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Unlocking the potential of digital twins in supply chains: A systematic review

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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

Digital Twins (DTs) developments are still in the pilot stages of deployment in supply chain management (SCM), and their full integration with real-time synchronization and autonomous decision-making poses many challenges. This paper aims to identify these common challenges and provide a conceptual framework for establishing a Digital Twin (DT) system to improve supply chain management performance. The paper presents a systematic literature review of 129 research papers on DT applications for SCM improvement. The selected papers were reviewed and classified into three categories: manufacturing and production, supply chain, and logistics. The development of digital technologies such as the Internet of Things (IoT), Radio Frequency Identification (RFID) devices, cloud computing, cyber-physical systems (CPSs), cybersecurity (CS), and simulation modeling has increased the opportunities to explore the creation of supply chain DTs. However, there are limitations and various challenges due to the complexity of most systems. The results indicate that DT for SCM should include external links (i.e. suppliers, distributors) and internal links (i.e. procurement, production, logistics) to deal with any disruption through data-driven modeling with real-time synchronization. Based on the review findings, this study proposes a three-layered conceptual framework to improve supply chain management performance. The proposed framework provides future directions for DT research in SCM. It provides a holistic and integrated approach to DT implementation, the common DT technologies, and data analytics techniques for improved supply chain performance.

1. Introduction

Digital transformation and the integration of digital technology into all business areas are still at its evolution stage. Over the years, technology has transformed into digitalization in several aspects. Industry 3.0 made modest progress in manufacturing technology, incorporating computers, automation, and PLCs. Industry 4.0 utilizes significantly more advanced technologies such as the Industrial Internet of Things (IIoT), Blockchain, cloud computing, augmented reality, and robotics [1–3]. The development of digital systems has enabled researchers to identify the potential of real-time data access for evaluating the current state of systems (known as prognosis diagnosis) [4]; [5]. Thus, the rise of digitalization improved connectivity and better overall performance through intelligent systems [6,7]. For instance, modern machines and systems have advanced with technology, leading to better control with cyber-physical systems (CPSs) and less human interaction [8]. The cyber-physical system (CPS) is a real-time convergence of physical and virtual systems.

One of the most significant technological advancements currently is the creation of an integrated digital twins (DTs) system. This system enables the precise monitoring and replicating its physical counterpart, making it highly valuable in various industrial and research applications. The concept of Digital Twin (DT) was first introduced in 1970 when NASA created a digital model of Apollo 13 after its oxygen tank exploded [9]. In 2003, Michael Grieves introduced DT for Product Lifecycle Management at the University of Michigan [10]. NASA defined DT as "A *comprehensive multi-physical, multi-scale, probabilistic simulation system for vehicles or systems. It uses the best physical model to describe the historical use of equipment to reflect the life of its corresponding physical equipment*"[9]. Since 2014, many leading engineering companies and

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scholars have conducted detailed research on DT technology and explored its definition [9]. DT enables digital capture of a component or system's physical state, allowing for real-time interaction from physical to digital and vice versa. This comprehensive performance evaluation includes diverse stakeholders, making DT a vital player in the system lifecycle, particularly connecting multiple "sub-systems" [11]. A digitally integrated system with DT attributes can provide intelligent interaction and synchronization to reduce time, improve quality, and improve real-time optimization [12]. Fig. 1 illustrates the evolution of DT, showcasing its remarkable growth since 2017. The maturation of Industry 4.0 technologies like Internet of Things (IoT), big data, and CPS has paved the way for technological advancements that unlock the potential for DT to be used in various industrial applications. As a result, different digital models and conceptual frameworks have emerged in the development phase. Moreover, digital shadows have been observed, where information flows solely from the physical to the digital components [13].

DT has many applications, including in manufacturing systems and supply chains (SCs) [14,15]. By utilizing real-time data acquisition, simulation techniques, data analytics, Artificial Intelligence (AI), and machine learning (ML), DT can investigate current or historical problems, monitor the system's current state, and identify future decisions. Constructing an informed decision support system for organizations is made easier with the help of DT. By utilizing innovative information technologies [16], DT can significantly improve production planning, logistics, and manufacturing processes by implementing smart manufacturing practices [13,17,18]. For instance, improved data acquisition practices in additive manufacturing have led to the development of a process framework on DT [19]. DT's significant integration with technology in the construction industry offers "data-centric construction management" [20]. High-level intelligent DT systems with semantic characteristics and Cognitive Digital Twin (CDT) capability have recently been reported [21]. Efforts have been made to integrate DT with Supply Chain Management (SCM) systems Studies on Human-Robot Collaboration (HRC) in integrated DT systems have also been reported [22].

Great efforts have been made to integrate DT with SCM systems [23]. With digitalization and technology adoption in SCM, improved interactive communication is observed to deal with unforeseen events such as epidemics or pandemic situations and provide more resilient supply chain (SC). The COVID-19 pandemic has heightened concerns about the resilience of SCs. Shortages of disinfecting and janitorial products for sanitization [24], disruptions in the supply of SARS-CoV-2 vaccines, and interrupted supply and rising costs of personal protective equipment (PPE) have all been reported [25,26]. To address these challenges, the digitalization of SCM has gained noteworthy attention [27]. DT-based intelligent systems have the potential to provide more resiliency to SC processes with digital informational technologies automating manufacturing processes and interoperability between technologies, offering better monitoring and decision support [7]. This transformation in technology is growing, and the new era of digitalization will offer proactive measures to manage risks and interruptions in the SC, achieving more resiliency with considerable economic benefits [8]. As reported by experts, strategic research in DT models exhibits tremendous potential in SCM [28,29]. DT provides real-time performance measurement capabilities lacking in traditional SC performance evaluation systems. This system enables users to track and manage critical factors such as resource utilization, performance flexibility, and output management [30], using evaluation metrics designed for this purpose [31].

The importance of DT in SCM has been growing in various industries in the past five years, as evidenced by the amount of research conducted [32]. However, DT is still developing, and more opportunities are available for further research. Interestingly, the amount of research done for DT in manufacturing and production is more than that for SCM. Nevertheless, most of the reported work is based on the conceptual framework and partially integrated DT, such as [13] and [33].

Advancements in technology have enabled researchers to develop DT, although with certain limitations due to the challenges they face [34]. Developing a comprehensive DT model involves the coordination between virtual and physical entities [35]. This intricate interplay is challenging for a virtual system, requiring constant real-time monitoring, analysis, and simulation [12]. A digitally enabled SCM system can achieve high performance by communicating in an interactive environment and leveraging emerging technologies like IoT and Blockchain. Table 1 provides an overview of recent studies that primarily explore Industry 4.0 DT-enabled technologies and their impact on manufacturing SC sustainability.

However, it is vital to understand the integration methodology of the DT systems for SCM, the components, and the applications that require a scientific approach to enhance the SCM performance, which is missing from the review studies. Therefore, this study is conducted to address the following research questions.

RQ1) What are the common DT-enabled technologies and data analytics techniques used for DT integration to enhance SC performance?

RQ2) What are the common challenges associated with integrated DT for SCM, and how could those challenges be addressed?

RQ3) How can a conceptual framework for DT SCM be developed

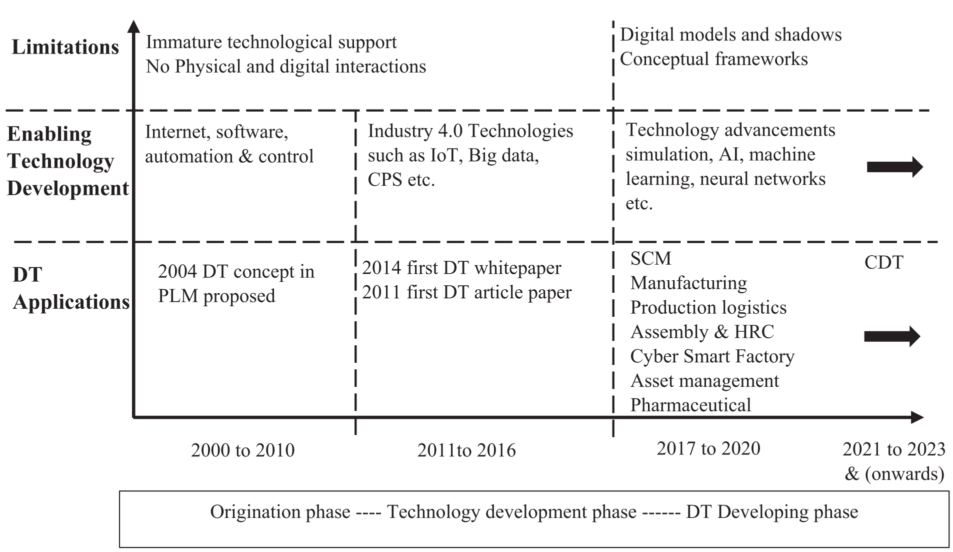

Fig. 1. Evolution of DT.

Table 1
Overview of recent review studies on DTs.

Author	Review objectives
[36, 37]	This study outlines the concept and traces the evolution and development of DT. The study also reviews the essential technologies that enable them, identifies the Industrial Internet of Things (IIoT) as the foundation of DTs, examines current DT trends, highlights significant challenges, and explores their applications in Industry 4.0.
[38]	This study carried out a systematic review to study the potential of DT for COVID−19-related issues. It provides an analysis to identify the trends, limitations, and future research directions. Moreover, a DT-based smart pandemic city concept was proposed for future pandemic situations.
[39]	The authors conducted a review to study the impact of COVID−19 on SC. The paper provides a comprehensive analysis of SC disruptions, resilience, and sustainability impacts. It further discusses the quantitative approaches and data-driven research potential with I4.0 and DT for SC sustainability.
[40]	Presented a comprehensive review of DT industrial application with merits and limitations. The authors acknowledged diverse prospects of DT implementation. However, they mentioned limitations such as lack of standardization, information integration in complex systems, and practical implementation.
[41]	The authors discussed and identified DT potential in production logistics (PL). They presented merits and limitations in numerous PL applications such as transportation, packaging, warehousing, and distribution. The review highlights simulation modeling as one of the potential future research directions in PL systems.
[42]	A review was conducted to evaluate the potential of AI in Warehouse DT to examine the use of technology, integration methods, and associated challenges. The authors identified better warehouse management, SC optimization, and operational efficiency as potential gains in this review.
[7]	A systematic literature review of 98 papers from 2015 to 2021 to address current research and future trends in manufacturing SC sustainability. The authors emphasized the technological advancements in DTs-enabled technologies.
[23]	A systematic literature review of 96 papers from 2010 to 2021 to identify the barriers and scope of data-driven simulation modeling in DT for SC and logistics. Focused on decision support systems through reinforced ML.

with DT-enabled technologies and data analytics by overcoming associated challenges for better SC performance?

This study aims to address various research inquiries by identifying the current state of research in integrating DT into SCM. Specifically, this study aims to explore DT-enabled technologies and integration techniques for SCM and associated challenges and develop an integrated conceptual framework for DT SCM to address the integrated data flow and management between each SC element and SCM network. A systematic literature review (SLR) is conducted to achieve these objectives. The review focuses on using emerging technologies and data analytics techniques to measure the overall effectiveness and efficiency of the SC system, providing flexibility and responsiveness at all levels. The study is structured as follows. Section 2 details the review methodology. Section 3 presents the results and analysis. Section 4 discusses the main challenges. Section 5 proposes a conceptual framework, and Section 6 concludes.

2. Review methodology

According to [43], a systematic literature review can build the foundation of a successful content analysis. The significance of the literature review in offering practical guidelines for comprehending the conceptual framework and theory for the research contents was highlighted by [44]. [4] indicated in their state-of-the-art review that the hybrid simulation can address the complexity of DT. Another literature review stated that DT provides optimal control over SC processes [45]. Additionally, [7] reviewed DT for the sustainability of manufacturing SCs.

This study uses a methodological review based on SLR to identify the essential aspects of the reported research in detail. it also evaluates the research methods used by the researchers to identify future research directions in DT SCM. As described by [7], a typical SLR uses a methodological approach to investigate the research on a particular topic. For the use of SLR for future research, [46] mentioned that it should have all the essential details to identify and support the cause. In addition, an SLR is also prominent as a method for identifying and assessing reporting research and studies [47].

Similarly, this study is conducted to search for answers to the research questions mentioned earlier by undertaking the SLR. The objective is to evaluate the current research on DT in SCM to identify the challenges in developing a fully integrated DT for SCM. In addition, this will also identify future research directions by assessing various research methodologies and applications of new and improved technologies. The review strategy of this study is in line with the guidelines provided by [48], which was also followed by [7]. A schematic view is presented in Fig. 2 to provide the SLR process overview.

Phase 1 includes the study's objective, the selection of the electronic database, the creation of inclusion and exclusion criteria, and the review protocol. The inclusion and exclusion criteria were defined and listed in Table 2.

