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Unveiling the potential of digital twins in logistics and supply chain management: Services, capabilities, and research opportunities

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ABSTRACT

Logistics is a labor- and asset-intensive industry, characterized by numerous operational processes managed by heterogeneous partners, which are tightly interconnected. Maximizing resource utilization and ensuring efficient stakeholder coordination within logistics operations pose significant challenges. Recently, Digital Twin (DT) technology has gained increasing interest for its potential to enhance asset and operations management in logistics. However, few studies offer a comprehensive view of DT applications across end-to-end global logistics services, particularly in relation to service innovations and the technological maturity of different service types. This paper conducts a Systematic Literature Review (SLR) to explore the state of the art in DT applications in logistics, offering an in-depth understanding of recent research foci, advancements, and opportunities for service innovation. Following the screening process, 70 papers were selected and analyzed. A three-axis framework is used to categorize key aspects of effective DT application, focusing on application areas, service types, and technological maturity as measured by the Technology Readiness Level (TRL). In logistics operations, DT has the potential to innovate or enhance eight key services: *Monitoring, Evaluation, Prediction, Optimization, Control, System Management, System Integration*, and *Adaptation*. DTs must be proficient in five core capabilities to deliver these eight services: *integration, computation, simulation, interoperation,* and *evolution*. In terms of DT technology maturity, most research focuses on early-stage development, emphasizing conceptual frameworks and exploring potential services. While many studies have tested proposed DT services in simulated environments, only a few have evaluated them in real-world operational settings. Finally, research avenues are explored, providing valuable insights for future investigations and continued development of DT applications in logistics and supply chain management.

1. Introduction

The Digital Twin was first introduced in the aerospace industry. Since the 1960s, NASA (The National Aeronautics and Space Administration) has applied this concept in space missions to create virtual replicas of physical systems, as demonstrated during the Appollo 13 mission [3]. More recently, along with the development of data acquisition technology (e.g., Internet of Things (IoT)/Information and Communications Technology (ICT)), data analytics technology (e.g., cloud computing, big data, Artificial Intelligence), and simulation technology, the concept of DT has evolved considerably. This advancement has made DT more powerful and impactful across various industries, particularly in manufacturing and production under the Industry 4.0 paradigm [43, 82]. For instance, Tao and Zhang [85] proposed a DT-based shop floor to study the convergence of the physical and virtual spaces, enhancing operations and manufacturing processes. Zhang et al. [104] proposed a DT-based approach merging system modeling and real-time data processing to generate individualized production line designs, thus enabling analysis capabilities to make decisions regarding system design and solution evolution. Beyond their application in manufacturing, where digital twins are often viewed as single systems, Jones et al. [32] emphasized the integration and interaction of multiple virtual entities, where data shareability and accessibility are the key points. They argued that this would increase the potential of DT operations in a broader system to achieve shared objectives through collaboration among multiple stakeholders.

DT research has extended its applications to other fields, including the emerging Logistics and Supply Chain Management (LSCM) field.

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Ivanov et al. [29] were among the first to propose the concept of the Digital Supply Chain Twin as a virtual representation of the network state for any given moment to predict problems resulting from disruption and anticipate responsive solutions. The importance of DTs has been highlighted during the COVID-19 pandemic, which revealed their potential to assess supply chain (SC) performance and predict short-term and long-term impacts. To fully leverage these advancements, digitalization is a prerequisite and has been a significant focus of research and implementation in recent years. Digital twins represent a step beyond digitalization, focusing on how to create value in a digitalized supply chain through enhanced capabilities and service innovation. Despite these advancements, there remains a shortage of comprehensive studies exploring how DT could enhance end-to-end global logistics, particularly in identifying which services DT technology can provide across different segments of LSCM. Hence, this review aims to provide a thorough understanding of DT applications in logistics and supply chain management and highlight future research directions. Specifically, this paper will address the following research questions:

Research Question 1 (RQ1). *What are the twinning objects of the digital twin technology in LSCM?* This question identifies the fields where physical twins operate alongside digital twins, i.e., **areas of application** of DT in LSCM.

Research Question 2 (RQ2). *What value can digital twins provide in logistics and supply chain management?* This question explores **DT-enabled services** in LSCM, addressing the diverse needs and characteristics of the field. It should be noted that these services include not only traditional logistics services in the physical space but also services in the digital space. This question expands DT's application beyond the traditional focus on manufacturing.

Research Question 3 (RQ3). *What is the maturity level of digital twin technology in various LSCM application areas?* This question assesses **the maturity of digital twin technology** in various LSCM areas using the Technology Readiness Level, exploring both challenges and opportunities for development and application.

The proposed three research questions are addressed by reviewing previous literature from multiple dimensions. A systematic literature review is an appropriate approach for this research. It allows for accurate retrieval and synthesis of prior research within a defined domain, evaluating their eligibility based on clearly defined criteria. After screening and filtering, the dataset allows for detailed analysis, yielding more precise results and a clearer perspective for future researchers. Hence, a SLR methodology was applied in this review to comprehensively examine existing studies relating to the RQs [17,60]. Furthermore, a three-axis framework was developed to analyze a dataset of 70 selected papers in-depth. Expert analysis was employed to gain insights and to outline the key capabilities of digital twins necessary to deliver the targeted services and identify future research directions.

The paper is organized as follows: Section 2 introduces the research methodology and the processes for processing the analysis dataset. Section 3 presents the preliminary results from keywords co-occurrence analysis, and the in-depth findings using the three-axis analysis framework. Section 4 discusses the core DT capabilities required to deliver innovative services and outlines future research directions. Finally, Section 5 provides the conclusions of the study.

2. Methodology

The systematic literature review methodology has been widely used to analyze LSCM literature [17,62,93]. This approach is primarily used to answer the three research questions in detail and provide insights into the research directions, conceptualized as positioning research within a three-axis framework. However, the degree scale of each axis is not clearly defined. To mitigate subjective bias in defining axes manually, an additional method, keywords co-occurrence analysis, is employed. This approach identifies frequently occurring keywords, refines the scale of each axis and informs the development of the in-depth analysis framework in SLR. Fig. 1 shows the steps comprised in the research methodology.

The first step is to define the research problem and questions for the review, i.e., the three RQs outlined in the introduction. The next step is to define the relevant keywords (based on the RQs) to query in databases. *Scopus, Web of Science*, and *ProQuest* are most used in the literature review, were selected as data sources. We defined the keywords for the database queries based on the conceptualized classic manufacturing supply chain (Fig. 2). We initially used a combination of *"digital twin*"* with *"logistics"* or *"transport*,"* where the asterisk was applied to include all synonyms. The first results showed many papers related to manufacturing and warehousing, which are part of intralogistics in the broad sense. We then updated the keywords and used "*digital twin*" plus "logistics" or "transport*" or "warehouse*" or "intralogistics" or "supply chain*" or "last-mile*" or "urban freight*"* in the query. All papers published before February 2024 (the query date) were included to ensure comprehensive coverage of related research. As a result, 558 papers were found for screening.

The next step involved setting exclusion and inclusion criteria to filter out irrelevant papers. The article type was limited to journal publications in English. After removing the duplicate papers from these three databases, 139 papers remained. We then evaluated the relevance of the papers based on the full text of the articles to check their eligibility. Seventy papers were finally retained for the preliminary and in-depth analysis. The preliminary analysis will access the keyword co-occurrence using the software VOSviewer[1], which visualizes bibliometric networks. The clustering results of the author keywords help identify the research streams and trends, refining the analytical framework. In the in-depth analysis, the literature will be categorized according to the predefined framework to identify areas of application, DT-enhanced services, and three levels of DT maturity. Finally, the analysis will outline the digital twin capabilities required to support these applications and propose research directions to guide future studies on digital twin applications in logistics and supply chain management.

