain systems (see Fig. 4). Our review has revealed that a digital supply chain twin drives the aggregation, integration, and dynamic allocation of manufacturing resources, creating a valuable link in complex supply chains. A digital supply chain twin needs to be integrated (externally) among the supply chain partners and should not be restricted to mapping internal processes. With the recent advancements in emerging technologies such as the IoT, virtual reality, additive manufacturing, artificial intelligence, and blockchains, the digital twin's scope of application has extended beyond manufacturing systems and should cover the entire supply chain. The digital twin leads to numerous coupling points between manufacturing operations and sustainable supply chain models. A digital twin based on the product life cycle approach can optimally allocate resources where they are most needed (Svensson and Wagner, 2011). The capability of the digital twin to integrate networks and manage resources efficiently results in better supply chain sustainability. The framework was validated by a team of five supply chain practitioners from the automobile industry in India. These practitioners have relevant experience in implementing and managing digital supply chain twins in the manufacturing industry and provided valuable insights into the implementation and operational challenges along with possible solutions. These challenges and implications are discussed in the Implications for Supply Chain Practitioners and Future Research Directions section.

The proposed framework has four layers. A digital supply chain twin can help reduce chaos in complex supply chains by identifying the trends and inefficiencies at any point in real time. The different layers in the proposed digital supply chain twin are discussed below.

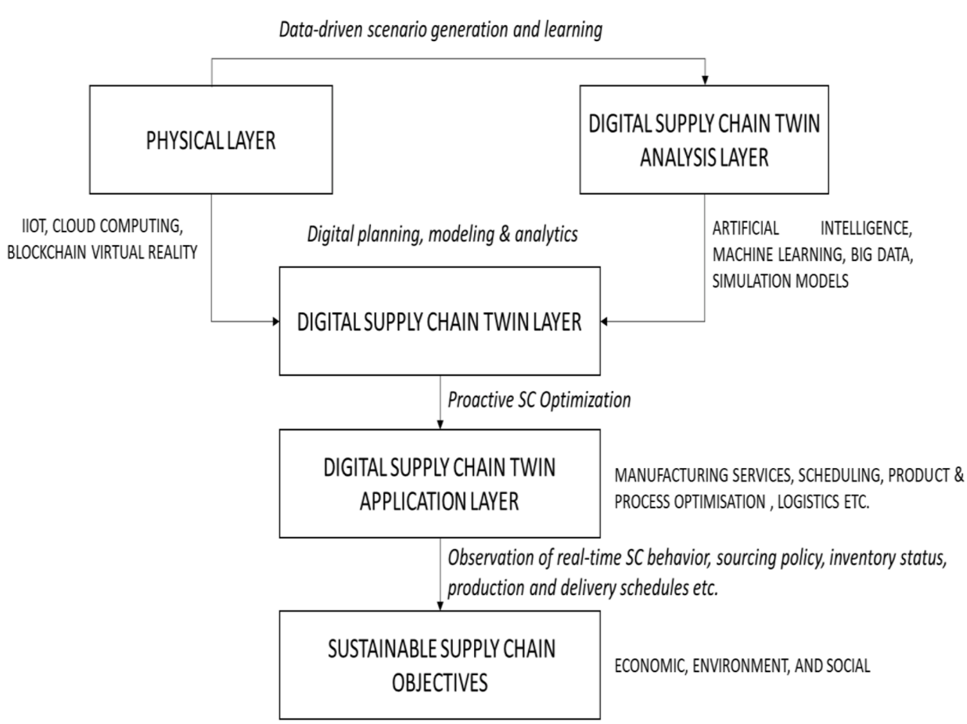

Fig. 4. Sustainable Digital Supply Chain Twin Implementation Framework.

3.18. Physical layer

The physical layer comprises the various *things* and *humans* involved in the supply chain at different locations. The things include the physical manufacturing systems, transport vehicles, material-handling equipment, and storage systems spread across the supply chain. The humans in the supply chain represent the human resources required to operate, manage, and control the physical systems, leading to desirable product or service outcomes. The physical layer involves detailing the number and type of sensors required to capture data such as torque, displacement, stress, etc., from the physical objects (operational data) and their surroundings (external data), including pressure, temperature, humidity, and so on. The collected data will then be converted to secured digital messages and transferred to the digital supply chain twin layer using encoders and network systems.