Phase 2 follows an SLR strategy, which is provided in Fig. 3. In the first step, the literature search was conducted on Web of Science (WoS) and Scopus databases because these databases are core article indexes for science and provide quality research coverage [49].

Two search strings were used to identify the most relevant and quality studies for the review objective (see Table 3). The main purpose of selecting these keywords and combinations was to assess the significant research conducted in DTs applied or related to SC, manufacturing or production, and logistics streams. This was the reason all closely related keywords were used to search the papers. Peer-reviewed work plays a main role in research communication [43]. Thus, the initial search process excludes non-refereed work (e.g., industrial reports, dissertations, white papers, book reviews, and theses). All papers are exported to Endnote 20 to combine in a single database. Since papers were searched in two electronic databases, they were checked for duplication from Endnote 20>Library>Find Duplicates. All duplicated papers were eliminated from the database.

The articles were filtered out in the next step by screening the titles, abstracts, and keywords. The appropriateness of the papers was studied by reading titles, abstracts, and keywords, and then any non-relevant papers were excluded. To ensure a high-quality search, we review the abstract and conclusion of each paper. Further, in some cases, a thorough study of the full paper was done to identify its relevance to SCM. A bibliography of papers was also reviewed to select the most relevant studies. The citation-chaining procedure was also used to identify and gather comprehensive details for the review to add more relevant research papers for this study. After conducting a thorough study of various papers to determine their relevancy with DT-SCM, 69 papers were omitted in the final stage. The papers were excluded if they did not discuss DT in the context of SCM or if they discussed topics such as mechanical design or chemical simulation. As a result, 129 papers were selected for the SLR. We also include relevant conference papers for this review. The search period was selected from 2017. The growth of Internet Communication Technologies (ICTs) envisioned DTs prospects in research started in 2011[32], and the evolution of DT (as also stated in Fig. 1) started gaining some significant research directions in 2017 [35].

3. Results and analysis

In Phase 3, the review is presented with qualitative and quantitative analyses, with results presented in the following sections.

3.1. Quantitative analysis

The review analysis is done to understand the multi-perspective view of the research conducted in DT SCM. Out of 129 papers, there are 98 journal articles representing 45 journals and 31 conference papers, as

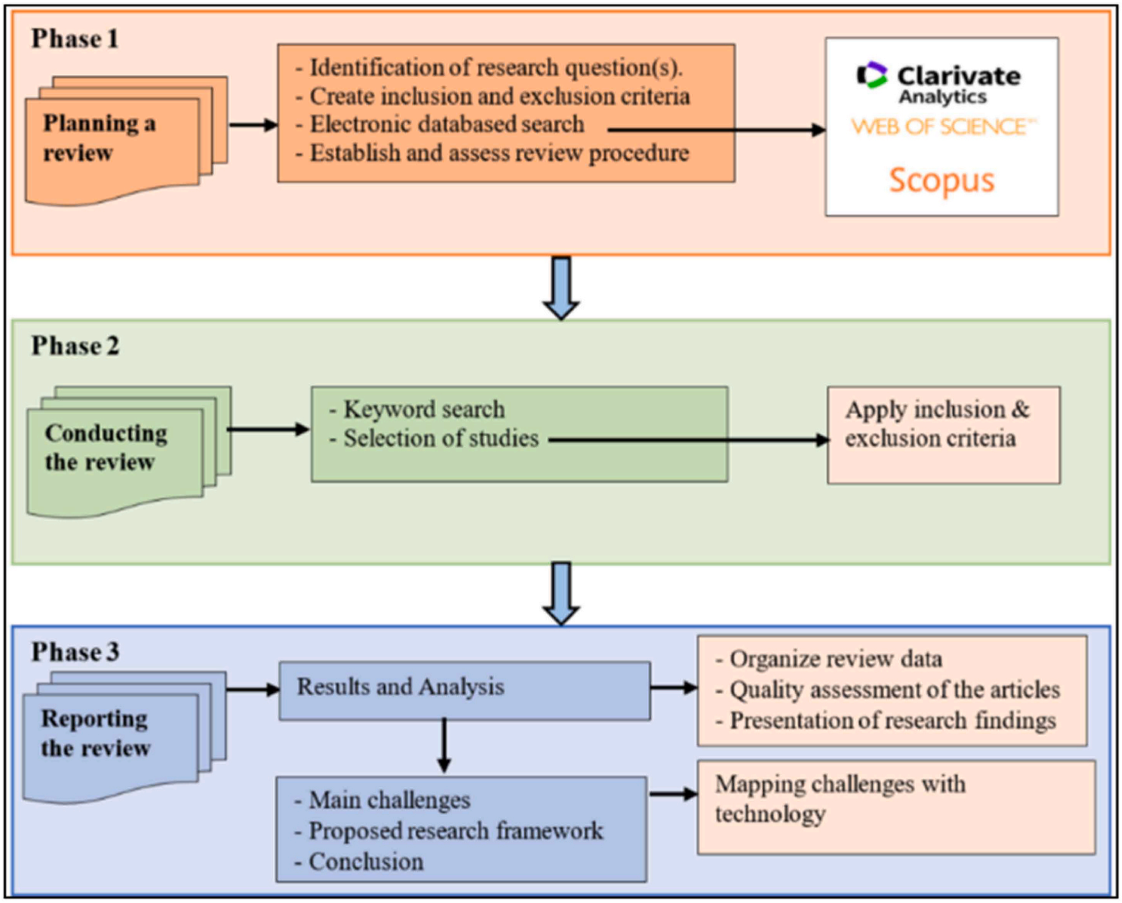

Fig. 2. SLR phases for DT SCM.

Table 2
Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
- Studies that have keywords are mentioned in Table 3. - Research papers published in the English language. - Selection of research papers based on title, abstract, and keywords. - Review the abstract and conclusion of the selected studies and, if necessary, the full content reading to filter the relevant studies further.	- Non-relevant papers. - Eliminate duplication - Eliminate non-refereed articles.

shown in Table 4 and Table 5a, respectively.

Nearly 83 % of publications selected for this review were published after 2020, indicating significant research growth in the area of DT and providing research potential and opportunities. The annual distribution of publications is presented in Fig. 4, which describes an increasing research trend and further validates the earlier statement.

As mentioned above, ample conference papers appeared during the review search, and some were also selected for this study. The selected conference papers accounted for 24 %, as shown in Fig. 5. One reason is that DT is a relatively new area of research, and scholars are investigating its integration with various systems, as reported by [51–53];

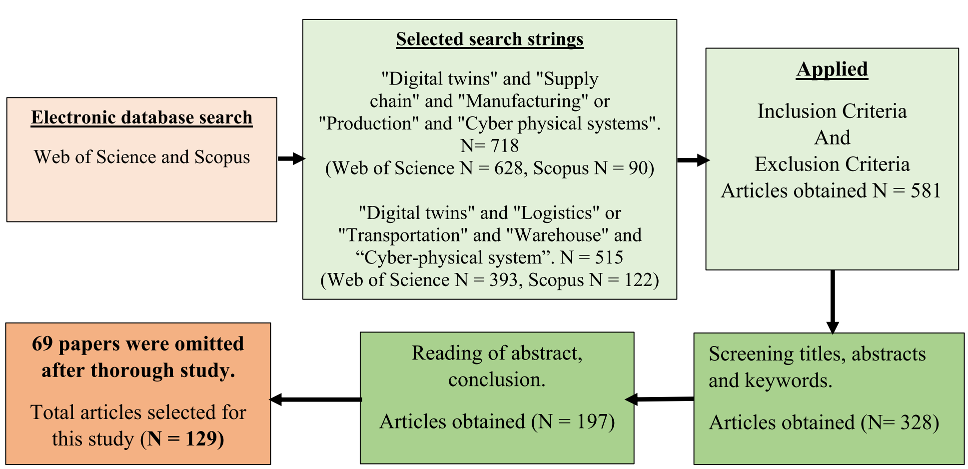

Fig. 3. Phase 2 SLR strategy.

Table 3
Search protocol.

Search protocol	Data type
Electronic Database	Web of Science and Scopus
Keywords and combination 1	"Digital twins" and "Supply chain" and "Manufacturing" or "Production" and "Cyber-physical systems"
Keywords and combination 2	"Digital twins" and "Logistics" or "Transportation" and "Warehouse" and "Cyber-physical systems"
Search fields	Title, abstract, and keywords
Period	From 2017 to December 2023
Document type	Article OR Proceeding Paper

Table 4
Journal representation of selected articles.

S. No.	Journal Name	No. of Articles
1	Academy of Strategic Management Journal	1
2	Applied Sciences	9
3	Competition & Change	1
4	Computational Intelligence and Neuroscience	1
5	Computer Communications	1
6	Computers in Industry	2
7	Computers & Industrial Engineering	6
8	Environmental Progress & Sustainability Energy	1
9	Environmental Science and Pollution Research	1
10	Electronics	1
11	Frontiers in Artificial Intelligence	1
12	Frontiers in Blockchain	1
13	IET Collaborative Intelligent Manufacturing	3
14	Industrial Marketing Management	1
15	International Journal of Computer Integrated Manufacturing	2
16	International Journal of Human-Computer Studies	1
17	International Journal of Industrial Engineering and Management	1
18	International Journal of Interactive Design and Manufacturing	1
19	International Journal of Precision Engineering and Manufacturing	1
20	International Journal of Production Economics	2
21	International Journal of Production Research	4
22	Journal of Food Engineering	1
23	Journal of Industrial Information Integration	1
24	Journal of Manufacturing Systems	3
25	Journal of Mechanical Design	1
26	Journal of Physics	1
27	Logistics-Basel	2
28	Machines	5
29	Manufacturing Letters	2
30	Manufacturing Technology	1
31	Mathematical Problems in Engineering	1
32	Mobile Information Systems	1
33	Mobile Networks and Applications	1
34	Nature	1
35	Processes	5
36	Research	1
37	Resources Conservation and Recycling	1
38	Robotics and Computer Integrated Manufacturing	3
39	Sensors	7
40	Supply Chain Analytics	3
41	Supply Chain Management-an International Journal	1
42	Sustainability	4
43	The International Journal of Advanced Manufacturing Technology	4
44	Transportation Research Part E-Logistics and Transportation Review	1
45	Trends in Food Science & Technology	2
	Total	97

hence, it is considered important to include quality conference papers by reviewing their integration methodology.

The country-wise research contribution is shown in Fig. 6, which provides a holistic approach to the study to consider papers published in different countries. China, with 28, and Germany, with 13 publications, are leading the list that indicates these countries' approach towards intelligent digital reality.

Table 5a
Selected conference papers.

S. No.	Conference Name	No. of Papers
1	7th Conference on Learning Factories, CLF 2017	2
2	CIRP Annals-Manufacturing Technology	2
3	CIRP Conference on Intelligent Computation in Manufacturing Engineering	2
4	IEEE International Workshop on Metrology for Industry 4.0 & IoT	3
5	IFAC International Federation of Automatic Control 2022	3
6	Miscellaneous (See Appendix A for details)	19
	Total	31

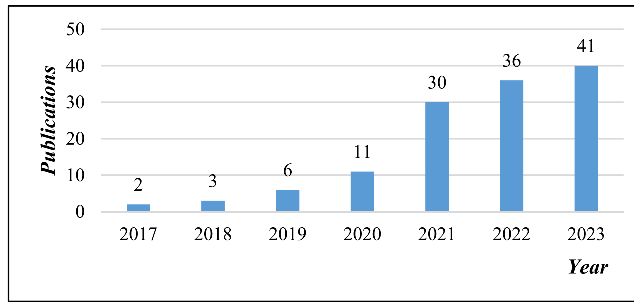

Fig. 4. Annual distribution of publications.

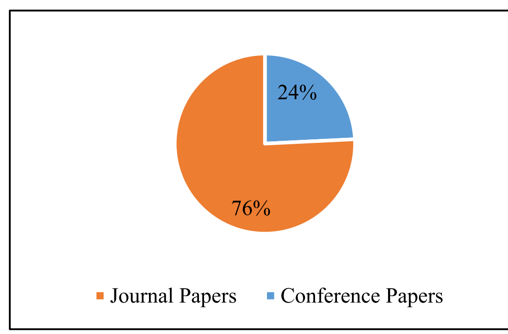

Fig. 5. Distribution of journal and conference papers.

The selected publications were reviewed carefully to identify the application of DT in each paper. After careful review, all papers were divided into three categories. The categories are: a) Manufacturing & Production, b) Supply Chain Management (SCM), and c) Logistics. The papers that discussed the application of DT in manufacturing or production were placed in the manufacturing and production category. Papers that discussed the application of DT in strategic SCs were placed in SCM. Finally, the papers that discussed the application of DT in transportation, production, and logistics were placed in the logistics category. Fig. 7 shows the highest percentage (49 %) of publications in manufacturing and production, meaning the researchers have expressed interest in this category. This is also due to the digitalization with the industry 4.0 perspective that has modernized the industry. SC and logistics shared 26 % and 25 %, respectively, indicating a potential to investigate the integration of DT applications in these categories. To provide a detailed analysis of the selected literature, the research findings are presented in the following section with respect to the selected categories.