3. Literature analysis

LSCM creates value by leveraging assets, facilities, workers, and operations, all of which can be considered physical counterparts that need to be digitally replicated and efficiently managed. Asset management and operations management are key areas where DTs offer potential for enhanced management through digital modeling. The first step is to categorize the application areas where DTs can unlock their full potential. However, identifying applications alone is insufficient; practitioners and researchers must also understand the specific roles that DTs play in these areas. This question is addressed through the second axis, which refines the specific activities DTs can support in different scenarios. The eight services outlined, inspired by digital twin-driven product services [49], have been adapted to address the specific needs of logistics. To assess the limitations and potential of DTs in LSCM, Technology Readiness Levels are used to evaluate their maturity. TRL, originally consisting of nine levels, was simplified to three levels by Wang and Wang [91] to better classify robotic technologies. We adopt this three-level classification for our analysis. This framework serves as a robust scaffold for a detailed analysis of digital twin development in LSCM, providing insights into future research avenues.

[1] https://www.vosviewer.com/

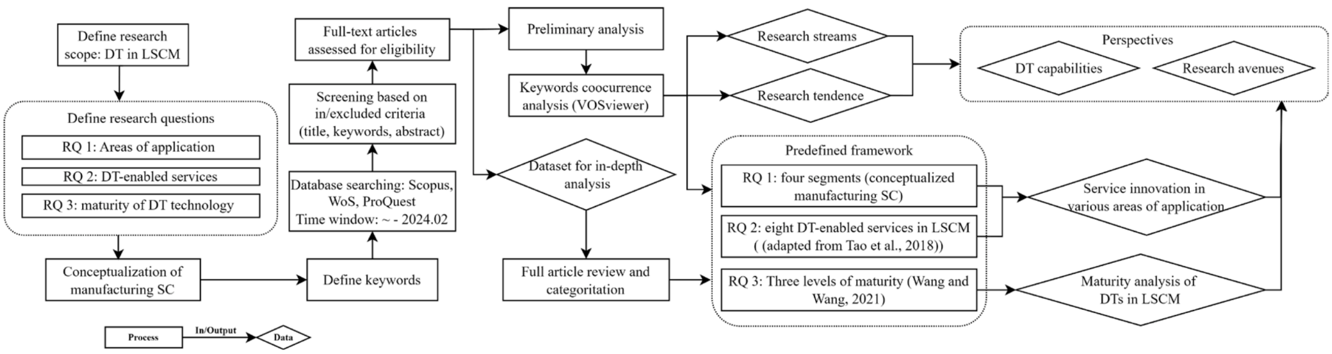

Fig. 1. The methodology applied in this work to address the research questions.

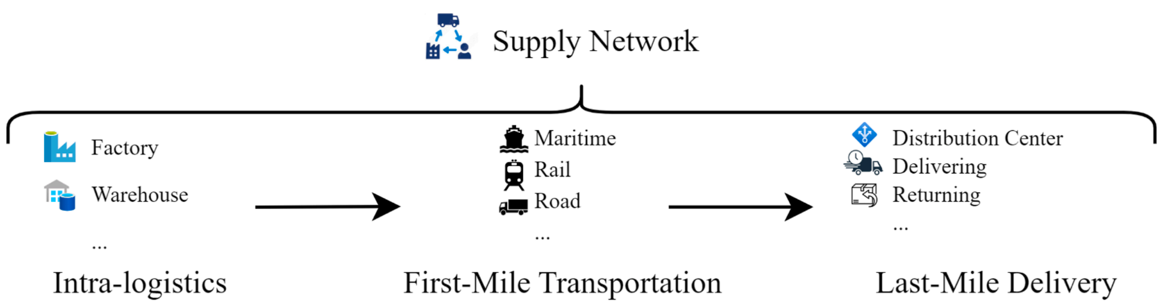

Fig. 2. Conceptualized processes of the manufacturing supply chain to initialize the literature search.

3.1. *Preliminary analysis*

At the beginning of the analysis, a snapshot of the literature will be obtained through the keywords co-occurrence analysis using VOSviewer software. This analysis helps identify research streams through keyword clustering and tracks the evolution of studies by analyzing trends over time.

Five clusters in total have been identified (Fig. 3). The first and third clusters focus on the application of digital twins in manufacturing. The first cluster shows that various technologies and algorithms have been implemented to innovate the system with multiple characteristics, such as cyber-physical, interactive, real-time, etc. Simultaneously, elements such as human resources have been considered to support the production logistics. The third cluster emphasizes the influence of technological advancements in Industry 4.0 on production. As a result, the production system can be better monitored and controlled, where sustainability is a vital objective of this advanced system. The second cluster focuses on adopting cutting-edge technologies, such as artificial intelligence and smart city-enabling technologies, to enhance intelligent systems capable of predicting and proactively managing dynamic stochastic

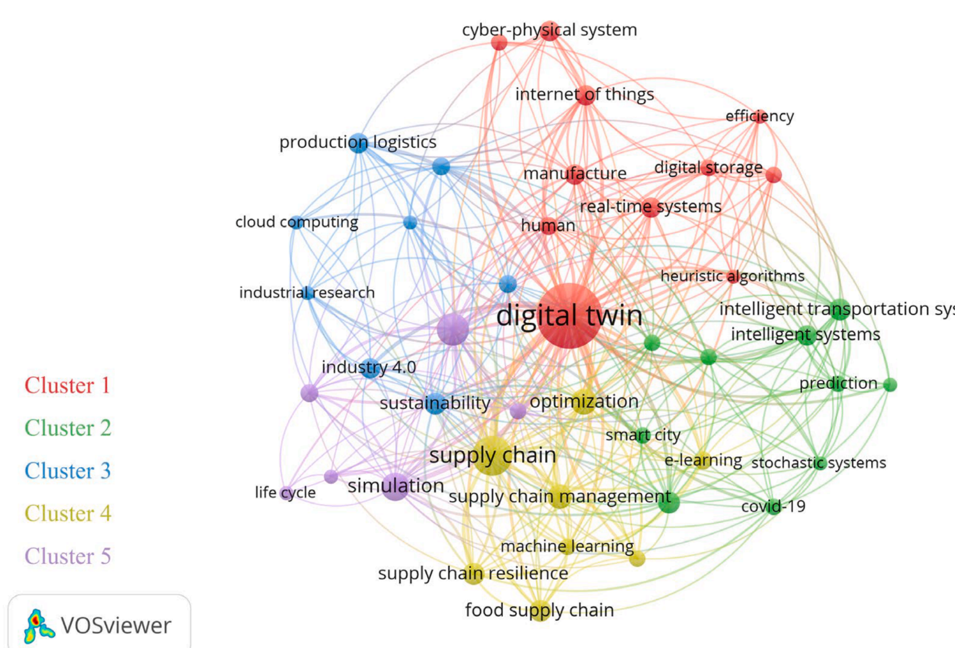

Fig. 3. Network visualization of the clustered keywords (co-occurrence more than three times).

environments. The fourth cluster examines the digital and resilient supply chain, where machine learning and optimization algorithms are employed for analysis and accurate prediction. The food supply chain, characterized by fragility and time sensitivity, has gained increasing attention in recent research. The fifth cluster focuses on simulations, combined with augmented reality technologies, to support real-time decision-making based on the lifecycle evolution of digital twins. The list of the keywords in each cluster has been presented in Table 1.