3.19. Digital supply chain twin layer

In this layer, we create the digital twin of the supply chain's things and humans. This digital supply chain twin layer requires support from software developers (vendors) to develop the best virtual system to represent the actual physical environment. The developers should envisage the product life cycle of the machinery and equipment in the supply chain and correctly describe their interactions with the supply chain partners. The digital supply chain twin layer will be integrated with the physical layer to support cyberphysical interface technologies such as the IoT (sensors and actuators), cloud computing, and blockchains. The digital supply chain twin layer should incorporate existing regulations on IPs and protect itself from cybersecurity threats to develop a robust system. There is a continuous flow of data in real time between the physical and the digital supply chain twin layers. An efficient digital supply chain twin layer is a must for the real-time bidirectional flow of data in the cyberphysical system. The cyberphysical interface should involve three elements:

- **edge processing:** interface that connects sensors with process and passes them along the platform. Edge processing enables faster communication by processing the absorbed data at the endpoints.
- **communication interface:** transfers the processed data to the integration function for monitoring and control.
- **edge security:** uses security approaches to firewalls, encryption, application keys, and so on, to minimize cyberattack threats.

3.20. Digital supply chain twin analysis layer

This layer performs the supporting analytics on the data collected in the digital supply chain twin analysis layer. The real-time data collected from the physical layer reside in the digital supply chain twin analysis layer and need to be examined and simulated for efficient decision-making. Various artificial intelligence and machine learning algorithms may be deployed to extract meaningful insights from the collected information. The use of predictive and prescriptive analytics in the analysis layer helps predict future performance and determine proactive actions for avoiding the issues. The digital supply chain twin application layer operates in close harmony with the digital supply chain twin analysis layer. The insights received from the analytics stage are presented on the dashboards or other display platforms, highlighting deviations between the simulated digital supply chain twin model and the physical world. The areas needing immediate attention should then be addressed.

3.21. Digital supply chain twin application layer

In the application layer, we define the various applications for deployment of the digital supply chain twin. For example, a company has developed a digital supply chain twin to reduce its manufacturing lead time. In such a case, the digital supply chain twin application layer should predict the failure of different machines in the manufacturing process. This will help avoid machine breakdowns and reduce the lead time. Similarly, specific digital twin applications can be developed to locate and pick up items from the store, reducing search time and improving logistics and warehouse management. Other applications may include quality control, the preservation of goods using temperature controls, and calculation of the utilization rates of the equipment.

The digital supply chain twin application layer should guide the implementation of corrective actions to overcome inefficiencies received from the insights. The insights should be transferred through the decoders and fed to the actuators, which control the parameters and physical movement of the equipment. The application layer operates through the digital supply chain twin layer.

Our proposed sustainable digital supply chain twin framework contributes to the theory of supply chain sustainability by providing insights into how supply chains can use the platform to achieve economic, social, and environmental performance goals. We recommend that supply chain practitioners adopt the digital supply chain twin to generate sustainable benefits. The digital supply chain twin enhances resource utilization, product design, and real-time manufacturing process design and optimizes customer and employee expectations, resulting in significant economic, environmental, and social benefits to the supply chain. The energy savings obtained from analyzing energy consumption data and optimizing energy schedules benefit the environment.

Further, the proposed model encourages integrating all supply chain partners to resolve collaboration and sustainability issues in multitier supply chains. In multitier supply chains, any unwanted or unsustainable behavior of the suppliers in the lower tier of the supply chain is attributed to the focal manufacturing firm. The use of a digital supply chain twin will help focal firms continuously monitor and control their suppliers' sustainable actions. Additionally, the digital supply chain twin helps link customers allowing them to participate in product design and improve their user experience. The digital supply chain twin platform can be used to capture employees' information such as work schedules and actual work content that can be used to calculate their wages and evaluate their working conditions, offering social benefits. However, supply chain practitioners must consider a few points that may act as barriers to implementing digital supply chain twin platforms. We discuss these in the Implications for Supply Chain Practitioners and Future Research Directions section.

3.22. Digital supply chain twin performance benefits

The literature identified sustainable performance benefits from deploying a digital supply chain twin. The models are effective, offering dynamic optimization of the supply chain performance and satisfying all dimensions of sustainability. The digital supply chain twin provides significant insights into sustainable supply chain performance, and its response to different inputs unveils hidden opportunities by offering answers to how and why various supply chain events occur, thereby providing opportunities for supply chain transformation.

3.23. Implications for supply chain practitioners and future research directions

In this section, we present the technological, environmental, and social implications of our review that practitioners need to consider for effective implementation of the supply chain digital twin platform and future research directions. Based on our study and the need to have a sustainable digital supply chain twin as discussed in the above section, we identified seven key areas that need immediate attention from researchers in future studies. The implications offered to address the challenges are based on our interactions with supply chain practitioners during development of the sustainable digital supply chain framework.