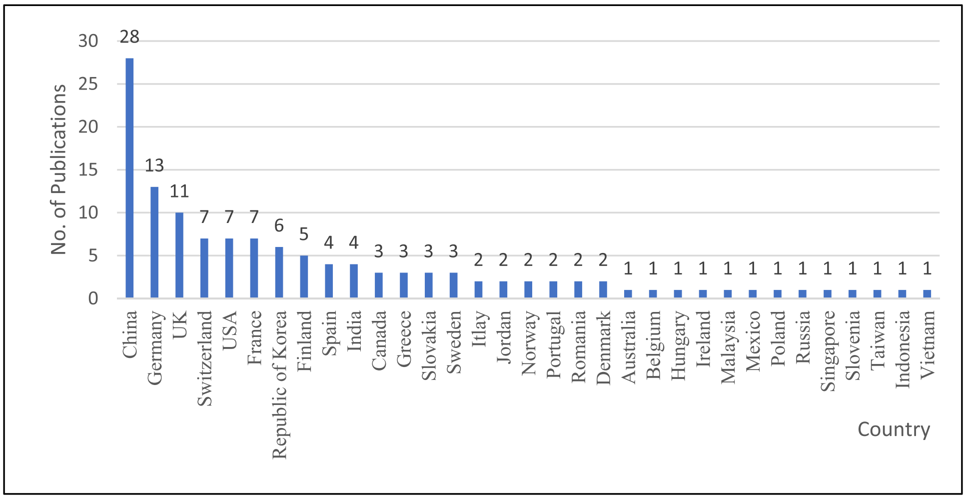

Fig. 6. Country-wise publication of journal and conference papers.

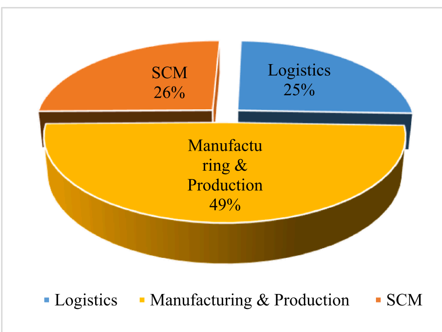

Fig. 7. Distribution of research papers according to categories.

3.2. Qualitative analysis

This section provides the analysis and extracted results on the selected literature for the categories in Fig. 7. The selected articles were reviewed and placed in three categories.

3.2.1. Manufacturing and production

In this section, manufacturing and production are considered interchangeable terms and are used specifically to address the reported work from the research papers selected for this category. The digitization of manufacturing systems has modernized the industry, focusing on innovative technologies to propose and create digital integration of production systems to implement DT. Similarly, smart shopfloor and smart production are also gaining interest due to the use of digital technologies.

[50] explored this opportunity with a 5-dimensional (geometry, physics, behavior, rule, and data) modeling approach for shop-floor DTs (SDT). The objective was to propose a DT-based virtual monitoring and prediction system (DT-VMPS) and to verify the practical effectiveness with a case study. In an effort, [51] developed an innovative digital shop-floor management system. The system was equipped with DT-enabling technologies (RFID and vision systems) to implement an integrated DT to demonstrate its effectiveness in cyber-physical machining. [52] studied digital lean principles to reduce non-value-added tasks with an Industry 4.0 perspective. The study was conducted at data, information, and knowledge levels for a CNC (Computer Numerical Control) machine to predict the machine health of the data by analyzing it in real-time.

[53] developed a DT reference model from an Industry 5.0 perspective with multi-agent systems in intelligent DT and internet of DT (IoDT) characteristics for a smart manufacturing system. Other research studies emphasized predictive analysis to optimize the production capacity for a smart factory by using collaborative manufacturing [54,55]. [56] also emphasized the importance of autonomous communication in smart factories by using IoT and RFID (Radio Frequency Identification) and proposed a hidden Markov model for optimal autonomous manufacturing in real-time. [57] introduced a framework to collect and analyze data from DT-based production systems for performance measurement with respect to the identified Key Performance Indicators (KPIs) for production monitoring processes. The authors also emphasized using IoT sensors and data transformation devices to collect real-time performance data for physical machines. [58] introduced a model to integrate reliability-centered maintenance, with Industry 4.0 as a perspective for sustainable manufacturing using a data-driven approach. The integrated model with IoT and cloud computing offers smart maintenance to provide information on KPIs for efficient performance evaluation.

In another research, [14] presented a virtual model for a 3-axis vertical milling machine. The virtual model was developed with the help of sensory and data acquisition systems to assist in diagnosis and prognosis. Researchers also proposed DT-driven flexible production systems for decision-making. To address this challenge, [59] proposed a framework to evaluate the system's flexibility by including all elements in the production system. The authors discussed the problems in flexibility evaluation for decision-making and emphasized dynamic prediction, data analytics, and simulation-based modeling. [60] proposed a DT-based reconfigurable manufacturing system equipped with intelligent sensing for manufacturing sustainability.

Semantic data models are also tested to provide digital continuity in manufacturing. Integrating real-time data between physical and digital counterparts has given simulation prominence in DT applications, such as [61], which created a digital simulation model to compare the results with the specific production data for a brake caliper plant. To address the importance of real-time simulation applications in DT, [62] discussed using Discrete Event Simulation (DES) for automated manufacturing systems. They proposed an autonomous real-time simulation model of a physical system with minimal manual intervention. Also, [4] investigated the simulation potential from an Industry 4.0 perspective and reported an increasing trend in research for hybrid simulation and modeling in DT.

[63] proposed inferring a simulation model of DT by ML to automate the DT process for complex systems. The authors focused on discrete event system specifications through DES models and ML to automate the process; however, this approach is only valid for some manufacturing

systems. [64] also emphasized simulation modeling and ML interfaces for high-fidelity virtual models in manufacturing. [65] proposed twins learning based on DT and reinforcement learning for real-time scheduling. [66] also presented a DT-based data model for CNC (Computer Numerical Control) machining equipped with sensors.

The work demonstrates the use of a simulation tool for the availability of real-time production data. [67] proposed a DT framework with 3D visualization for real-time data interaction with integrated simulation modeling for production systems. The approach was also validated for flexible manufacturing systems, and the benefits of real-time simulation with the potential for cost reduction were determined. To address the re-manufacturing difficulties, [68] demonstrated an IoT-enabled flexible simulation framework for engine re-manufacturing process planning, analysis, and optimization. [69] emphasized real-time synchronization by integrating IIoT-device-based sensor data with commercial microcontrollers to update the digital system with real-time information for DES simulation. [70] utilized multi-agent-based DES for autonomous production control in a smart factory environment. The simulation study proved that the distributed manufacturing control approach could be useful without specialization network topology.

Some scholars also reported DT integration in specific manufacturing processes. [17] proposed a CPS system for data integration in production planning by parsing stations or robots for body-in-white (BIW) production. They highlighted the requirements for DT integration planning for BIW plants. [71] discussed the CyberFactory#1 ITEA project and emphasized CPS's secure formation and integration in DT. To a further extent on CPS, [72] provided a systematic framework for web-based DT for CPS and demonstrated a prototype on a 3D printing machine. [73] also proposed a DT-based CPS for personalized production to improve manufacturing performance. [74] reviewed the necessary tools and techniques to obtain the required information from CPS and further explored how to protect a CPS system from any risk and failure in an automated production environment. [75] developed a CPS focussed on physical identification, information collection, and transmission to improve integration, interaction, and collaboration of physical entities for a case assembly facility.

The embedded semantic modeling in DT to provide cognition capabilities is a new concept known as Cognitive Digital Twins (CDT). To investigate the vision of CDT, [76] summarized key features, challenges, and opportunities in constructing the CDT interface. [77] also explored the CDT concept from a systems engineering approach and provided a framework with enabling tools and technologies. [78] also explored the self-learning cognitive capabilities with augmented reality to offer resilience in production systems. [79] reviewed cognitive architecture to develop a framework with an integrated AI for CPS and give prominence to online ML algorithms for high-precision performance in manufacturing systems. The paper also highlights the challenges due to the lack of standardized interfaces that make human intervention necessary.

Another important aspect of digital integration is synchronizing the system's components, where [80] identified factors causing difficulties in acquiring DT-based manufacturing in Indian industries. They explored real-time synchronization, technology integration, information, and data-driven attributes of DT, which are the most critical factors in acquiring DT in manufacturing.

[81] investigated the synchronization for a cutting tool manufacturer and developed a four-layered framework (physical space, DT data, digital space, and cloud services). The proposed layers were subjected to integration with the Industrial Internet of Things (IIoT) to create an intelligent manufacturing system. [82] discussed essential components of real-time integration for intelligent manufacturing systems such as IoT devices, data networks and communication, data applications, and cloud manufacturing. The intelligent factory demonstration was done with a digitally integrated drilling process. [83] explored the impact of DT-enabled technologies on the manufacturing sector with an Industry 5.0 perspective. The authors discussed key technologies and modeling techniques used in DT architectures for real-time processing, data-driven, and efficiency improvements. [84] studied the importance of IoT devices for production monitoring and data transmission across cloud and edge computing. The role of Industry 4.0 with respect to DT-enabled technologies was discussed by [85]. The authors suggested that the use of IoT can assist manufacturing companies in avoiding or recovering from unforeseen situations such as the recent pandemic. The interoperable data model for practical DT application was demonstrated by [86] for the Korean automotive industry. The emphasis was given to sharing information in real-time by using IoT, sensors, and 3D visualization data.

[87] presented an Industry 5.0 survey and addressed the importance of enabling technologies like cloud computing, IoT, and blockchain in various manufacturing sectors. [88] highlighted the problem of inadequate monitoring in labor-intensive manufacturing sectors and proposed an intelligent monitoring and control framework using a configurable virtual workstation that provides a real-time flow of information through IoT and sensors from warehouse and production lines. [89] proposed a standard framework that collects data offline to train online systems to avoid real-time production failures. Their effort is to standardize the data, information, and interfaces for production processes. [35] proposed a 5-dimensional layer for the DT model based on physical and virtual services, DT data, and dynamic connections between the components of the systems. Emphasis was placed on adopting a common model approach to support the implementation of DT in multiple fields of manufacturing applications. Regarding product design, the application of DT is tested to a certain extent, where [90] investigated the potential gaps and proposed a functional-based modeling approach for a COVID-19 breathalyzer. The study perspective establishes a product DT for design, manufacturing, and service for the product lifecycle.

Some assembly production lines are required to identify the human-machine interaction (HMI) for intelligent operations. The concentration of this interface is to provide real-time communication for smart assembly. [22] described HMI as a key technology for a product life cycle and proposed a 5-dimension DT-enhanced HMI framework. The framework identifies the crucial aspects in each dimension between physical and virtual domains, from design to product life cycle service. Another similar aspect of the HMI environment is HRC, which combines human experience and robot precision to obtain high productivity. [91] explored the human robot interaction HRI concept by using AI for intelligent manufacturing. They identified key characteristics such as complementarity, shared knowledge/goals, bounded autonomy, mutual trust, and benevolence for a human-centered integration in a complex CPS for manufacturing. In interesting research, [92] presented a model to converge DT and virtual reality (VR) for operators training for higher visual and realistic learning. The proposed digital platform was experimented on operating an industrial robot that significantly improved operator training. Further, [93] discussed the importance of a human-centered approach concerning complex socio-technical issues in integrated CPS. [94] proposed a digital framework to monitor human skills and measure operators' performance by incorporating human factors in DT. [95] investigated this complex and dynamic HRC environment for a linear actuator sub-assembly with object-oriented event-based simulation. The virtual models were developed to understand the potential of an integrated DT assembly operation. [96] analyzed the maximum possible integration between the manufacturing execution system and simulation modeling for real-time simulation of production processes. They also offered various levels of HMI in CPS by using real-time simulation.

The growing research on DT may lead to some misconceptions since the opportunities for DT model implementation increase with the amount of research in this area. To an extent, [18] addressed the misconception about DTs by creating a generalized 4 R framework for DT applications for any machine or system. They categorized the 4Rs as Representation, Replication, Reality and Relational. The study emphasized the importance of DTs maintaining continuous communication with physical systems to represent an actual system accurately.

3.2.2. Logistics

The varied needs of customers and environmental limitations necessitate sustainable practices in logistics., which requires the high monitoring of logistic elements. To review the requirements, [97] conducted a qualitative analysis based on current and future needs for sustainable logistics with an industry 4.0 technology perspective.