Research trends were identified by analyzing two primary groups of keywords: those from 2023 (highlighted in yellow in Fig. 4) and the latter half of 2022 (highlighted in light green). Regarding the technologies, blockchain and artificial intelligence, specifically machine learning and deep learning, have received increasing attention. Blockchain is primarily used for data storage security, while AI technologies, particularly machine learning and deep learning, aim to derive value from big data-trained models and support complex decision-making. Regarding the supply chain, digitalization, resilience, and sustainability are the primary relevant aspects. The advancement of various technologies, including ICT and IoT, has accelerated the digitalization of the supply chain. In the post-pandemic era, the importance of supply chain resilience has been well-recognized and has gained increased research interest. It includes predictive risk detection and the capacity for quick response and recovery from disruptions. The third trend centers around intelligent systems and the role of human intervention within those systems. Key topics include Intelligent Transportation Systems (ITS) and Human-Robot Collaboration (HRC). HRC explores how humans and machines collaborate to complete tasks, their respective roles, interactions, and the safety of their shared environment. Real-time systems are emphasized, as process control systems and robotics in production are closely linked to this technology.

3.2. In-depth analysis

The preliminary analysis highlights key research areas of DTs in LSCM through keyword co-occurrence analysis. However, this overview lacks the depth needed to inform future studies, requiring further details to clarify the current research landscape and identify potential research avenues.

3.2.1. Framework definition

This section presents specific cases from the dataset and provides an in-depth analysis of DT applications in LSCM. This part of the work aims to identify where DTs come into play (areas of application), the role they perform (service types), and the advancement of their role (Technology Readiness Level). These insights offer researchers and practitioners a clear understanding of the potential and functions of DTs in LSCM, supporting further development, implementation, and value creation.

3.2.1.1. Areas of application. The four primary areas of application are defined based on the typical manufacturing supply chain, with Fast-Moving Consumer Goods (FMCGs) as one example. The four coarse-scale graduations along this analytical axis are based on material flows, including transportation (*first-mile transportation* and *last-mile delivery*), temporary storage or on-site handling (*intralogistics*), and the *supply network* as a whole. The finer graduations corresponded to the co-occurring keywords described in Section 3.1.

Regarding transport, global or local logistics and supply chains can be segmented into two legs: *First-Mile Transportation (FMT)* and *Last-Mile Delivery (LMD)*. Here, we define FMT broadly as the transportation of goods during the first leg of the supply chain, from the origin (e.g., factory) to an intermediate stop (e.g., transit warehouse or distribution center) before delivery to the final destination. FMT is directly followed by LMD. It is also known as city logistics or urban freight distribution, dealing with the multi-objective optimization of freight distribution in urban areas considering service level, environmental impact, traffic congestion, transportation safety, and energy savings [80].

Intralogistics (IL) refers to the storage (including warehousing and inventory management) and movement of materials within facilities such as factories, warehouses, transit hubs, construction sites, and ports. More generally, it represents a form of optimization, automation, integration, and management of the flow of materials and information circulating within a business unit.

In this work, *Supply Network (SN)* refers to the coordination of

Table 1
The clustering results from the keyword occurrence analysis (Occ. = occurrence, TLS = Total Link Strength, computed by VOS Viewer).

Cluster 1			Cluster 2			Cluster 3			Cluster 4			Cluster 5		
Technologies and algorithms for system innovation			Cutting-edge technologies as responses to the dynamism and intelligence of systems			The objectives and tools of LSCM development in Industry 4.0			Resilient and digital supply chain			Digital twin-driven decision-making tool kit		
Keyword	Occ.	TLS	Keyword	Occ.	TLS	Keyword	Occ.	TLS	Keyword	Occ.	TLS	Keyword	Occ.	TLS
Digital twin	63	216	Artificial Intelligence	7	34	Sustainability	7	26	Supply chain	23	91	Simulation	12	49
Real-time systems	6	34	Intelligent Transportation System	7	32	Production logistics	6	24	Optimization	10	48	Decision making	15	76
Manufacture	6	27	Intelligent systems	6	31	Industry 4.0	6	17	Supply Chain Management	9	48	Decision Support System	5	25
Internet of Things	6	25	Prediction	4	22	Synchronization	5	27	Supply chain resilience	7	33	Virtual Reality	4	18
Cyber-Physical System	6	20	Integer Programming	4	22	Blockchain	5	23	Food supply chain	7	24	Real-time	3	12
Human	5	26	COVID-19	4	20	Production control	3	17	E-learning	5	28	Life cycle	3	7
Interactive computer systems	4	25	City logistics	4	16	Industrial research	3	15	Digital supply chain	4	22			
Digital Storage	4	17	Smart City	4	14	Cloud computing	3	10	Machine Learning	4	21			
Embedded systems	4	15	Stochastic systems	3	12									
Heuristic algorithms	3	18	Deep Learning	3	10									
Efficiency	3	17												

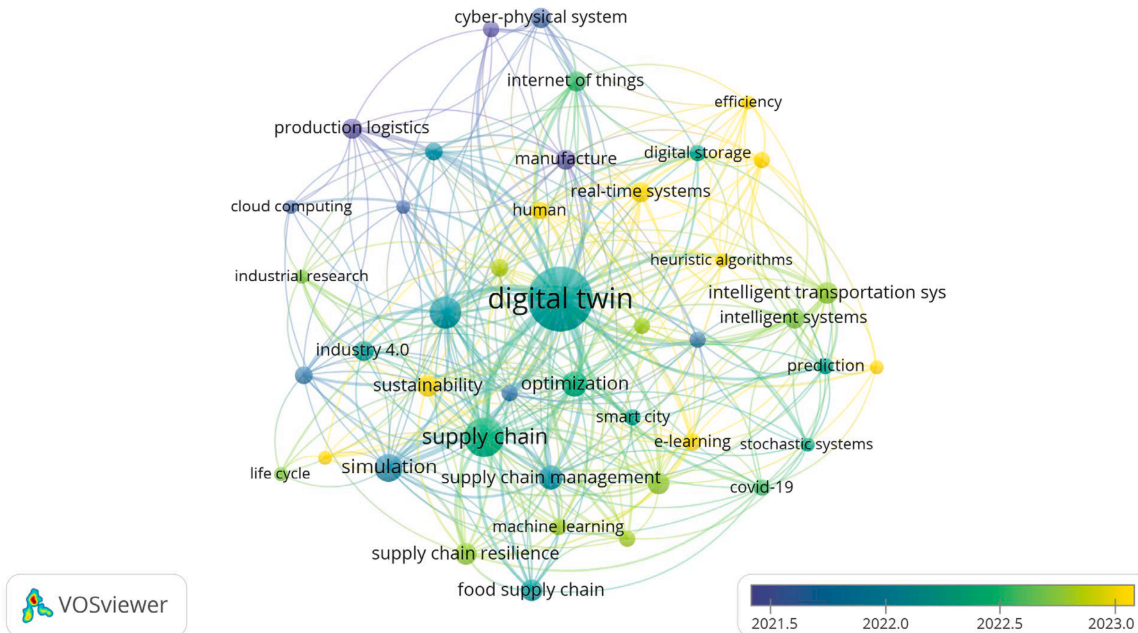

Fig. 4. Overlay visualization (showing development over time) of the clustered keywords (cooccurrence more than three times).

entities (DTs) within logistics networks, differing slightly from traditional definitions. It is defined as a collection of interconnected agents (suppliers, logistics service providers, customers, etc.) that interact via communications and flow exchanges to fulfill their objectives or a set of common goals [35]. SN coordination is crucial for integrating multiple logistics operations, including transportation and storage, through structured control across the network.

3.2.1.2. Service types. Many studies consider DT technology as an enabler and driver of service innovation. For example, Tao et al. [81] suggested nine types of product-centric services: failure analysis and prediction, maintenance strategy, virtual maintenance, and virtual operations. These services monitor product or machine degradation and abnormal events or predict disruptions and dynamics. Padovano et al. [57] argued that a service-oriented DT could offer seven services to physical assets in a smart factory and three more to workers to enhance their working experience. Tao, Qi, and Nee [83] summarized six services for the product manufacturing processes that can be provided by the full-fledged digital twins (data, physical twin, digital twin, and inter-connections), namely monitoring, optimization, simulation, control, prediction, and evaluation. However, logistics and supply chain systems differ from factories or individual products, requiring management across multiple scales, including flows, stakeholders, resources, and operations, all of which are more complex and pose different requirements for service innovation. Therefore, based on previous studies, this paper suggests eight DT-enabled services in LSCM: *monitoring, evaluation, prediction, optimization, control, system management, system integration,* and *adaptation*, as shown in Fig. 5.