3.24. Foreseeing extended access life cycles

The review revealed that even though organizations are adopting openness and standardization across their information technology deployments, there is a significant need to address the technical and commercial barriers to managing big data that the digital twin generates (Kamble et al., 2018). The existing literature does not address the life cycle perspective in detail. Few authors have addressed employing DTs in production systems or products (Gabor et al., 2016; Rosen et al., 2015), whereas others have not restricted their work to the product--production system's dichotomy and instead focused on the technical system life cycle that involves different phases such as design, processing, recycling, services, and disposal (Cai et al., 2017; Zhang et al., 2017). They believed that the entire life cycle would benefit from the information generated in different phases and the use of advanced predictive analytics and simulation tools (Min et al., 2019).

The digital supply chain twin relies on AI and simulation methodologies developed by specific developers (vendors), making it impossible to replicate or create them later using other developers. It is thus implied that organizations implementing a digital supply chain twin should make sure to envisage long-access life cycles that include factories, logistical equipment, and industrial equipment. Liu et al. (2018) identified that maintaining data partitioning and IP security throughout the extended life cycle is a significant challenge and requires innovative solutions. Innovative technologies such as blockchain, traceability, and translation techniques supported by supply chain stakeholders may help overcome this challenge (Huang et al., 2020). The existing proprietary design software used in digital supply chain twins for data storage, analysis, and deriving insights is expected to require an upgrade with new data formats and analytical techniques in the future (Goasduff, 2018). This review identified that the digital supply chain twin concept and its applications are evolving and include the possibilities of using open-source technology with software, hardware, and hybrid solutions (Damjanovic and Behren, 2019; Park et al., 2020). Further, a digital supply chain twin is continuously fed data collected from geometrical models, process simulations, and the IoT, implying that the digital supply chain twin's owner has an increased probability of getting locked with a vendor through the increasing data accumulation. Therefore, it has been suggested that IT architects and digital supply chain twin owners work on increasing the viable life of the digital supply chain twin, which should accommodate changing data formats and storage configurations (Liu et al., 2019c).

Based on the above implications for practitioners, researchers need to address the following questions in future studies.

- What are the possibilities of using open-source technologies that include software, hardware, and hybrid solutions?
- Which business model allows the supply chain owner more flexibility to select vendors instead of getting locked with a vendor because of data accumulation?

3.25. Stakeholder participation and change management

This review suggests a requirement for supply chain stakeholders to strongly support the aggregation of DTs for the exchange of information on different modeling parameters, quality, and performance outcomes. This is often accomplished by formally connecting the DTs as objects in a supply chain (Moyne et al., 2020). The deployment of a digital supply chain twin will require various stakeholders, such as employees, suppliers, and customers, to build capability with a new style of working and overcoming change-management challenges (Li et al., 2020). The transition from traditional manufacturing systems to digital-supply-chain-twin-based systems must be sufficiently motivated and the necessary skills developed (Bilberg and Malik, 2019). A digital supply chain twin could resolve key supply chain challenges such as a lack of supply chain visibility and cross-functional collaboration. Blockchain and artificial intelligence are expected to offer a high level of integration and, therefore, demand investments in the digital supply chain twin, enabling the supply chain stakeholders to control and operate the products and services in more structured and holistic manners (Huang et al., 2020). Thus, it is implied that organizations should allow their supply chain stakeholders to participate in digital supply chain twin efforts.

Based on the above implications for practitioners, researchers need to address the following questions in future studies.

- What capabilities are required by the various stakeholders such as employees, suppliers, and customers for deploying a digital supply chain twin?
- How can supply chain partners be encouraged to participate in digital twin efforts?
- How do new technologies such as blockchains offer increased supply chain visibility and cross-functional collaboration for digital supply chain twins?

3.26. Data sources, privacy, and security

The review identified that a digital supply chain twin acts as an interface between the digital and physical systems that need to capture data, perform simulations, and make improvement decisions. The existing architectures are based mainly on collecting data from sensors and project limited abilities to perform simulations in the future (Kuts et al., 2019; Lu et al., 2019). It is expected that enriched information in newer formats and sources in the future, for example, from blockchains, may not support existing architectures (Moyne et al., 2020). Therefore, it is also implied that IT architects and digital supply chain twin owners need to work on improving the utility of the digital twin to define newer designs that will allow the access to and use of data from many different sources.

Studies have reported that because DTs will be often deployed in supply chains operating in heterogeneous environments with multiple applications and users, keeping the data, models, and related information secure and managing the privacy and propriety of that information will be highly challenging (Harper et al., 2019; Laaki et al., 2019). Further, the information stored in a digital supply chain twin is an extensive reservoir of intellectual property and know-how. Managing sensitive data about product design and performance simulations; customer interactions and usage data; and issues related to ownership, governance, access, and control creates a new set of challenges for organizations to address. The vast reservoir of information available in a digital supply chain twin is as a lucrative target for cybercriminals. The data connecting CPSs provide opportunities for people with malicious intentions to disrupt an organization's operations, which can have a devastating impact on the real world. The digital twin presents a new set of challenges to organizations in developing cybersecurity systems to prevent such attacks (Kamble et al., 2018).