The focus on CPS systems in logistics has provided a reason to explore more opportunities for DT integration in logistic networks. Stochastic modeling, dynamic programming, and ML algorithms can support this integration. To extend this, [98] proposed a methodology to organize the physical distribution DT model to manage trade networks. They aimed at real-time data collection and using stochastic and mathematical modeling to find optimal solutions. [99] also proposed a CPS-integrated DT to automate the logistic system for a warehouse facility with the support of digital technologies for data collection and ML algorithms. [100] conducted a study with a Logistics 4.0 vision and proposed a data-driven DT embedded with simulation to offer adaptability and resilience for product-on-pallet distribution. [33] developed a framework with an adaptive modeling approach for urban logistics to support better planning. [101] utilized design, science, and research methodology (DSRM) to develop a DT implementation strategy for German rail transport.

The concept of a Physical Internet (PI) hub offers efficient and structured transportation of goods by transforming closed networks into open networks for better relocation of physical goods using DT-based synchronization with the use of IoT devices and supported by ML, as described by [102] can provide optimization in logistics. [103] also proposed a DT framework for a composite container to identify hubs' loading and unloading phases. Based on IoT and blockchain technology, [104] proposed an optimized warehouse locational method for intelligent transportation. [105] also proposed a conceptual framework based on blockchain and DT-enabled technologies for DT-integrated analytics and improved logistics performance. Similarly, [106] presented the logistics-based DT platform supported by big data technology for better planning and optimizing logistics processes. [107] also proposed an IoT-enabled blockchain framework to present the trade-in strategies for disassembly-to-order systems. Similarly, [108] proposed an IoT-based framework for SC logistics. [109] presented the use of RFID devices and DES for a non-stacking warehouse. The results showed that the applied DT has the potential to assist in making quick adjustments in the physical layout for non-stacking warehouses. Considering IoT as a key technology in warehouse management, such as loading, unloading, distribution, and processing, [110] reviewed the importance and applications of IoT technology for smart logistics. To address the intelligent logistics for cold chain applications, [111] proposed battery-powered IoT for temperature monitoring and a framework consisting of a dashboard for continuous monitoring with an IT (Information Technology) support system that identifies and reports anomalies. [112] used the DT concept for an intelligent container to track the ocean transport of banana fruit. [113] emphasized the benefits of DT for horticultural produce. [114] identified the opportunities to improve food logistics from the perspective of Industry 4.0 technologies. The authors also addressed the challenges of transportation, planning, warehouse management, and data security. [115] discussed the critical problems in global fresh produce for the reefer market related to temperature control and uniformity, sustainability issues due to greenhouse gas emissions, and the potential of digital feed twins to address key bottlenecks. The authors emphasized using a data-driven approach integrated with sensors to control the reefer atmosphere for better energy saving and food quality.

Production Logistics (PL) plays a significant role in improving the in-house productivity of any production system. An intelligent PL system can support an efficient material flow that generates a high-quality output with high profits. [116] analyzed spatial-temporal values of a production system through deep NN and proposed a dynamic special-temporal knowledge graph (DSTKG) enabled with DT. [117] identified the problems in PL and proposed a DT control framework coupled with emerging technologies and optimization algorithms for synchronization between production and storage. In another study, [118] proposed a DT framework for synchronizing production service systems under a highly dynamic interface. [119] developed a small-scale demonstrator to demonstrate the IoT-driven CPS system for production logistics. A dashboard was used to visualize the data chain for acquiring and processing a conveyer testbed.

Because of collaborative environments in PL, [120] proposed a contact system method to identify the location of autonomous mobile robots (AMR) in a production system with the help of a mathematical model that identifies objects with six degrees of freedom to calculate the deviation between AMRs. [121] presented EtherCAT model and TwinCAT HMI server for AGVs (automated guided vehicles) operations in a smart warehouse to provide potential collaboration between virtual reality and physical space. DT modeling and simulation have enhanced PL systems' adaptability and disruption response as [122] presented an intelligent workshop DT-based design of multi–Automatic Guided Vehicles (AGV) simulation for optimization of paths in the aerospace industry.

[123] produced a simulation model by utilizing reinforcement learning to simulate factory operations and optimize storage for production logistics. The proposed method proved promising for storage optimization tasks in complex production logistics systems. [124] also presented a virtual model for AGVs (automated guided vehicles) fleet management. The study indicated a need for more research in DT for AGVs (automated guided vehicles) and proposed to develop an ecosystem for a fleet management system to enhance the collaboration between factory layout modeling and AGV control. [125] investigated the validity of simulation systems in implementing DT and the automatic generation of simulation models. [126] developed a simulation-based intelligent framework for in-house logistics decision support. [13] created a digital model for a physical testbed to perform several scenario-based experiments to evaluate digitalization in PL. [127] investigated how cognitive DT can optimize logistics operations planning by automating freight parking management system and proposed a four-layered architectural framework integrated with enabling technologies, including agent-based simulation, property graphs, web ontology language, and web of things. The work manifests the potential of enhanced resource utilization and collaboration with improved logistics efficiency. [128] proposed a universal CPS to simulate production processes to optimize production logistics. The simulation model could reproduce a physical workspace to perform with real conditions for production simulation. [129] identified the current problems in production and distribution (PD) logistics and proposed a linkage-oriented decision-making platform based on DT.

3.2.3. Supply chain management

Sustainability in distributing products and commodities plays a vital role in managing disruptions due to unforeseen situations such as the recent COVID-19 pandemic. As mentioned previously, DT can improve SC performance. This study also analyzed various scholars who have used DT-enabled technologies to establish frameworks to support SC performance. [130] investigated the benefits and challenges of Industry 4.0 technologies in improving SC performances and integrated the findings into a framework for future research opportunities. Similarly, [131], [132], [133] and [134] identified and described the use of emerging technologies for DT integration in SC. [135] also examined the implementation of DT in SC disruption to identify the challenges. In another research [136] studied the impact of DT on the sustainability of SCs by examining the hypothesis utilizing least square structural equation modeling after collecting surveys and interviews with top management of manufacturing companies in India. The authors concluded that DT can significantly improve SC performance and resiliency. [137] discussed the SC business eco-system for zero-waste value chains and provided a framework with key enabler technologies for effective and secure quality data transmission for end-to-end data traceability. [138] provided an investment conceptual model to assess the essential DT-enabling technologies for SC systems. Important parameters concerning the applicability to different companies were evaluated for investment purposes.

Another research described DT's potential for assisting decision-makers and investigated the SC disruption for a single FMCG product during the recent pandemic [139,140]. The inventory and financial problems were analyzed, and a framework integrated with ML and DES was proposed to counter the SC disruption. Likewise, [28] also presented a SC resilience model based on DES to address the food retail supply disruptions during the pandemic in Germany. Further, [39] in a study on the impacts of COVID-19 in SCM, emphasized the use of dynamic simulation models, empirical methods, and data-driven techniques to identify the short and long-term effects. [141] proposed DES to monitor the quality of transport goods with the help of a digital model. They relied on sensory data for simulation modeling to reduce the safety stock levels for automotive SCs.

[23] discussed the importance of the data-driven DT with reinforced ML and simulation for decision support in SC. [142] presented an idea to use Systems Applications and Products (SAP) for real-time data integration and developed virtual space on AnyLogic software for real-time simulation. The emphasis was on using sensors, RFID, and IoT to flow data efficiently to ERP (Enterprise Resource Planning) systems and simulation models. [29] discussed N95 medical protective mask supply disruption during the COVID-19 outbreak in China and provided a numerical and simulation-based DT resilience model. Further, [143] proposed a DT system based on simulation modeling coupled with sensors and data-interoperable devices to mitigate SC disruptions on the production shop floor. The proposed framework for the FMCG domain addressed a potential solution to manage disruptions. [144] defined DT framework based on data, domain, analytics, and outcome elements to optimize SCs. AI and simulation are considered the core of the implementation of DT. [145], [15] studied technology evolution and suggested the technology implementation layers for DT SC systems. The study suggested that synchronization and simulation modeling are key elements for implementation layers. To address the demand and forecast prediction, [146] designed a prediction model based on a convenience store's BP NN supported by IoT devices. Simulation tools and data analytics with an online dashboard for performance monitoring were proposed as an integrated interface. [147] addressed the importance of ML in SCM and proposed a ML regression algorithm to predict the severity of late supplier delivery for the German machinery industry.

Another aspect of DT in SC is using emerging technologies in the food SC. The research in this area indicates a real potential to measure food quality from postharvest to retailers. The focused study by [148] on the DT transformation of agrifood indicated the potential for improvement in SC performance. [149] also discussed in detail the use of advanced technologies to identify food quality loss during packaging, storage, and transportation. The study emphasizes the integrated DT coupled with the technology for real-time biodegradation monitoring. Similarly, [150] delivered a mechanistic modeling-based DT to simulate and quantify the biochemical degradation for the cultivar Kent mango. After collecting temperature-dependent data during the transport, the model was designed and later simulated in multiphysics software. [151] also developed a physics-based DT for mapping and optimizing postharvest SCs for fruits and vegetables. Both [150] and [151] reported significant quality losses and recommended using real-time data integration for the cold SC. The literature review for this study also identified the use of Blockchain technology with regional database management systems (RDMS) systems for SC mapping. To reduce food waste in agribusiness, [152] proposed a risk mitigation matrix integrated with multi-objective binary linear programming (GMLOP). An event-based modeling framework was reported by [153] to support the decentralized transportation of coffee.

3.3. Summary of results and implications

After thoroughly analyzing the existing literature, it becomes evident that DTs hold tremendous potential across various systems. Researchers have advocated for multilayered frameworks, digital technologies, and digital models of physical systems, underscoring the critical role of real-time connectivity and synchronization. The ultimate aim is to develop a CPS featuring a real-time data interface and virtual layers that accurately mirror the physical system. A pivotal insight from this review is the significance of data-driven frameworks in bolstering resilience for efficient operations. Achieving synchronization between every component of the physical and digital layers is crucial for facilitating intelligent operations. To realize these objectives, Industry 4.0 technologies, alongside advanced data analytics techniques such as simulation modeling, NN, AI, ML, and numerical modeling (Num.), are vital in the development and implementation of DT.

After conducting a thorough analysis of the findings, it is evident that substantial research has been dedicated to proposing various sub-DT systems for different components and processes within SCM. However, there is a discernible requirement for a systematic approach to explore the integration of existing sub-DT systems (sub-systems/building blocks) in order to develop a comprehensive DT system for SCM. In addition, this study's findings have substantial implications for manufacturing, logistics, and SC (SC) performance. A comprehensive overview of DT-enabling technologies and data analytics techniques, as discussed by various authors in the papers selected for this review, is provided in Table 6 (see Appendix B). Additionally, Table 6 maps each implication to the selected studies as indicated by the authors, highlighting SCM performance as a particularly promising area for further research. Moreover, the use of DT-enabled technologies and data analytics techniques is compared, with respect to their implications, in Fig. 8(a, b, c). This comparison shows that IoT and RFID, as DT-enabled technologies, together with simulation and ML in data analytics, are most prevalent in the selected studies. This indicates that simulation and AI technologies will play a crucial role in data analytics for DT integration, facilitating dynamic modeling and predictive analysis for real-time performance measurement.

The comprehensive analysis of current literature underscores a pressing need for a conceptual framework tailored to DT-SCM. This framework will be critical for harnessing DT's full potential to revolutionize various systems through enhanced real-time connectivity, synchronization, and the integration of CPS. It would systematically address the integration process, leveraging DT's capabilities to improve SCM performance.

The analysis of a literature review demonstrates great progress in the development of sub-DT for each SC component. Most authors addressed the importance of DT at the sub-level due to a better practical implication or to reduce complexity. However, the literature doesn't provide any proposed framework at the sub-DT and SCM network levels. The sub-DT approach in SCM is a focused and refined application of DT technology. It targets specific sub-components or processes (sub-systems) within the broader SC. This approach helps organizations manage complex systems better by breaking them down into smaller, more manageable processes. Given the significance of DT-enabling technologies and data analytics techniques enabling resilient and efficient operations, such a framework would outline the essential components and their interactions within the SCM.

As identified through the review, it would also guide the adoption and implementation of industry 4.0 technologies, including IoT, RFID, simulation modeling, NN, AI, and ML. This conceptual framework is not just a theoretical necessity but a practical blueprint for advancing SCM performance, emphasizing the strategic role of DT in enabling dynamic modeling, predictive analysis, and real-time performance measurement. The evidence suggests that developing such a framework is imperative for leveraging DT technologies to pave the way for more intelligent, efficient, and resilient SC operations.