Two points should be noted here. One is that simulation has not been defined as one of the services. This is because simulation serves as an

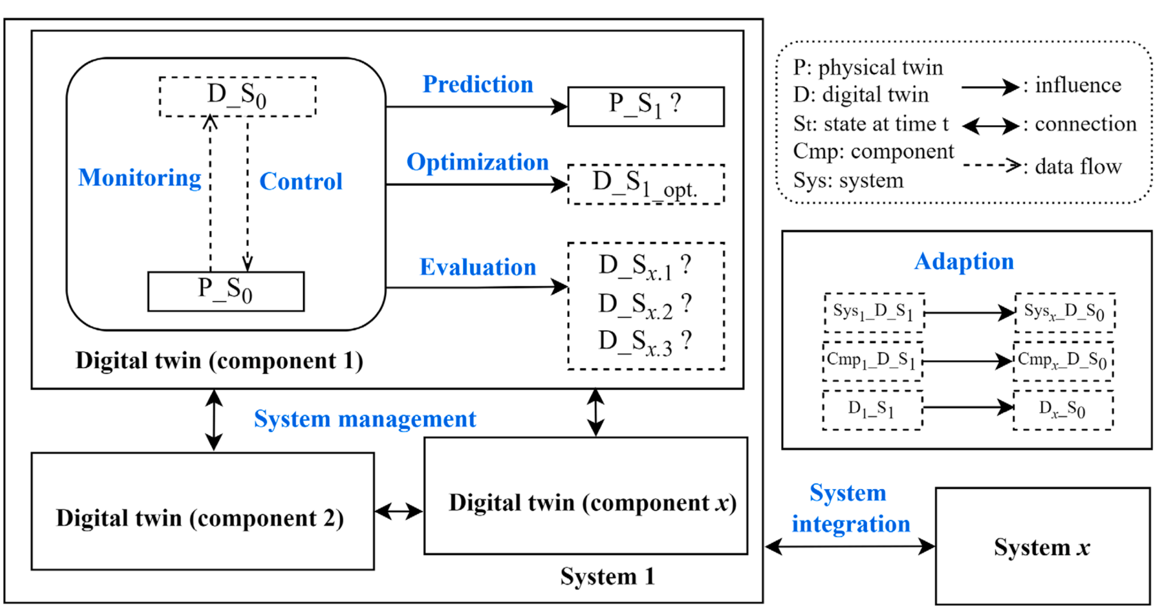

Fig. 5. Eight innovative digital twin services for LSCM applications.

intermediate procedure for achieving *evaluation* (or validation of the performance of multiple strategies or policies) or *optimization* (to support selecting the best-performing initiative based on the simulated results). Thus, it is recognized as one of five independent capabilities of digital twins, as discussed in Section 4.1. Another point is that while both *system management* and *system integration* involve resource integration, *system management* focuses on internal processes, whereas *system integration* emphasizes external coordination between heterogeneous stakeholders.

Monitoring involves visualizing various parameters of physical objects or systems as digital twins, synchronizing and updating them in real-time to ensure data accuracy and quality for further processing or decision-making support.

Evaluation involves assessing the current performance of operations or systems and testing various follow-up scenarios, system settings, decision-making rules, or potential strategies through simulation, a key capability of digital twins. These scenarios may be predefined or derived from machine learning models or parameter configurations.

Prediction involves analyzing historical data (such as state changes or processes) stored in digital twins and combining this with real-time captured events (e.g., disruptions or interactions with other digital twins) to forecast future actions. The goal is to optimize resource allocation or reduce waste from disruptions, using machine learning or simulation as the primary approaches.

Optimization is based on monitored status and potential state changes of the digital twins to improve operational decisions through expert evaluation, simulation, or mathematical modeling, often solved using algorithms.

Control involves the connection, synchronization, and communication between digital and physical twins, executing decisions made in the digital space and applying them to the physical objects via actuators.

System management involves mirroring tangible assets, such as physical twins (assets, workers, infrastructure, operation-supporting resources), into digital twins, while integrating intangible assets like data and knowledge. This facilitates the integration of components within a single system, enhancing interaction and synchronization. It essentially connects the components belonging to one stakeholder within the value chain and manages them as a closed cyber-physical system.

System integration connects multiple Cyber-Physical Systems (CPSs) from various stakeholders along the value chain to create an open system. This collaboration, coordination, and synergy – through the integration and sharing of digital and physical twins – enhances understanding of the entire ecosystem and facilitates global optimization.

Adaption refers to the capability of digital twins to consider their own lifecycle data, the detected operational context, the status of the overall system, and the objectives and behaviors of interconnected digital twins. They adjust their subsequent actions to achieve their specific goals. Although each digital twin may have distinct objectives, they must ultimately align with the global system goal. Mechanisms must be designed to address conflicts and promote interaction and cooperation among digital twins.

3.2.1.3. Technology readiness level. NASA initially proposed the Technology Readiness Level framework to evaluate technological readiness and risks for space applications, using nine levels to describe a technology's capabilities and maturity in a detailed manner. Over time, the use of TRL has been gradually extended to other industries. In the aerospace industry, technology implementation is characterized by highly integrated products and a structured development process, which involves sequential stages: design, production, and testing in simulated and operational environments. In contrast, the logistics field involves multiple heterogeneous stakeholders and distributed resources to manage global freight flows. Research on the applications of DT technology in logistics focuses on managing these distributed segments. The nine-level TRL framework may be too detailed and unsuitable for the segmented nature of LSCM. Therefore, this paper adopts a simplified three-stage TRL framework to assess DT in the logistics industry. The low stage (research stage), covering TRL 1–3, represents the development of basic principles and experimental proof of concept. The medium stage (development stage), covering TRL 4–6, indicates the technology has been validated or demonstrated in a laboratory or relevant environment. The high stage (deployment stage), covering TRL 7–9, refers to DT technology that has been demonstrated or proven in an operational environment and is ready for industrial deployment [91].

3.2.2. Result reporting

3.2.2.1. Service innovation in various areas of application. Table 2 demonstrates that in digital twin studies across various logistics and supply chain management segments, intralogistics and supply networks are the two leading areas of application. The dominant sub-areas of focus are factory (manufacturing) operations, digital transformation, and supply chain resilience.

3.2.2.1.1. Monitoring. Monitoring is the most widely used and critical service in the literature, with 42 out of 70 studies applying this service.

In Last-Mile Delivery, DT is applied to monitor resource status and availability in crowdsourcing and freight parking management, which is crucial for supporting dynamic resource allocation based on accurate spatial-temporal data. In urban planning and policy-making, Marcucci et al. [52] argued that DTs can monitor real-world parameters to inform decision-making. However, it is important to consider additional contextual information and both exogenous and endogenous variables to complement the abstract nature of digital twins, enabling the development of effective long-term policies.

Digital twins support sustainability in urban freight transport and the supply chain by monitoring vehicle emissions in cities [99] and improving visibility and traceability in supply chains such as prefabrication and food supply chains [75,102].

In production logistics, digital twins are used to capture and represent the real-time states of resources such as Automated Guided Vehicles (AGVs) and operators, as well as the dynamic material handling demands, to enhance resource allocation through effective matching [4,107,108]. In warehouses, digital twins are primarily used to monitor storage status (location and quality) and environmental conditions such as temperature and humidity, which are crucial in cold chain warehouses [25,94]. On construction sites, digital twins can monitor silo fill levels to ensure timely refills [22].