Based on the above implications for practitioners, researchers need to address the following questions in future studies.

- What new digital supply chain twin architectures could handle information in more unknown formats and from additional sources?
- How can the cybersecurity of a digital supply chain twin be enhanced to minimize the malicious intentions to disrupt an organization's operations?

3.27. Monetization strategies modeled on the digital supply chain twin

The findings of our review suggest that digital models have been widely deployed in manufacturing setups for connecting manufacturing equipment. However, the latest development in the field indicates that a digital supply chain twin combined with machine learning techniques and newer technologies such as 5 G connectivity will allow increased deployment for logistics and supply chain modeling (Deloitte, 2020). It offers an increased ability to track, monitor, route, and optimize product flow and provide real-time visibility on the movement and specific parameters such as temperature and humidity (Lee et al., 2020). These developments are expected to reorient organizations and help them move from selling products to selling bundled products and services. In the future, a digital supply chain twin can contribute extensively to financial analyses and projections, enabling organizations to refine and optimize their forecasts, pricing, and upsell opportunities (Li et al., 2020). Therefore, it is implied that as organizations build their digital supply chain twin capabilities, they will be in better positions to manage the increasing business sophistication and develop new monetization strategies for products and services modeled on a digital twin.

Based on the above implications for practitioners, researchers can address the following question in future studies.

- What different monetization strategies are available for owners of supply chains with digital twin capabilities to explore?

4. External integration

As discussed earlier, the current focus on digital supply chain twins is to establish an efficient internal process integration. However, to realize the full potential of this technology, integrating systems and data across the entire supply chain and building a supply chain twin are required (Ivanov and Dolgui, 2019). This will require integrating external supply chain entities with the internal digital ecosystem that is real to an organization. In the future, it is expected that organizations may use blockchains to control, manage, and validate the information that goes into digital twin simulations to make the outcomes more efficient, dynamic, and transparent (Mandolla et al., 2019).

5. Application layer assessment

In the deployment of a digital supply chain twin, it is essential to assess how the various applications can meet the needs of the supply chain. The supply chain should be able to model its critical requirements accurately. For example, a digital supply chain should replicate all the existing constraints and accommodate the trade-offs. The selected modeling tools should have the ability to update and revise the digital supply chain with ease.

Therefore, we recommend that future researchers focus on identifying the best programming languages and modeling interfaces for providing excellent supply chain visibility and supporting decision-making.

6. Social implications

The supply chain practitioners with whom we worked emphasized the implications of digital twins on society and the environment, and the technology that may directly or indirectly impact their applications in supply chains. For instance, in their research, Popa et al. (2021) recommended that future research should be conducted on how companies address the socioethical benefits and socioethical risks of using digital twins. An assessment of the effects of emerging technologies on ethical considerations would be significant for various reasons (Cotton, 2014). These assessments should detect and prevent any negative impact of the technology on society. Inconsistent gaps between the real and virtual models will lead to the development of a poor digital twin that fails to recognize the real activities. In such situations, the digital twin may become uncontrollable and destroy the ecosystem, increasing stress and anxiety for the employees, stakeholders, and society (Takahashi, 2021). The employees and various stakeholders of an organization represent society; therefore, they should be allowed to deliberate and reflect on the resulting cost–benefit aspects of implementing digital twins in their supply chains (Popa et al., 2021).

7. Conclusion

This study presents a review of the current literature on the use of digital twins in manufacturing supply chain environments. With ready access to digital twins, most industries have started leveraging these technologies to manage their critical assets. Our review shows that the digital twin is becoming a core part of a product, asset, and infrastructure operation to achieve sustainable objectives in a supply chain. A digital twin enables the owners to predict operational failures, improve product quality, and reduce downtime. This review identified the IIoT, simulation, machine learning, artificial intelligence, cloud computing, and so on, as critical components of a digital twin. The current applications of a digital twin point toward the much more significant role it can play in achieving sustainability objectives. Future perspectives show that to leverage the benefits of a digital twin, there is a need to integrate external supply chain partners with existing manufacturing systems. Presently, the applications of a digital twin are highly focused on achieving manufacturing excellence. However, increasing the scope of a digital twin to include all the things and humans in the supply chain will help its owners make more proactive decisions at the supply chain level. The challenges identified for developing an efficient digital supply chain twin are the scope of the product's life cycle, cybersecurity, IP protection, and unstructured data sources (Liu et al., 2019d). Based on these findings and future perspectives, we developed a sustainable digital twin implementation framework for supply chains.

Declaration of Competing Interest

No conflict of interest exists.

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