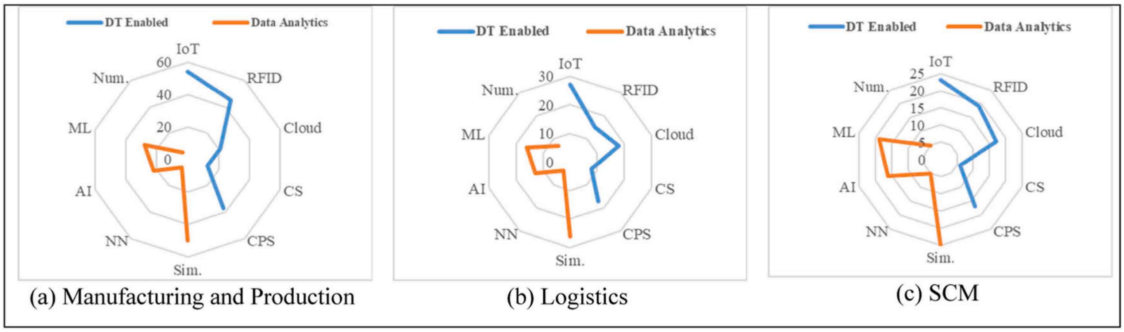

Fig. 8. Potential of DTs in SC.

To establish a conceptual framework for DT-SCM, a diverse approach comprised of a real-time performance dashboard, an effective SCM measurement system, and strategies for SCM optimization are mandatory requirements for elevating SC performance. This integrated approach enables the transformation of DT with industry 4.0 technologies and advanced data analytics to foster a seamless, interconnected, and intelligent SC ecosystem. The real-time performance measurement requires a digital model to be connected with the operational model, which identifies the main strategies for the SC ecosystem, such as SC strategy, policies, sourcing, and procurement. A real-time performance dashboard offers immediate insights and transparency across the SC, facilitating swift decision-making and operational excellence. At the same time, a robust SC performance measurement system, grounded in DT capabilities, enables quantifying and analyzing KPIs, ensuring a data-driven strategy for continuous improvement. Optimization efforts are further enhanced through the strategic application of AI, ML, and simulation modeling, which refine operational efficiencies and predict future trends, allowing for preemptive adjustments. Collectively, these elements exemplify the practical implementation of the proposed conceptual framework, steering SCM towards unparalleled efficiency, resilience, and competitive advantage in a dynamically evolving SC system.

3.4. Common components of DT identified for SCM digital twins

3.4.1. DT-Enabled Technologies

IoT technology has grown significantly to provide real-time connectivity for machine-to-machine or human-to-machine interfaces. The International Telecommunication Unit (ITU) defines IoT as *"A global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies"* [154]. Applying IoT in data collection for various operations in physical spaces is beneficial for SCM DT integration. Using IoT in applications such as manufacturing, SC, and logistics can maximize the overall efficiency and productivity of the system. RFID devices are smart devices connected to IoT networks and assist in monitoring the product's lifecycle by tracking it through QR codes and Unique Identifiers (UID) [155]. This study also identifies some challenges to integrating IoT, such as heterogeneity, dynamic, and spontaneous communication for IoT interoperability [154]. To solve this, various Application Programming Interfaces (APIs) have been developed to address IoT compatibility. IoT protocols play a prominent role in networking physical devices and providing interoperability in the IoT network. These protocols include Open platform communication (OPC), OPC unified architecture (OPC UA), transmission control protocol (TCP/IP), and message querying telemetry transport (MQTT) and Zigbee [156]. The majority of IoT devices have limited capacity to store data, and these devices depend on the structured architecture used for DT integration. Therefore, cloud technology is an essential component in DT-integrated system.

Data storage, management, and security are other central aspects of DT integration due to the large amount of data and information. Cloud computing provides high-speed, secure, limitless data collection and the sharing of resources to and from the physical and digital spaces. Moreover, cloud computing is a mature technology, and organizations such as Microsoft, IBM, Amazon, and Google all provide cloud services. The data can be collected in the cloud from IoT devices to use further with cloud applications. However, if the data comes through many IoT devices and is based on a large region, fog or edge computing technology can provide a network node to store and process the regional data [157]. SCM systems sometimes require data access from various remote locations. Hence, integrating cloud/fog/edge computing can provide data visibility for a decentralized decision support system [158]. However, cloud implementation in a conventional SCM system is a challenge that demands a layer-by-layer implementation to collect data from IoT devices and store it securely for further processing [7].

An integrated DT system with a large amount of data flowing from various components and elements requires impeccable cyber protection and data privacy. IoT devices and cloud services provide secure data transactions in the network for internal and external stakeholders. Large information networks such as SCM networks comprised of cyber-physical systems connected with business facilities and logistics performing operational functions require mutual efforts between stakeholders to protect the informational network for trade uniqueness and cyber-attacks.

CPS is an intelligent interconnectivity of physical elements with the digital space of the system for real-time data collection and monitoring. It is also necessary to distinguish CPS from the architecture of IoT, as described by [157]. CPS is a system that connects IoT, RFID (Radio Frequency Identification), and sensors as the primary technologies sourcing this connectivity with digital spaces. [82] defined CPS as *"The combination of physical and virtual spaces is referred to as cyber-physical systems (CPSs), and it aims to create a communicative interface between the digital and physical worlds by integrating computation, networking, and physical assets"*. CPS is a mandatory component for DT integration. As identified in this study, many researchers addressed the CPS in manufacturing and production systems. However, the scalability of CPS, including sustainability and life cycle, is yet to be addressed fully. CPS integration in traditional SCM systems is a challenge. It is a convergence of physical and digital spaces for advanced computing to achieve dynamic modeling and decision making for SCM systems. This includes hardware such as sensors, actuators, machines, men and software for communication, networking and control. The challenge is to automate the system with real-time data collection, execution and interoperability for various heterogeneous systems and data analytics for decision support.

3.4.2. Data analytics

Simulation plays a crucial role in integrating DTs for optimization, operational planning, and the design of intelligent production systems. It enables the testing of engineering solutions by mimicking the behavior of complex production systems in a real-world environment before making investments. Leading software companies, such as Siemens, have developed practical solutions to integrate simulation into Industry 4.0, thereby enhancing production efficiency by creating factory twins that incorporate IoT and simulation. [144]. This review identifies simulation as a commonly used tool for DT integration in manufacturing and SCM, discussing methods like discrete event simulation, system dynamics, and agent-based modeling. Additionally, some researchers have explored hybrid modeling, which combines two or more simulation methods. [159] proposed using simulation alongside big data technologies for SCM applications, indicating that data-driven DT systems with real-time simulation modeling could advance DT integration within CPS environments. [160] and [161] also covers simulation-based control for systems engineering approaches, proposing simulation-based experimental DT for virtual testbeds, and [145] discussed the importance of simulation in process optimization, cause analysis, and decision-making within DT systems. [67] Implemented simulation-based frameworks for flexible production management and [126] proposed decision support in production logistics highlight the value of simulation. The importance of FMUs-supported simulation models is also discussed by [34]. Some studies, such as [4,114] further acknowledges the integration of AI, NN, and ML with simulation modeling for adaptive behavior and self-optimization alongside the use of numerical (e.g., MATLAB) and Multiphysics modeling e.g., FEA (Finite Element Analysis), such as ANSYS, COMSOL) in DT applications. Researchers have evaluated the need for numerical modeling by collecting real-time data to investigate further the quality degradation over time in SC and logistics [150].

Recent advancements in autonomous digital data analytics through simulation, AI, ML, reinforcement learning, and NN are highlighted, underscoring the potential of AI-trained models in real-time data analytics within SCM systems. [158,162] demonstrated the concept of integrated AI and ML approaches for DT-SCM applications. [163] conducted a detailed analysis of DT analytics and emphasized on ML and AI smart data analytics for DT integration. Similarly, [164]evaluated the possibility of AI integration with the simulation tool anyLogistix. [165] also explored AI for generative modeling, optimization, and predictive analysis to determine better decision-making. [166] discussed self-taught ML algorithms for DT analytics. [65] proposed reinforcement learning for real-time scheduling. [86] highlighted the importance of ML and deep learning in real-time data-driven architecture for big data. [64] viewed ML approaches for high-fidelity DT models for a cyber-physical factory. [105] discussed ML in an intelligent distributed manufacturing system for accurate predictions. In another study, [128] proposed ML algorithms for production optimization in a CPS environment. Several researchers, such as [7,23,116,146], also proposed frameworks based on AI, reinforcement learning, and deep NN for SCM.

The review highlights the major potential in data-driven simulation modeling in real-time with the support of AI integration. Moreover, the integration of AI with simulation offers hybrid solutions for data analytics, paving the way for multimethod and multi-agent-based modeling as the future of DT data analytics. To suffice data-driven modeling, the digital layer of the DT-framework must be connected with informational model of the SC that also provides KPIs for performance analytics. Further, a performance model in a digital layer plays a role to store and provide visual performance of the KPIs for better analysis and control. These models will assist digital modeling of physical spaces and real-time communication between physical and virtual entities for data-driven simulation and performance measurement via an online dashboard presents realistic solutions for enhancing SCM resilience.

4. Main challenges

The development and implementation of DT are sophisticated processes where all system components are connected and share information in real-time. The system requires various technologies to replicate a physical system in a virtual world. The emergence of Industry 4.0 and the development of key-enabled technologies have seemingly given a wide range of prospects to build a DT-integrated platform. The review conducted in this study finds conceptual frameworks, digital models, and digital shadow integrated with Industry 4.0 technologies that indicate DT is still in its infancy.

Most authors have proposed a DT conceptual framework after investigating the particular system for integration, such as [167] and [81]. This also indicates the importance of DT at the sub-level to create sub-DTs for various SC processes to enhance the visualization and control for complex systems. The focused sub-DT provides detailed insights and analysis for better integration at SCM network level. Similarly, it helps each SCM process design, test, and optimize before integration into a larger system. However, the creation of sub-DT also posses several challenges at technical and organizational levels, and its practical implementation still needs to be addressed in detail. The complexity of DT infrastructure that needs high volume data, seamless transmission, technology integration with compatibility, scalability, high cost, use of resources, maintenance, and sustainability at the sub and network level are significant challenges.

In addition, the digital shadow of the actual physical system is also presented after collecting real data to simulate the physical space, as demonstrated by [13]. Several other authors [150,168] also used real data to simulate a digital model. This indicates the lack of real-time integration and synchronization between physical and virtual models. Table 7 (see Appendix B) provides some of the common challenges highlighted during this study. Another aspect is to investigate the use of suitable DT-enabled technologies for the architecture and complexity of the system. The challenge is understanding each system element to establish real-time interconnectivity to create an integrated DT. It requires the investigation of all relationships and an understanding of dependency at all levels of the design. Several researchers have proposed multiple layers in their DT framework to describe that perfect synchronization is gradual.

The heterogeneous data sources and formats pose data integration challenges in DT. Real-time data processing requires an uninterrupted flow of high-quality data to integrate with different sources for reliable operations. The consistency of data accuracy and quality can contribute to real-time simulation modeling to produce real-world behavior of the physical model. Simulation models can be highly dynamic depending on the nature of the physical system. Therefore, data integration and scalability are challenges requiring particular focus and attention.

Further, scalability is also a challenge in DT models due to the large volume of data collected over time, which also requires high computational capabilities. Data privacy and cyber security are other main challenges in DT due to the probability of cyber-attacks, and companies take this matter seriously to protect critical information. Interoperability is another critical factor that needs attention for intelligent connectivity among smart devices for system integration. This smart connectivity could be problematic if the system's existing components are incompatible with establishing an interface with data or information exchange devices. Since the internal and external flow of information plays a prominent role in intelligent operations, the data quality or information flow also needs maturity and a collaborative approach between stakeholders.

Integrating information systems (e.g., Enterprise Resource Planning - ERP) allows data-driven modeling for decision support and prediction. These models are required to digitalize to support different decision scenarios at decentralized levels. Another aspect is investigating DT adoption in various enterprise-level infrastructures such as manufacturing plants, SCs, or logistic facilities. Authors have proposed the use of big data analytics and deep neural networks. However, these also require heavy computation and appropriate infrastructure resources.

Implementing DT also raises the need for training and skills due to introducing digital technologies to employees. Companies require a holistic approach to embrace DT by measuring its success and harvesting it in its culture to deal with any resistance. It demands strong leadership support that devises strong policies after assessing the risks of digital transformation.

5. Proposed conceptual framework

During this review, challenges pertinent to the integration of DT within SCM were identified. This critical analysis laid the foundation for developing a conceptual framework predicated on the synergy between DT-enabling technologies and complex data analytics. The evolution of IoT, RFID, and smart sensors has markedly expanded the capacity for handling voluminous datasets, a development that is quintessential for constructing CPS that synergizes IoT devices. Such integration facilitates a seamless integration of physical systems with their digital counterparts.

Furthermore, incorporating cloud computing into existing systems is a pivotal strategy for enhancing data quality and bolstering cybersecurity measures. Given the intrinsic nature of DT as a data-intensive system, it necessitates an infrastructure characterized by seamless connectivity, high-fidelity data transmission, and system-wide compatibility. Herein lies the critical role of interoperability, bridging the gap between the physical and digital realms and harnessing the power of real-time data analytics for synchronous monitoring.