In supply networks, digital twins are valuable for monitoring the refrigerated supply chain, tracking changes in fruit quality, marketability, and storage and transport conditions (e.g., temperature, humidity) [16,23,74]. These processes can be displayed in a multi-dimensional dashboard, functioning as a control tower [23].

In the transport sector, digital twins detect anomalies and update the fundamental properties and characteristics of the pipeline transport systems [18,78]. In road transport, DT can track the transportation of hazardous chemicals to enhance security [41], monitor the arrival of construction modules to improve project progress control [38], and synchronize real-time traffic status [37]. Additionally, DT can provide monitoring services in Intelligent Transportation Systems to mirror and understand the components such as vehicles and infrastructure, supporting connections and communications within the V2X (vehicle-to-everything) network [44,98].

3.2.2.1.2. Optimization. Monitoring is a widely recognized prerequisite for digital twin-driven optimization services, providing the necessary foundation for real-time operational decision-making. Optimization plays a central role in digital twin-driven operational decision-making, allowing decisions to be based on the real-time status of the

Table 2
Digital twins service innovation in various sub-fields of logistics and supply chain management.

Service types	Areas of application	Monitoring	Evaluation	Optimization	Prediction	Adaption	Control	System management	System integration	Num. of papers
First-Mile Delivery	Pipeline	2			1			1		2
	Railway				1				1	1
	Road	3	1	1	2			1		3
	ITS	4	4	1	4		1	1	2	8
Intralogistics	Factory	10	5	6	1	1	3	3	1	15
	Warehouse	5	1	4		2		2		4
	Airport						1			1
	Construction site	1		1						1
Last-Mile delivery	Crowd-sourcing	2			1	1			1	3
	Urban transport system	1	2	2		1				2
	Policy making and urban planning	1	1							1
Supply Network	Digital transformation	7	8	5	4		1	6	1	14
	Resilience	4	6	3	3	3	1	1	4	11
	Sustainability	2	3	2	1	1	1		1	4
Total		42	30	25	17	8	7	15	10	70

system and ensuring accurate responses to dynamic environments. This service relies on three key components: optimization algorithms, simulation methods [13,101], including discrete event and agent-based simulations [46,53], and machine learning techniques [6,40]. Optimization services support a wide range of operations, including routing problems in the urban deliveries, factories, and warehouses [4,19,46], job scheduling on the shop floor [15,101,108], layout optimization and storage assignment in the warehouses [19,39], replenishment decisions for silos and warehouses [22,40], robust optimization for resilient supply networks [13,97], and task matching between demand and service providers in Intelligent Transportation Systems [42].

3.2.2.1.3. Evaluation. In Last-Mile Delivery, digital twins can evaluate and report overall delivery performance through simulation, assessing factors such as resource utilization and environmental impact, including carbon emissions [46]. In the urban transport system, the relationship between stakeholders can be assessed via a series of behavioral and simulation models. Digital twins monitor the heterogeneous objectives and interactions of stakeholders, providing a clearer understanding of the relationship between stakeholder behaviors and their context. This understanding can stimulate participatory planning [52]. Digital twins can evaluate and compare the performance of the proposed strategies aimed at urban sustainability. For instance, they assess eco-driving strategies, incorporating human factors to select the most effective strategy for mitigating emissions [99].

In factories, digital twins evaluate system performance through simulation, comparing results with physical experimentation to assess the accuracy and reliability of the digital simulations [54]. Pan et al. [63] studied how to systematically evaluate operational status, enabling efficient computation and resource allocation to respond to dynamic demand in production logistics. In warehouses, digital twins simulate and validate joint optimized decisions, such as stacked packing and storage assignment, to ensure proper implementation [39].

In supply chains, particularly food supply chains, digital twins evaluate food quality and marketability based on factors like chilling injury, pest mortality, and remaining postharvest life [55]. In the Agri-food supply chain, digital twins are used to evaluate indicators at strategic, tactical, and operational levels. Multiple scenarios, such as supply chain length, level of centralization, and lead time, are assessed through simulation to tailor distribution strategies [23]. Other studies in refrigerated food supply chains focus on evaluating strategies in the digital space to validate storage and transport environment configurations. These measures will help maintain the food freshness until the last end of the supply chain [16,74]. In resilient supply chains, digital twins evaluate current operational performance to detect bottlenecks, assess risks, and analyze the impact of disruptions through simulation or analysis [9,11,75].

In transportation systems, digital twins analyze the security and efficiency of infrastructure, evaluate strategies, and select the most effective one for implementation [37,86,100].

3.2.2.1.4. Prediction. Before implementing proposed policies, it is crucial to evaluate or predict their impact by considering the key actors and their interactions within the given context. Digital twins can assist in predicting the performance and impact of policy implementations [52]. A key application of digital twins is forecasting asset degradation and determining optimal maintenance schedules based on lifecycle data. This can be applied broadly to transport assets [2] or specifically to railway maintenance [71]. Digital twins are often used to predict and mitigate risks by forecasting potential disruptions with precision. Examples include predicting supply chain disruptions [27], delays in modular construction transport [38], potential accidents during hazardous chemical transport [41], and issuing warnings to reduce unsafe driving behavior in V2X networks [44]. In addition, multiple research studies have studied digital twins to predict the traffic flow in the intelligent transportation system [56,86]. In food supply chains, digital twins predict shelf life based on factors such as temperature, humidity, and air velocity in refrigerated spaces. This extends product life and enhances transportation quality [75]. Additionally, predictive capacity planning and resource investment are supported by monitoring comprehensive processes such as freezer production and packaging line stages [50].

3.2.2.1.5. Control. Digital twins can be integrated into ground traffic control systems by reporting real-time locations and conditions of ground vehicles and aircraft and coordinating with human controllers to manage and optimize movements in the airport apron area [72]. In smart manufacturing, digital twins support the synchronization of real-time resource status, such as Automated Guided Vehicles, to enable dynamic resource allocation. Results show that the simulated digital twins for AGV routes closely align with actual AGV trajectories, demonstrating that digital twins can effectively manage task allocation and route planning [54]. In factory maintenance, digital twins provide control services during the operations and before issues arise. Digital twins can optimize maintenance sequences based on simulations. When combined with machine learning, they conduct predictive analysis to anticipate breakdowns and schedule maintenance in advance, minimizing impact [69]. Jiang et al. [31] proposed that digital twins assist in monitoring real-time information and performing online optimization, allowing them to autonomously control production and logistics processes by taking the right actions at the right time. Generally speaking, in supply chain and operations management, timely synchronization in digital twins provides instant feedback from the physical to digital realm, enabling descriptive, predictive, and prescriptive decision-making. Collaboration between digital twins and humans primarily involves managers for decision-making and operators for task execution. Digital twins generate solutions or insights from simulations, which can be combined with managers' experience and judgement to continuously refine and adjust decisions. Digital twins well define and control the movement of the machines, which will facilitate the seamless interaction with the human operators and automated systems [28]. In cold supply chain, digital twins control storage and transportation environments, such as temperature, humidity, and air velocity, to extend product life and maintain quality during logistics [75]. In Intelligent Transportation Systems, digital twins are proposed for global planning and control, including adjusting roadside signal lights to optimize intersection flow, minimize vehicle and passenger wait times, and ensure smooth traffic flow [44].

3.2.2.1.6. System management. In logistics and supply chain management, many components – including resources, processes, information systems, real-time events, and optimization algorithms – are often managed in silos. This segmentation necessitates the integration of digital twins to achieve more effective management. It is important to note that this refers to internal integration only, meaning external resources for cooperation, coordination, or collaboration are not included. The primary goal is to enhance the performance of the organization's internal system.

The literature often emphasizes stakeholder integration, particularly the interaction between customers and logistics service providers, to enable continuous feedback and improve logistics processes. Closed-loop feedback is especially crucial in the agri-food supply chain, where production-to-consumption time is short and product quality can vary significantly. Instant feedback in this context can significantly enhance performance [23]. Several studies explore the integration of the operational processes, including procurement, production, and distribution, as well as the design and production processes [50,68].

Another major research focus is on data processing, collection, management, and integration. These studies highlight the importance of data fusion to enhance the consistency and quality of input data [2,40]. Several studies investigate the role of humans in the decision-making process. As digital twins evolve, their role in decision-making gradually shifts. Initially, humans evaluate and correct digital twin decisions, allowing the twins to learn from these processes. As digital twins advance, human intervention decreases, enabling autonomous handling of less critical tasks and decisions [67]. Research also highlights the development of intelligent Digital Twin (iDT), which enhances traditional digital twins by integrating human intelligence with Artificial Intelligence. This advancement goes beyond standard digital twins, which rely on human decision-making, and cognitive digital twins, which incorporate AI-supported decision-making. By combining human intelligence – including knowledge, experience, and creativity – with AI capabilities such as algorithms and training models, iDTs enhance supply chain resilience by enabling anomaly detection, event-driven responses, and proactive measures to mitigate risks or disruptions [27].

3.2.2.1.7. System integration. As digitalization advances in the supply chain, it is becoming increasingly feasible to integrate internal resources with external ones. The integration amplifies the profitability of facilities, systems, and equipment that were previously segmented and dedicated to individual stakeholders. Most importantly, visibility has significantly improved in this open, digital logistics system, enabling seamless cooperation among multiple parties and ensuring the smooth flow of processes, materials, and data throughout the supply chain.

Liu et al. [46] proposed adopting a semantic model for communication to avoid ambiguity and seamlessly integrate digital twins owned by different stakeholders. They validated this model with a use case, involving data integration from public and private logistics sectors to manage freight parking for parcel deliveries. Emphasizing data security and interoperability during integration, Sahal et al.[71] proposed using blockchain to manage data, enabling real-time data exchange and collaboration between digital twins in distributed manufacturing systems.

In Intelligent Transportation Systems, data from multiple sources are often diverse and difficult to utilize. Zhang et al. [106] proposed a framework to fuse and manage data within digital twins to enhance Intelligent Transportation Systems, capturing spatial-temporal movement traits and visualizing the infrastructure systems. Liu et al. [44] focused on connecting physical infrastructure – such as traffic lights, cameras, lidar, and roads – with both human-driven and autonomous vehicles to achieve vehicle-road coordination.

Another area of research focuses on integrating processes that involve multiple stakeholders. Zhang et al. [105] examined the integration of production and logistics to achieve coordinated planning in response to real-time dynamics, including task and resource allocation, scheduling, and control parameters. Lv et al. [48] emphasized integrating manufacturers and suppliers into emergency decision-making to share costs and profits, thereby building a more resilient supply chain. Coordination among stakeholders is crucial for achieving supply chain resilience and sustainability, as Singh et al. [75] pointed out. Improved coordination enhances visibility, which in turn reduces food waste and increases overall supply chain efficiency.

3.2.2.1.8. Adaptation. The dataset reveals two main research streams related to DTs' adaptation service applied in LSCM. The first stream views digital twins as individual entities capable of learning from operational data and human behavior to generate reusable knowledge and instructions, allowing them to adapt to future operations [67]. Digital twins can efficiently monitor the states and changes within the food supply chain, providing flexibility by adapting to varying storage and transportation conditions [75]. In pharmaceutical distribution center cold rooms, digital twins can self-adapt and respond to environmental changes through continuous calibration [94]. The second research stream takes a systems-level view, where digital twins are considered components that work together to achieve the overall system's functionality. Digital twins are viewed as agents equipped with diverse goals, requiring them to understand the system and each other over time. They act autonomously and cooperatively to achieve both local and global objectives [26,51].

3.2.2.2. Maturity of digital twins in LSCM. More than half of the research is categorized under the development stage (medium TRL), where simulations are conducted to evaluate proposed approaches [46,94,105], analyze real-world cases from companies [13,26,53,99], test solutions in simulated environments [18], and conduct 'what-if' multi-scenario analyses [23]. It is important to note that in these studies, simulation is primarily used for validation rather than as a fundamental digital twin capability to enable other services, such as evaluation. The former focuses on validating the effectiveness of digital twin technologies in LSCM, while the latter involves multi-domain, multi-level of detail, and multi-actor interactions, taking into account the operational context.

Many studies are still at the research stage (low TRL), where the focus is the feasibility of digital twins in various application areas [52,69,76,78], their enabling technologies, their combination with other technologies to unlock potential, and the development of frameworks for implementation [20,28,38,41,71,106]. These studies primarily concentrate on first-mile transportation, last-mile delivery, and supply networks. In comparison to intralogistics applications, such as those in factories or warehouses, large-scale exploration and implementation in these fields demand significantly more effort. Implementing digital twin technologies in these areas requires greater stakeholder cooperation to fully realize their potential (development stage). Additionally, the projected benefits must be simulated in advance to encourage stakeholder participation in the implementation process (deployment stage).

The most advanced research (high TRL) is concentrated in factories [15,25,94,96,108] and digital transformation [55,73,74]. These two sub-fields exhibit the highest number of studies. It can be inferred that advanced research is more likely to emerge in fields with higher research activity. However, a high volume of studies does not necessarily lead to advanced research. For instance, despite considerable research on supply network resilience, no advanced studies have emerged in this domain. This may be due to the broad nature of supply chain resilience, which requires the involvement of multiple stakeholders. Implementation is complex without a clear mechanism for sharing pain and gain, strategic collaboration, and system interoperability for cooperation and tactical scheduling. Similarly, the complexity of implementing ITS lies in the need for infrastructure development, supporting facilities, and the integration of communication systems like vehicle-to-everything (V2X).

4. Discussion

This review has identified several key gaps and opportunities for research into DTs in LSCM, underscoring the vast and interdisciplinary scope of this field. This section outlines the capabilities digital twins must possess to deliver the previously discussed services, along with promising future research directions and potential applications. To support this discussion, a schematic framework has been developed to broaden perspectives on DT research in LSCM, as shown in Fig. 6.

4.1. Digital twin key capabilities

To deliver the eight services mentioned earlier, digital twins must possess five key capabilities: integration, computation, simulation, interoperation, and evolution. Integration is essential for digital twin applications in LSCM, as it enables the incorporation of multiple operational processes and stakeholders, facilitating asset and operations management in a collaborative supply chain. Computation and evolution are fundamental capabilities for digital twins, enabling seamless synchronization from physical twins to digital twins (monitoring) and vice versa (control). Simulation plays a crucial role in supporting digital twin services by modeling the performance of various scenarios. This capability is vital for evaluating multiple strategies or policies, selecting the best-performing scenario (optimization), and predicting future states based on potential parameter changes and the overall operational environment.

4.1.1. Integration

Data is the most crucial component of digital twins, as it determines their applicability and ability to provide services. Two primary concerns are the scope and quality of the data sources. At the individual level, digital twins manage data throughout the entire lifecycle of an object. At the system level, digital twins must connect and collaborate with others to collectively perform system-wide functions. Ensuring data quality is equally important. Raw data from sensors or external partners must be processed into usable formats and managed within digital twins to accurately represent the status of physical objects and their relationships with others. Therefore, integration from multiple sources and ensuring high data quality are essential for effective digital twin operations.

A key prerequisite for integration is the digitalization of logistics processes, with documentation playing a crucial role in administrative and contractual processes. One ongoing initiative is the European Union's eFTI regulation[2], which aims to digitalize all transportation documents, replacing traditional paperwork. Multiple benefits are predicted with the implementation. For businesses, administrative costs will be significantly reduced due to improved efficiency and accuracy. Supply chain partners can collaborate more effectively through instant data sharing. Improved digitalization allows the authorities to better monitor the policy-implementing performance with fewer inspections. Enhancing data integration into digital twins improves the visibility of data sources both within and across ecosystems. For this reason, countries and alliances have put effort into multiple projects and initiatives.