Technological interventions, including simulation, ML, AI, and NN, have profound potential in offering analytical solutions that aid in decision support, predictive analytics, and the timely identification of systemic disruptions. The deployment of data analytics avails hybrid solutions conducive to continuous systemic adaptations, thereby augmenting SC performance.

The conceptual framework proposed herein is designed to be applied across various components of SCM. Fig. 9 demonstrates the use of sub-DT at different levels of the SC, from individual components to overall strategic planning in an SCM network. This model highlights the importance of incorporating DTs at every stage of the SC to enhance efficiency and decision-making capabilities. Each SCM component features a sub-digital twin (sub-DT) that captures and processes information in real-time from its physical counterparts. This allows for detailed monitoring, analysis, and optimization of operations at a granular level.

Integrating these sub-DTs forms a comprehensive DT network, offering a detailed view of the SC. This integrated perspective enables well-informed strategic decision-making and holistic management of SC operations. Moreover, this level of integration equips the system with advanced features, such as predictive analytics, network optimization, and strategic planning. The harmonization and optimization across the SC boost overall performance and strengthen resilience.

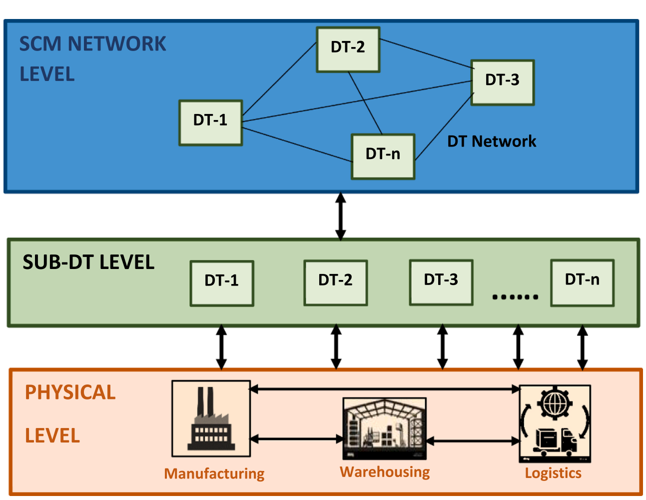

Fig. 9. Levels in Sub-DTs for DT SCM network.

The proposed framework in Fig. 10 advocates for integrating real-time data collection devices within physical systems, facilitating direct data transmission to simulation modeling tools. This approach enables real-time simulations that critically assess system performance. Additionally, the framework allows for the real-time evaluation of processes to identify bottlenecks and empower stakeholders to make informed decisions. This research underscores the indispensability of a robust, technology-driven approach to SCM, promising enhanced efficiency, resilience, and adaptability in the face of evolving market demands and operational challenges.

Figs. 9 and 10 collectively demonstrate a complete SCM CPS, where physical operations are mirrored by sub-DTs for each component, and advanced analytics and services are used to optimize and manage the overall SC effectively. The sub-DTs integrate into a cohesive network, allowing for comprehensive monitoring and management of the entire SC. The DT network ensures that the data from all DTs are synchronized and can be analyzed collectively for optimization.

5.1. Physical layer

This layer consists of the elements or components of the SCM in a physical system, such as things, machines, and humans. Things and machines are referred to as products, facilities, equipment, workstations, and freight. The physical layer can be defined further as internal and external physical layers. Internal layer terms within the same system and the external layer include suppliers, vendors, and other stakeholders within the SCM network. To create a CPS, the physical layer elements are embedded or equipped with DT-enabled technologies, including IoT devices, RFID (Radio Frequency Identification), sensors, cloud computing, software resources, and cybersecurity. The technology collects, stores, and transmits the real-time operational and surrounding data of elements in a cyber-secure environment to the digital layer of the DT framework. Identifying the physical components required to embed with what type of sensors to collect the data is essential. Table 8 provides an overview of DT-enabled technology applications in the physical layer.

5.2. Information processing layer

This layer in the framework is tailored specifically to enhance SCM at the sub-DT level. By breaking down the data journey into distinct phases, this model ensures that information flows smoothly and securely, supporting critical decisions throughout the SC. Data collection begins with the collection of raw data, which flows in from various points, such as IoT devices and sensors actively monitoring the daily operations across the SC. This stage involves capturing critical data in real time, ensuring no valuable data slips through the cracks. Data mapping is an important aspect of DT in which collected data is carefully organized and assigned to specific models or parameters. This step is like setting up a library system, ensuring each piece of information is where it should be and making it easy to find and use later. Data is stored in secured databases such as cloud-based data systems for future use. Data processing at the sub-DT level transcends efficient data handling; it involves converting data into a strategic asset that enhances SC agility, responsiveness, and efficiency. Running parallel to these stages is the CS, which protects the integrity and confidentiality of large amounts of data throughout its lifecycle. CS plays a key role in preventing threats and ensuring compliance with regulations. The information processing layer systematically transforms raw data into actionable intelligence that supports enhancements in SC effectiveness and security.

5.3. Digital layer

The digital layer comprises a digital model of a physical system. It is an exact replication of the physical elements in a virtual model. This layer operates at the sub-DT level and SC Network level and is

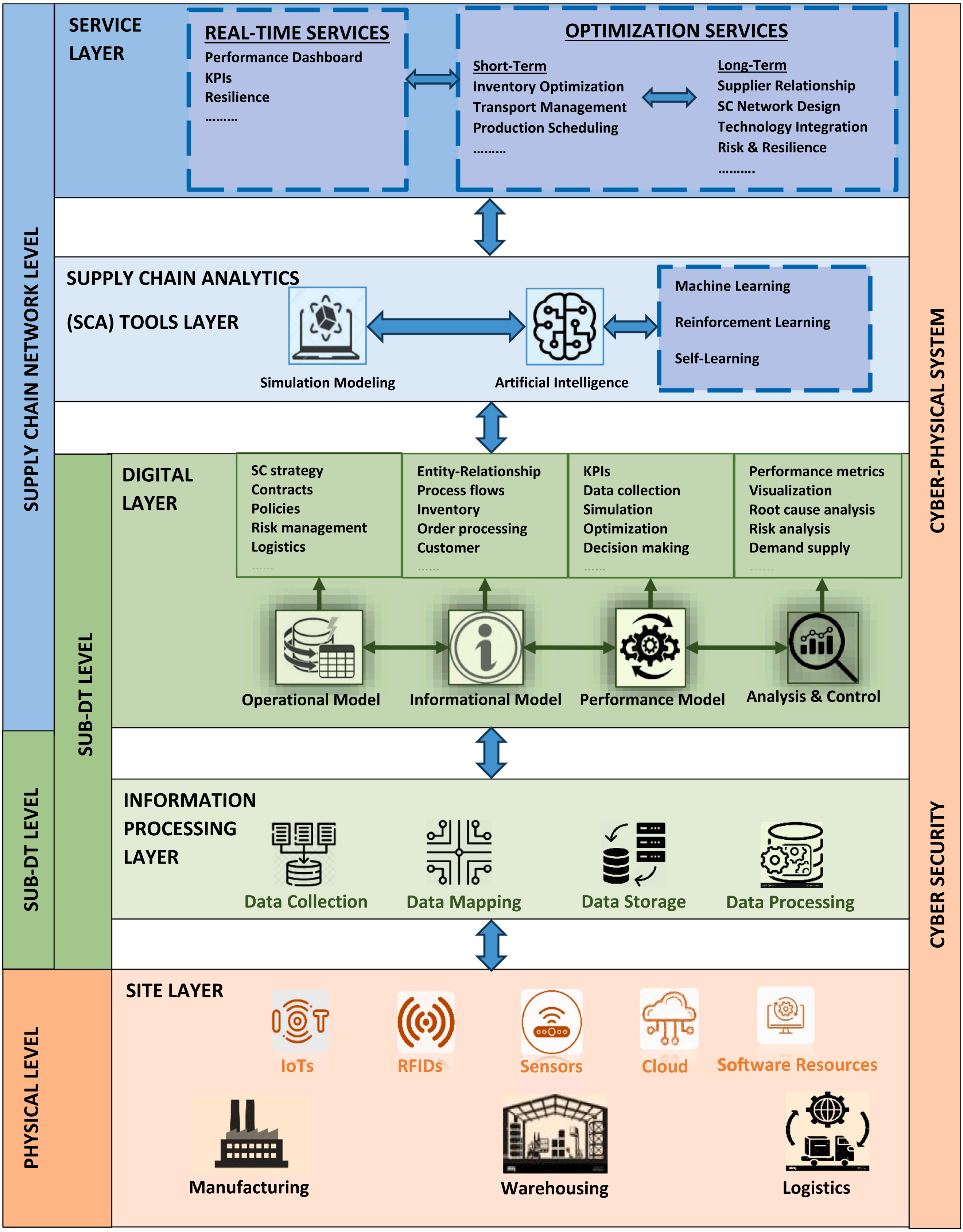

Fig. 10. Proposed Conceptual Framework for DT SCM.

Table 8
Various applications of some DT-enabled technologies in DT-frameworks.

IoT devices data collection	RFID data collection	Cloud computing models	Cybersecurity measures	CPS delivers
Environnemental (e.g., temperature, humidity, noise)	Authentication	Software as a Service (SaaS)	Data protection, malware, phishing protection	Convergence of physical and digital layers
Geographical (e.g., proximity, GPS, GIS, traffic status)	Timestamp	Platform as a Service (PaaS)	Security such as firewalls, encryption	Maintain Real-time synchronization
Industrial production (e.g., energy, operations, equipment health)	Identification	Infrastructure as a Service (IaaS)	Protect misuse of access privileges	Maintain Data-driven modelling
Utilization (e.g., patterns)	Locational	IoT services	Protect social engineering	Interoperable communication network
Security and surveillance	Sensor	Big data and analytics	Compliance on data and security regulations	Efficiency and optimization

instrumental in synthesizing data, strategies, and operational insights to optimize SC performance. The digital layer will be integrated with the physical layer with real-time interconnectivity to create a CPS interaction. The real-time interface will be developed with the help of enabled technologies such as IoT devices and cloud computing. This layer supports bidirectional data connectivity to create a DT. While creating a digital layer, detailing is required to establish the real-time connectivity and synchronization of each element in this layer for a SC system. Dynamic data collection from multiple sources in the physical layer and high-quality virtual modeling and simulation are the main attributes of the digital layer. A change in a physical state, updates automatically in the digital layer. Therefore, intelligent data connectivity is required to support an adaptive data-driven process consistently. The digital layer also attains capabilities to receive real-time data from local and cloud-based repositories. The architecture of this layer effectively manages the bidirectional flow of large amounts of information. A performance dashboard is proposed in this layer to provide continuous monitoring of the system's performance. This layer's primary functions are to support and maintain real-time operational data, ERP system updates, informational and performance analysis, monitoring, and control.

5.3.1. Operational model

It will define the process flow for SC operations, such as demand planning, strategic sourcing, and procurement. This model defines the main operational elements, particularly the SC strategy, policies, risk management, network design and sourcing/procurement, inventory management, and logistics. In addition, this model defines the interactions and processes between various SC elements and resources. It defines the roles and responsibilities of each element and identifies key strategies for the overall SC ecosystem.

5.3.2. Informational model

The informational model develops the data structure, supporting decision-making and data accuracy in SC. This model comprises product and supplier relationships, process flow, inventory, and order processing data. It holds order information from origin to customer. Informational models may have details such as.

a) Supplier information with product specifications and delivery schedules.
b) Resource location and utilization data.
c) Data storage from sensors and actuators.
d) Energy consumption data collection.
e) Information systems, such as ERP systems and product details with inventory levels and locations, means a complete database such as a Bill of Material (BOM).
f) Performance levels of various actors in SC such as entities, resources, locations and variables for progress tracking.
g) KPIs for performance analytics.

The KPIs lead the development of a dashboard for performance measurement in informational models. A performance dashboard with real-time data integration for KPIs can provide SC with an efficient decision support system.

5.3.3. Performance model

This model stores and provides a visual indication of the system's progress with respect to the identified and defined key metrics in the informational model. It will be based on a dashboard outlining and monitoring the system's real-time performance. Some examples of monitoring KPIs are as follows.

a) Order picking and fulfillment time and accuracy.
b) Supplier lead time.
c) Resource utilization.
d) Energy consumption.
e) Efficiency and overall productivity.
f) Flexibility and responsiveness

5.3.4. Analysis and Control

It supports the visual examination of performance metrics by identifying trends and control limits per the standards set to determine the difference between performance and goals. It provides statistical analysis, root cause analysis, and structured performance analysis. Any deviation will predict future scenarios, allowing implementation control measures to avoid failure and provide system resilience.