For example, the Common European Data Spaces[3] initiative pools data descriptions from multiple domains and stakeholders, rather than centralizing all data into a single data lake. This method can improve visibility while maintaining scalability. In this platform, multiple actors, including private and public stakeholders, companies, and government, can exchange data based on understanding data sources and providers. From this perspective, the eight service types mentioned can work as the root category, where sub-services can be detailly found to support the contract construction. Further steps include establishing contracts that define data usage, legal responsibilities, and mechanisms for sharing benefits and risks.

Data quality can be improved by addressing inconsistencies through rule-based methods, machine learning techniques, or statistical approaches, which enhance accuracy and precision compared to relying on a single data source.

It is important to note that digital twins are not intended to store vast amounts of data from every stage of an object's lifecycle, as highlighted by Boschert and Rosen [10]. Instead, managing dynamic data relationships is key. From this perspective, the following two insights are vital for *integration* in digital twins. First, data collection does not need to occur every second or minute. Instead, data collection frequency should be based on operational needs to ensure that the data remains both usable and high-quality. Several examples can refer to the tolerable delay of the synchronization to maintain the data quality in smart cities [103]. Second, data retrieval should be prioritized to meet specific needs and deliver concrete services, rather than viewing integration as an end in itself. Excessive data collection can lead to processing challenges such as storage, transfer, and confidentiality. This consideration is not only based on data security but also on the efficiency of data exchange.

4.1.2. Computation

Smaller, lighter, cheaper, and more powerful sensors can now be embedded in objects to monitor their states and synchronize with digital twins. Sensors in parking spaces, for example, can report occupancy to facilitate final fifty feet delivery in city logistics, reducing cruising time and illegal parking. In cold supply chains, sensors can monitor critical parameters such as humidity and temperature inside vans or trucks, ensuring the quality of transported goods. Advancements in sensing technology have fueled Big Data growth, offering a more comprehensive understanding of objects and processes that create value in the digital space. However, the influx of data places pressure on storage and processing technologies, necessitating a trade-off between computing performance, time, and cost.

To meet diverse and growing computational demands, various computing resources, including cloud, fog, and edge computing have been developed. These resources are chosen based on factors like latency, timeliness, and responsiveness to ensure cost-effective computing services. Though optimization algorithms have improved and reduced computation times, complex problems still require balancing optimization and computing time, often favoring near-optimal results to keep computation time manageable and costs affordable. Data security remains crucial, including where data is stored and how it is transferred and processed. A lot of discussion and research have been conducted on this topic. For instance, federated learning trains machine learning models using decentralized data sources from multiple parties without possessing or storing the data. This approach improves the model's quality and applicability across various players in the ecosystem.

4.1.3. Simulation

Simulation is a crucial capability for digital twins. Although digital twins can monitor real-world conditions via their physical-virtual connection, this remains a passive approach. Simulation shifts decision-making from reactive to proactive and predictive. What-if

[2] https://transport.ec.europa.eu/transport-themes/logistics-and-multimodal-transport/efti-regulation_en?prefLang=fi

[3] https://www.dataspaces-radar.org/radar/

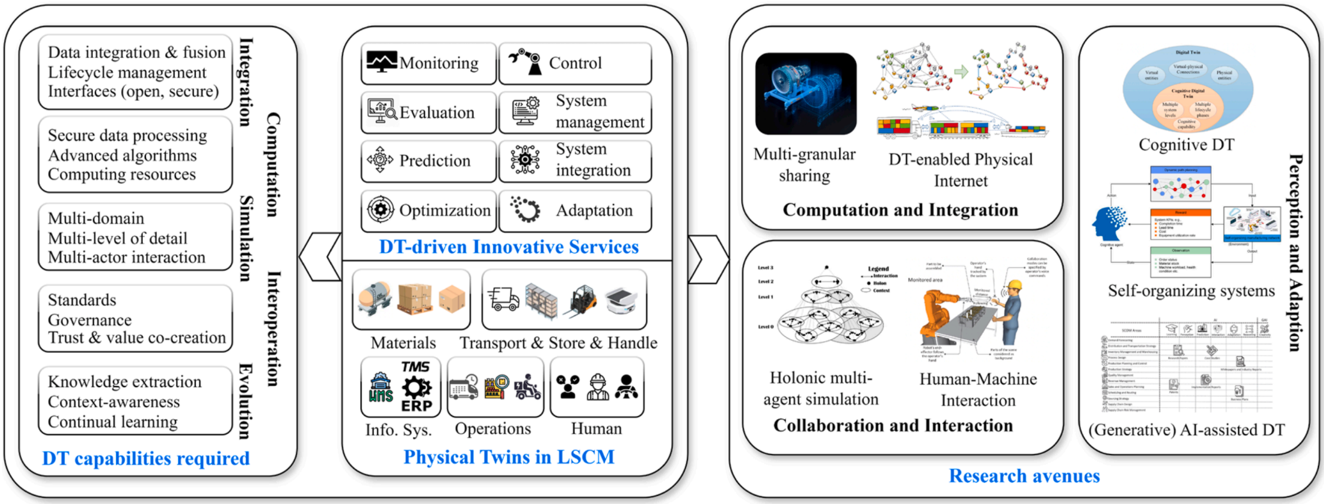

Fig. 6. Perspectives of DT technology in LSCM.

scenarios allow the evaluation of different configurations, with the best-performing option selected for implementation. This enhances operational efficiency, predicts anomalies, and facilitates proactive risk mitigation.

In LSCM, where multiple actors collaborate, simulations must extend beyond closed systems with static components and relationships. In open ecosystems, simulations should consider specific applied scenarios, retrieving data from various life phases of digital twins, across multiple domains, and with different levels of detail. For example, to predict the ideal maintenance time for a delivery van, historical data including maintenance records, vehicle age, and component repair history would be retrieved. When performing city deliveries, only real-time location data from the van's digital twin is retrieved. Additionally, weather data and specific zone regulations (e.g., emission and traffic limits) would be retrieved to optimize scheduling and real-time navigation.

Tailoring data demands to specific scenarios enables large-scale actor participation and long-term, cross-domain implementation. It is necessary to reduce the pressure and costs associated with data transfer and computation. For example, Reduced Order Models can simplify high-fidelity, complex models while maintaining service effectiveness. Kapteyn et al. [34] demonstrated substantial reductions in model dimension and solution time using an unmanned aerial vehicle and its digital twin.

4.1.4. Interoperation

Many carriers in the logistics and transportation sector are small and medium enterprises (SMEs) with limited digital capabilities and investment capacity. Thus, digital solutions must offer broad benefits, reducing costs by not only improving operations but enabling their collaboration based on system compatibility and interoperability. Interoperability is the goal, but processes and participants must be regularly reviewed to avoid redundant and overlapping initiatives. Without thoughtful review, multiple initiatives from alliances and groups aimed at promoting interoperability can inadvertently undermine the goal. Establishing industry-specific standards can offer a solution. For instance, the International Air Transport Association (IATA) sets standards for air transport, the Digital Container Shipping Association focuses on maritime logistics, and the Terminal Industry Committee oversees terminal operations. Additionally, global solutions have also been proposed to address these interoperability challenges. A notable European initiative addressing interoperability is 'Data Spaces,' which spans various aspects, sectors, partnerships, and development stages. 'Data Spaces' establishes a framework for secure data sharing across distributed systems, offering standards, technical, and governance support as the foundation, clearly aligning with specific logistics operations and use cases.