5.4. Supply chain analytics (SCA) layer

The proposed SCA analytics layer is pivotal in enhancing system resilience and optimizing performance for an SCM network. This layer receives real-time data from the digital layer. It performs digital analysis to support resilience using advanced tools such as simulation modeling, AI, ML, self, and reinforcement learning to interpret data and generate actionable insights. These technologies collectively optimize the SC by analyzing the system's current state and predicting future behaviors to counter disruptions. This prediction and optimization are facilitated by maintaining an uninterrupted real-time connection between the digital and SCA layers, ensuring efficient interconnectivity. The SCA layer extends its support for performance optimization, where it links with a real-time performance dashboard to monitor trends, patterns, and real-time performance metrics (KPIs) within the SC processes.

Moreover, integrating the SCM performance measurement system into the data analytics aims to comprehensively evaluate the overall SC performance, filling a notable gap in DT-based performance measurement. This layer's significance is magnified by the broad integration of digital technologies across SC, enabling extensive data collection and analytics. Such capabilities allow complex simulation modeling and dashboard analyses, contributing to DT performance measurement systems' effectiveness. Additionally, this layer is instrumental in improving quality and optimizing resources by providing performance data for scenario analysis, risk assessment, and predictive analysis, thus offering autonomous decision support. By providing a collaborative platform for real-time communication and continuous learning and adaptation. The SCA analytics layer cements itself as a critical component of the DT ecosystem, bringing enhanced resilience to SCM.

5.5. Service layer

The service layer within the SC network highlights its division into real-time services and optimization services. This layer is pivotal in enhancing the SC's operational efficiency and strategic adaptability.

5.5.1. Real-time services

The real-time services segment focuses on the SC's immediate operational needs. Following are some of the key features of the service layer.

- Performance Dashboard: This tool offers a real-time graphical representation of crucial metrics, enabling managers to monitor the SC health and quickly address any emerging issues.
- Key Performance Indicators (KPIs): These metrics are essential for assessing the operational success of the SC against pre-set strategic targets, providing a clear measure of performance.
- Resilience: This aspect emphasizes the ability of SC to anticipate, respond, and recover from disruptions promptly. Access to real-time data underpins this resilience, facilitating rapid decision-making to mitigate risks.

5.5.2. Optimization services

The optimization services are strategically split into some short-term and long-term initiatives. Short-term services are listed below.

- Inventory Optimization: Manages stock levels to balance demand fulfillment with cost-effectiveness, avoiding overstocking or shortages.
- Transport Management: Optimizes the movement of goods and materials to maximize efficiency and minimize costs.
- Production Scheduling: Aligns production activities with demand forecasts and resource availability to streamline operations.

Following are some long-term optimization services.

- Supplier Relationship Management: Aims to cultivate robust relationships with suppliers to secure a reliable SC and favorable procurement terms.
- SC Network Design: Strategic planning of the SC configuration to enhance performance and cost efficiency.
- Technology Integration: Incorporates cutting-edge technologies to bolster SC capabilities and operational efficiency.
- Risk and Resilience Planning: Focuses on identifying potential long-term risks and developing strategies to enhance the SC's overall resilience.

The interplay between real-time and optimization services enables a balanced approach to the SCM network, merging immediate data-driven actions with comprehensive strategic planning. This synergy is crucial for sustaining a competitive edge and ensuring a robust SC capable of navigating present challenges and future uncertainties.

5.6. DT performance benefits

This study identified the associated challenges in Table 6 and further provided the mapping of those challenges with DT technologies in Table 7. This assisted in developing the conceptual framework by focusing on the common DT enabling and data analytic technologies. The technological development in IoT, RFID, and smart sensors has brought the capability to communicate with large volumes of data. This is also significant for constructing a CPS system that embeds IoT devices to help bridge the physical system with digital models. Cloud computing can also be integrated with conventional systems to manage data quality and cybersecurity. DT is an extensive data-driven system with significant connectivity, high-quality data transfer, and compatibility. This is why interoperability plays a vital role between physical and digital models and DT, enabling data analytics technologies for real-time monitoring and synchronization. Simulation, AI, and ML have a high potential to provide analytical solutions for decision support, predictive analysis, and identification of disruptions. Data analytics can provide hybrid solutions for continuous adaptations to enhance SC performance. The provided conceptual framework can be implemented in SCM components such as warehouses. Physical systems can be embedded with real-time data collection devices, and information can be transmitted directly to a simulation modeling tool for real-time simulation to evaluate the system's performance. In addition, several processes such as order picking, Human-Robot Collaboration, and kitting can be assessed in real-time to identify the bottlenecks and make informed decisions.

6. Conclusion

This study presents a systematic literature review on the application of DT to evaluate the research methods used by the researchers and determine future research directions in DT SCM. This review shows significant growth in the development of DT systems for SCM, specifically during the last five years. The review findings are categorized (refer to Section 3) to understand the application of DT in various fields. This study attempted to answer three research questions (RQ1, RQ2, and RQ3) by identifying the common DT-enabled technologies, data analytics techniques, and main challenges in DT integration. Finally, the review proposes a novel conceptual framework for a fully integrated DT for SCM applications, which capitalizes on the foundation of SCM DT based on previous sub-DT systems. Following are the responses to all three research questions:

RQ1) What are the common DT-enabled technologies and data analytics techniques used for DT integration to enhance SC performance?

This study reviewed the emerging DT-enabled technologies and data analytics techniques addressed in manufacturing, production, SC, and logistics. The qualitative analysis in Section 3.2 and Table 6 identified the common technologies discussed by various scholars in DT integration. This study recognizes IoT, RFID, cloud computing, CPS, and CS as the most enabled technologies. Further, this review determines that simulation modeling, AI, ML, and NN were common data analytics techniques in DT integration. Simulation modeling is the most widely used data analytics reported in this study.

RQ2) What are the common challenges associated with integrated DT for SCM, and how could those challenges be addressed?

In response to RQ2, this review outlined the main challenges in DT integration, as stated in Section 4. Table 6 summarizes these challenges involving interoperability, data-driven modeling, real-time synchronization, and ERP integration. Based on the analysis, a fully integrated DT in SCM with a data-driven and synchronization approach can enhance SC performance. However, a fully integrated DT is a complex reproduction of a physical system in a CPS environment. A mapping is provided in Table 7 to address these challenges for an integrated DT in SCM.

RQ3) How can a conceptual framework for DT SCM be developed with DT-enabled technologies and data analytics by overcoming associated challenges for better SC performance?

In addressing Research Question 3 (RQ3), this study delineates a comprehensive conceptual framework for integrating DT within SCM, as detailed in Section 5. This integration is pivotal, offering a unique capability for real-time operational monitoring and the ongoing evaluation of SC process performance. The framework supports a decision-support model that operates effectively at decentralized levels, reflecting the complexities and dynamic nature of modern SCM. The proposed framework merges the functionalities of prevalent DT-enabled technologies with advanced data analytics techniques to address the primary challenges SCM systems face today.

Central to the framework is the sub-DT network (DT for SCM) principle, coupled with data-driven modeling techniques aimed at refining and optimizing the multifaceted functions inherent in SCM operations. Furthermore, the discourse within the framework extends to the critical issue of interoperability among the various hardware and software components that constitute an integrated DT system. This aspect is essential for facilitating seamless real-time communication across the diverse layers of DT integration, ensuring that data flows efficiently and actions are coordinated across the entire SC network. Thus, this framework proposes not just a theoretical model but a pragmatic approach designed to enhance SCM's resilience, efficiency, and adaptability through the strategic application of DT technologies.

6.1. Theoretical contribution

The theoretical aspect of this review is to answer some fundamental questions, such as why this review was necessary and if the qualitative analysis presented in this review comprehends the research questions. This review's qualitative analysis contributes to exploring DT integration by identifying the common components of DT architecture. Moreover, the qualitative analysis provides an understanding of the complex structure of DT embedded with technologies and its associated challenges. This review provides an all-important theoretical scientific study with a guided conceptual framework for a DT SCM system development.

6.2. Implications

This review outlines the significant implications of DT in SCM systems by providing real-time performance monitoring and optimization. Several researchers addressed this significance and provided conceptual frameworks. However, this review first identifies the common DT-enabled technologies and data analytics techniques. Then, it addresses the main challenges to overcome before establishing a fully integrated DT for improved performance. This review's attempted proposed conceptual framework comprehends the enhanced performance for overall SCM. It gives managers a realization of applications of enabled technologies and data analytics for a decentralized decision support model. This study also identifies the significance of hybrid data analytics combining simulation technology with AI and ML algorithms. The framework also recognizes the potential of technology integration to improve SCs. It gives managers a realization of applications of enabled technologies and data analytics for a decentralized decision support model. Increased visibility of operations allows real-time tracking and monitoring that helps identify predictions ahead of the event. Moreover, better risk management can be planned for efficient operations and optimization. DT is also significant in providing customized SCs based on the market demand and needs. An enhanced integrated DT connected with external suppliers and resources can create a synchronized collaborative environment for dynamic processing to adjust fluctuations and mitigate risk on time. Further, continuous improvement and refinement of operations at each level offer better responsiveness in the SCs.

6.3. Future research direction

Based on the systematic literature review findings, multiple future research opportunities exist; few are highlighted in this section.

a) The proposed framework in this review stated various important components of DT. A future aspect is to validate the proposed framework with industry experts. This will allow further refinement by incorporating real-world experience with enhanced applicability. In addition, this study identified five future research directions (Table 9) to comprehend the impact of Industry 4.0 technologies in transforming SCM systems in DT integration.
b) Another future direction of this study is to test the framework with a real case study. The lack of empirical testing needs to be addressed for validation. A proposed DT architecture must be constructed with enabled technologies in a SC setting to capture the dynamic nature of the framework. Assessing how various technologies can converge to build a digital environment for a physical SC system is important. Then, the application of selected data analytics, such as simulation modeling, AI, or a combination of multiple data analytics, will be tested to identify the applicability for enhanced SC performance.

Table 9
Future research directions.

Research direction	Specific topics
Integration of Cyber-Physical system	• High volume of data synchronization through various devices and entities in internal and external resources of the system. • Integration of IoT devices, sensors, simulation, data analytical models for real-time decision support. • Interoperability challenges to address heterogeneity due to the use of diverse technologies and standards. • Cybersecurity and privacy to maintain secure communication networks.
Data analytics for DTs	• Specialized data infrastructure to use Big Data analytics for processing of large amount of data. • Role of Industry 4.0 technologies such as simulation, AI, ML, NN in processing data analytics in complex infrastructure. • Role of hybrid simulation modeling in quality data analytics for complex systems.
Simulation modeling in DTs	• Integration of simulation tools with DT-enabled technologies such as IoT, cloud computing for real-time data-driven modeling. • Real-time decision support and optimization for various SCM application.
Cognitive digital twins (CDT)	• Explore CDT architecture and framework for SCM with the help of Industry 4.0 technologies.
Human-Centered Approach Industry 5.0 and Sustainability	• Focused approach and conceptualization on human cantered Industry 5.0 to expedite more research on HMI and human social factors. • Impact of collaborative technologies in SCM in various dimensions such as social factors, human factors, sustainability, and transformation. • Impact on economic, social, and environmental performance goals for SC sustainability.

Although this research offers diverse contributions, it also highlights some limitations. Firstly, the authors may have introduced some bias by selecting specific studies related to DTs in SCs and potentially missing out on related studies during the search process. Moreover, the authors may have inadvertently excluded relevant studies or included studies that align with their preconceptions during the selection process.

Secondly, the paper focuses on "Unlocking the Potential of Digital Twins in Supply Chains," which is considered a system view. Therefore, the proposed framework may not be generalizable to other specific domains with less complexity, such as object/process twin, where we require a digital representation of a basic part or component/process within a system. Similarly, the framework may not be applicable in domains that have high complexity, where multiple system/process twins operate in a business-defined environment. In such cases, modeling the highest order of systems is necessary to provide a macro-view of the environment.

CRediT authorship contribution statement

Amin Chaabane: Validation, Supervision, Project administration. **Sharfuddin Ahmed Khan:** Validation, Supervision, Project administration, Conceptualization. **Syed Adeel Haneef Zaidi:** Writing – review & editing, Writing – original draft, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table 5b
Miscellaneous Conference Name

S. No.	Miscellaneous Conference Name	No. of Papers
1	IEEE International Workshop on Factory Communication Systems (WFCS)	1
2	11th CIRP Conference on Industrial Product-Service Systems	1
3	2018 International Conference on Smart Grid and Electrical Automation	1
4	23rd International Conference on Control Systems and Computer Science	1
5	2nd International Conference on Applied Mathematics, Modelling, and Intelligent Computing	1
6	3rd International Conference on Industry 4.0 and Smart Manufacturing	1
7	45th SME North American Manufacturing Research Conference	1
8	4th World Conference on Mechanical Engineering and Intelligent Manufacturing (WCMEIM)	1
9	53rd CIRP Conference on Manufacturing Systems	1
10	6th International Conference on Smart Sustainable Technologies	1
11	8th International Conference on Information Technology and Quantitative Management	1
12	IEEE International Conference on Model Driven Engineering Languages and Systems Companion	1
13	IEEE Transactions on Cybernetics	1
14	IEEE Transactions on Engineering Management	1
15	IFIP International Conference on Advances in Production Management Systems	1
16	International Conference on Industrial Engineering and Engineering Management IEEM	1
17	International Symposium on System Integration (SII)	1
18	Proceedia Manufacturing	1
19	Springer Nature 8th International Conference LDIC 2022	1
	Total	19

x = Discussed

Appendix B

Table 6
DT enabling technologies and data analytic techniques

References	Focused Area	DT Enabling Technology					Data Analytics					Implications		
		IoT	RFID	Cloud	CS	CPS	Sim.	NN	AI	ML	Num.	Manufacturing Performance	SC Performance	Logistics Performance
[144]	Framework	x	x	x	x	x	x		x	x			x	
[69]	Simulation Modelling	x			x	x	x					x		
[134]	Resilient SC and I4.0 Technologies	x	x	x	x	x	x	x	x	x			x	
[82]	CPS integrated DT	x	x			x	x					x		
[169]	DT predictive diagnosis Elman-IVIF-TOPSIS	x	x			x	x			x		x		
[109]	DT warehouse optimization	x	x				x			x				x
[111]	Cold chain transportation	x	x	x						x				x
[138]	DT supply chains	x	x	x		x	x		x	x			x	
[136]	Sustainable supply chains	x	x	x		x	x						x	
[80]	Real-time synchronization	x	x			x	x					x		
[57]	DT-Framework	x	x			x	x					x		
[79]	AI based DT Framework	x	x			x	x		x	x		x		
[52]	Digital lean framework	x				x	x					x		

(continued on next page)

Table 6 (*continued*)

References	Focused Area	DT Enabling Technology					Data Analytics					Implications		
		IoT	RFID	Cloud	CS	CPS	Sim.	NN	AI	ML	Num.	Manufacturing Performance	SC Performance	Logistics Performance
[88]	Intelligent monitoring & control framework	x	x			x			x	x		x		
[91]	Intelligent manufacturing	x	x	x		x	x		x	x		x		
[58]	Data-driven approach	x		x		x	x					x		
[92]	DT & virtual reality framework	x	x	x		x	x		x			x		
[120]	Autonomous mobile robots					x	x							x
[170]	Resource allocation framework	x	x	x		x	x					x		
[53]	Industry 5.0	x	x	x		x	x		x	x		x		
[137]	Zero-waste value chains	x	x	x		x	x		x				x	
[171]	Knowledge-based system	x				x	x		x			x		
[93]	Industry 5.0	x	x	x	x	x	x	x	x	x	x	x		
[94]	Framework to monitor human skills	x				x	x					x		
[70]	Multi-agent-based modeling	x	x			x	x		x			x		
[74]	Framework on autonomous production	x	x			x	x		x	x		x		
[127]	Cognitive DT	x	x	x		x	x		x	x		x		
[121]	Smart warehouse	x	x			x	x		x	x				x
[115]	Data-driven approach	x	x			x	x							x
[123]	Simulation modeling	x					x			x				x
[96]	Real-time simulation	x	x	x		x	x		x	x		x		
[172]	Smart production					x						x		
[89]	DT framework					x						x		
[173]	Smart production	x				x						x		
[75]	CPS framework	x	x	x		x				x		x		
[174]	DT flexible production					x	x					x		
[67]	DT Flexible Manufacturing System	x	x	x		x	x		x	x		x		
[86]	DT integrated monitoring	x	x			x						x		
[85]	Industry 4.0 Technologies	x	x	x	x	x	x		x	x	x	x		
[64]	CPS integrated DT	x	x		x	x	x			x		x		
[87]	Industry 5.0	x	x	x	x	x	x	x	x	x		x		
[84]	CPS integrated Production Monitoring	x	x	x		x				x		x		
[175]	DT Flexible Manufacturing System	x		x			x		x	x		x		
[104]	Intelligent Transportation	x		x					x					x
[145]	DT Implementation and Technology	x		x	x	x	x			x			x	
[90]	Functional based modelling	x	x	x	x		x		x	x		x		
[59]	Conceptual Framework						x				x	x		
[18]	Framework	x	x			x	x		x	x		x		
[77]	CDT framework		x		x	x	x	x	x		x	x		
[65]	Reinforcement learning DT	x	x				x	x		x		x		
[60]	DT reconfigurable manufacturing	x	x			x	x		x	x		x		
[176]	Self-learning cognition	x					x			x		x		
[139]	Framework			x			x		x	x			x	
[131]	Emerging technologies	x		x		x	x		x	x			x	
[151]	Mapping & optimization	x	x	x			x				x		x	

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Table 6 (*continued*)

References	Focused Area	DT Enabling Technology					Data Analytics					Implications		
		IoT	RFID	Cloud	CS	CPS	Sim.	NN	AI	ML	Num.	Manufacturing Performance	SC Performance	Logistics Performance
[153]	Simulation modelling	x			x		x						x	
[130]	Investigated Industry 4.0 challenges	x	x	x	x	x	x	x	x	x			x	
[29]	Simulation modelling		x				x				x		x	
[177]	DT implementation	x				x	x		x	x			x	
[148]	DT implementation	x	x			x	x						x	
[97]	Sustainable logistics	x	x	x	x	x	x		x	x				x
[99]	CPS integrated DT					x	x		x	x				x
[129]	Decision-making DT platform	x				x	x	x	x	x				x
[102]	Synchronization	x	x	x	x	x	x	x		x				x
[112]	Concept of intelligent container	x	x				x				x			x
[149]	Proposed DSTKG	x	x	x		x	x	x		x				x
[157]	Ecosystem for FMS					x	x		x	x				x
[178]	ADR methodology.	x		x		x	x		x	x				x
[125]	Investigated simulation	x				x	x							x
[179]	Data-driven DT framework	x	x			x	x	x	x			x		
[121]	Implementation of CDT operational model	x	x	x		x	x	x	x	x			x	
[61]	DT automated manufacturing system	x	x			x	x			x		x		
[143]	DT manufacturing shop floors	x	x				x		x			x		
[180]	DT Implementation	x		x			x			x				x
[142]	Blockchain empowered DT	x	x	x			x		x	x				x
[144]	IoT applications in smart logistics	x	x	x	x	x			x					x
[145]	Food logistics 4.0	x	x	x	x		x		x	x				x
[147]	DT for fresh horticultural produce	x	x			x	x							x
[15]	5D framework	x	x	x	x	x	x	x	x	x		x		
[51]	5D framework	x	x							x		x		
[55]	Optimize production line	x	x			x	x			x		x		
[71]	Universal CPS system	x	x		x	x						x		
[87]	4 layered framework	x	x	x	x							x		
[11]	Investigated CDT vision		x		x	x	x	x		x	x	x		
[46]	Automate DT process	x					x		x	x		x		
[51]	Simulation modelling			x			x		x				x	
[162]	Framework	x	x	x		x	x		x	x			x	
[119]	Emerging technologies	x		x		x	x		x	x			x	
[114]	Real-time integration	x	x	x		x	x		x	x			x	
[121]	Cognition modelling		x			x		x		x	x		x	
[131]	DT platform			x		x	x		x	x				x
[133]	DT platform	x	x		x		x		x	x	x			x
[135]	Data-driven DT with simulation	x		x			x			x	x			x
[36]	Framework	x	x		x		x							x
[103]	DT framework	x	x											x
[150]	DT framework	x		x		x	x				x			x
[155]	Intelligent workshop	x					x							x
[160]	Simulation based framework	x		x		x	x				x			x
[13]	Digital model for a physical testbed	x	x	x		x	x				x			x
[152]	CPS performance monitoring	x		x		x	x				x			x
[61]	Simulation modelling	x					x					x		
[4]	Hybrid simulation	x	x	x	x	x	x		x	x		x		
[74]	DT personalized manufacturing	x				x	x					x		
[56]	Autonomous manufacturing	x	x			x				x		x		
[72]	Web-based DT	x	x			x	x					x		

(*continued on next page*)

Table 6 (*continued*)

References	Focused Area	DT Enabling Technology					Data Analytics					Implications		
		IoT	RFID	Cloud	CS	CPS	Sim.	NN	AI	ML	Num.	Manufacturing Performance	SC Performance	Logistics Performance
[151]	6 layered framework	x	x	x	x	x	x		x	x			x	
[17]	Synchronization	x					x						x	
[156]	Physics modelling	x	x	x			x			x	x		x	
[107]	IoT-enabled framework	x		x	x		x	x	x	x	x			x
[118]	Synchronization framework	x		x		x	x							x
[36]	Simulation modelling		x			x	x					x		
[25]	5D framework					x	x					x		
[102]	Framework	x	x				x					x		
[19]	Framework	x				x	x					x		
[75]	Flexible framework	x	x			x	x				x	x		
[157]	Physics modelling	x	x	x			x			x	x		x	
[71]	Cybersecurity in CPS integration	x	x		x	x	x					x		
[143]	Simulation modelling	x	x				x						x	
[149]	Neural network framework	x	x					x					x	
[69]	Shop management system	x	x	x		x	x			x		x		
[16]	Cyber physical manufacturing	x	x				x					x		

Table 7
Common challenges in DT integration

Cat.	References	Challenges			
		Interoperability	Data-driven	Real-time synchronization	ERP integration
Manufacturing and Production	[88]		x	x	
	[90]	x		x	
	[55]	x		x	
	[66]		x		
	[57]		x		
	[84]		x	x	
	[64]		x	x	
	[96]		x	x	
	[98]		x	x	
	[58]		x	x	
	[99]		x	x	
	[52]		x	x	
	[53]		x	x	
	[95]		x	x	
	[100]		x	x	
	[101]		x	x	
	[89]		x	x	
	[67]		x	x	
	[135]		x	x	
	[103]		x	x	
	[77]		x	x	
	[97]		x	x	
	[78]		x	x	
	[68]		x	x	
	[79]		x	x	
	[63]		x	x	x
	x = Discussed [93]	x			
	[92]	x	x	x	x
	[62]	x	x	x	
	[94]	x	x	x	x
	[91]		x	x	
	[65]		x	x	
	[80]		x	x	
	[85]		x	x	
	[20]		x	x	
	[87]	x	x	x	x
	[73]			x	x
	[83]	x	x	x	x
	[23]	x	x	x	x
	[76]	x	x	x	
	[60]		x	x	

(*continued on next page*)

Table 7 (*continued*)

Cat.	References	Challenges			
		Interoperability	Data-driven	Real-time synchronization	ERP integration
	[146]		x	x	x
	[14]		x	x	x
	[50]		x	x	x
	[54]		x	x	
	[70]				x
	[86]		x	x	x
	[61]		x		
	[18]	x	x	x	x
	[59]			x	x
	[74]	x		x	x
	[56]		x	x	
	[72]	x		x	x
	[4]	x	x	x	x
	[36]	x		x	
	[25]		x	x	
	[102]	x			
	[19]	x	x	x	
	[75]			x	x
	[71]		x	x	
	[69]			x	
Supply Chain	[147]	x	x	x	x
	[153]	x	x	x	x
	[154]	x	x	x	x
	[148]	x	x	x	
	[138]		x	x	
	[139]		x	x	
	[140]		x	x	x
	[15]	x	x	x	
	[174]	x	x	x	
	[160]		x	x	x
	[136]	x	x	x	
	[31]		x	x	
	[137]		x	x	
	[155]		x	x	
	[152]	x	x	x	x
	[30]		x	x	x
	[169]	x	x	x	x
	[150]	x	x	x	
	[145]	x	x	x	x
	[151]		x		
	[17]		x	x	x
	[156]	x	x	x	
	[157]	x	x	x	
	[143]		x	x	
Logistics	[117]			x	
	[120]	x	x	x	
	[127]		x	x	
	[128]		x	x	
	[122]		x	x	
	[130]		x	x	
	[115]		x	x	x
	[104]	x	x	x	x
	[108]		x	x	
	[110]		x	x	
	[112]	x	x	x	
	[114]	x	x	x	
	[123]		x	x	
	[131]			x	
	[133]	x	x	x	x
	[132]		x	x	
	[111]	x	x	x	
	[116]	x	x	x	
	[118]	x	x	x	
	[119]		x	x	x
	[121]	x	x	x	
	[105]		x	x	
	[107]	x	x	x	
	[109]		x	x	x
	[35]	x	x	x	x
	[113]		x	x	
	[124]	x	x	x	
	[129]		x	x	
	[134]		x	x	x
	[12]	x	x	x	

(continued on next page)

Table 7 (*continued*)

Cat.	References	Challenges			
		Interoperability	Data-driven	Real-time synchronization	ERP integration
	[126]	x	x	x	
	[106]		x	x	
	[125]		x	x	

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