4.1.5. Evolution

Digital twin evolution occurs along two primary dimensions. The first dimension involves the lifecycle of digital twins, encompassing historical data, real-time event detection, and future behavior prediction. Data mining plays a key role in analysis and prediction within this dimension. The second dimension places digital twins within intelligent systems, such as multi-agent systems, where each agent pursues individual objectives while contributing to system-wide goals. In these systems, digital twins act as agents, both contributing to and depending on the broader system. Key factors include operational context, component roles, interdependencies, and heterogeneity of their behaviors and objectives. Various technologies can unlock the potential of these systems. Reinforcement learning, employing penalty and reward mechanisms, aids agents in adapting to their environment and achieving global optimization. Continual learning, another emerging machine learning approach, enables intelligent systems to adapt to dynamic changes within components and across the broader system [90].

4.2. Research avenues

Digital twins are expected to drive transformative changes in LSCM across operations management, organizational models, and industrial paradigms. This section outlines ongoing examples and potential research directions.

4.2.1. Computation and integration

4.2.1.1. High-fidelity modeling but multi-granular sharing. DT modeling must consider data granularity, consistency, and accuracy to determine the level of detail in parameters exchanged between physical and virtual twins. High-granularity DT models with timely synchronization offer precise, real-time information about physical entities, aiding simulations in making accurate behavior predictions. In manufacturing, high-fidelity, frequently synchronized DT models are recommended throughout product lifecycle phases, especially for complex products. However, in LSCM, the data load on digital twins expands significantly due to the involvement of multiple stakeholders, their assets, operational processes, and intertwined relationships. In some cases, detailed information about the physical entities may be unnecessary, and high-fidelity modeling may be neither affordable nor feasible due to computation and processing constraints. High implementation costs and technical challenges may prevent frequent processing and transfer of numerous parameters [32]. Therefore, appropriate data granularity and synchronization timeliness are crucial for effective DT connections and collaboration. Similarly, simulation models require DTs with varying granularities and synchronization rates to align with use case requirements, supporting system operations and service optimization. Kapteyn et al. [34] proposed a component-based reduced-order model, where only essential components are selected from the model library, to provide the crucial parameters to the simulation. It can significantly reduce the extreme processing cost of the high-fidelity model. Therefore, multi-granular sharing or simplifying the digital twin model to maintain functionality and service delivery is a key challenge for implementation.

4.2.1.2. Digital-twin driven physical internet. For several years, data-driven management has transformed LSCM by utilizing historical data and technologies like data mining and machine learning for descriptive, predictive, and prescriptive analysis to support decision-making. Recently, DT-driven management has emerged, monitoring real-time object statuses and managing their connections between the cyber and physical world. DT-driven management complements data-driven approaches, as DTs are built on data and, in turn, provide real-time operational and simulation data for analysis. Ivanov et al. [29] were among the first to suggest the application of DT to the supply chain, coining the term "Digital Supply Chain Twin". They argued that DT-driven management could be more potent in managing disruption risks in supply chains, thanks to the ability of real-time monitoring and data generation for predictive analysis and simulation. Likewise, Pan et al. [59] considered the digital supply chain twin as an industrial cyber-physical system (ICPS), where data and DTs interplay to enhance decision-making and system intelligence. They suggested that the DT-driven approach should be extended to intralogistics (e.g., factory, warehouse) to inter-site and Last-Mile Delivery. However, operational environments are highly complex and prone to disruption. Cognitive DTs have the potential to address these challenges by enhancing logistics systems' intelligence, from perception to cognition, warranting further research.

The Physical Internet (PI) is an emerging paradigm in global LSCM designed to enhance logistics efficiency, sustainability, and resilience. Inspired by the global digital internet, PI seeks to interconnect segmented logistics networks to seamlessly share and coordinate services, resources, and infrastructures [7,58]. PI integrates physical and digital components to coordinate physical and information flows, enabling operations management and resource planning by sharing real-time information on system and object statuses across logistics networks. In this vein, PI also represents a new research field, providing opportunities to change LSCM through DT technology.

First, digital interoperability is crucial to seamless cross-company or cross-system cooperation in PI [60]. DT can break down data silos to achieve this interoperability. However, further research is needed to evaluate effectiveness and efficiency, especially regarding data connectivity, granularity, and accuracy in large-scale systems. Second, PI proposes interconnecting logistics networks, systems, and objects, which are often intricately interrelated. The CPS and DT paradigms emphasize a system-of-systems approach, contributing to the control and coordination of objects in PI networks [59]. Third, DT data consistency and synchronization of logistics systems are essential to PI in managing and monitoring global end-to-end logistics services and disruptions. DT modeling and simulation can contribute to these aspects, especially for networking flow control and routing [59]. Finally, efficiently connecting the physical and digital worlds remains a key challenge for PI, especially in coordinating resources and operations through the cyber world. Initial research has been conducted on the DT modeling of PI containers to monitor supply chains [14]. These research challenges underscore the significant opportunities for further exploration of DT in PI.

4.2.2. Collaboration and interaction

4.2.2.1. Holonic multi-agent simulation. The challenge of DT modeling is particularly significant in logistics and supply chain management, which involves complex systems comprising numerous objects and stakeholders, each with its own DT, forming a System of Systems (SoS). CPS and holonic multi-agent systems have been proposed to address complex systems, and when combined with DT, they enhance communication and computation capabilities. Although CPS and DT both integrate physical and cyberspace, CPS emphasizes mapping physical functions to improve resource allocation and control, whereas DT focuses on accurately mirroring components and relationships in a high-fidelity model to monitor status changes and provide services [84]. While DT has been extensively studied in manufacturing, it requires further exploration in LSCM. The complexity of logistics and supply chains comes from the number of stakeholders with different objectives involved in the services, loosely coupled components, and a lack of comprehensive understanding of the entire system, from modeling to operations. Given this complexity, different modeling approaches – such as bottom-up or top-down – may be used to construct the cyber part. The bottom-up approach is more suitable for logistics systems with openness and plug-and-play features, while the top-down approach is critical for intralogistics systems. The efficiency and practicality of these modeling approaches should be further investigated in specific contexts.

4.2.2.2. Human-machine interaction. The COVID-19 outbreak has severely challenged current practices concerning managing operations and the work environment in LSCM worldwide, especially problems such as flexible operator shifts or remote work and personal protective equipment policies imposed. Moreover, the global logistics worker shortage continues to affect global supply chains. These problems will lead to higher operating costs and more difficulties in operations management. DT-based automation and remote control service offer a new approach to address the problem. In the long term, DT-enhanced Human-Machine Interaction (HMI) has the potential to revolutionize the logistics industry by facilitating seamless communication, cooperation, and interaction between humans and machines.

DT can enhance HMI across the product lifecycle in three key areas: high-fidelity virtual models for immersive interaction, simulation for insights into physical entities, and user-friendly interfaces [49]. Collaborative robotics, or Human-Robot Collaboration, is one of the four DT-based HMI scenarios applied in manufacturing, where humans and robots share the same workspace and resources to complete tasks [92]. HRC aims to boost overall productivity by leveraging the strengths of robots (e.g., strength, endurance, repeatability, and accuracy) and humans (e.g., intuition, flexibility, problem-solving, and sensory skills) [89]. DT-based HMI applications should incorporate human DTs to capture expertise, preferences, and skills, while analyzing posture, gestures, and location for seamless interaction and collaboration [79]. So far, most of the research mentioned above has focused on manufacturing, with limited applications in logistics. As automation advances in logistics, including the development of Automated Guided Vehicles/Autonomous Mobile Robot (AMR), drones, or androids, DT-based HMI will be crucial for integrating human, machines, and their digital twins.

4.2.3. Perception and adaptation

4.2.3.1. Cognitive DT. Beyond data acquisition, DTs can create and manage connections between objects. Cognitive DT (CDT) is an emerging concept that expands the traditional DT by incorporating semantic communication and enhanced interoperability with context awareness, enabling self-adaptation and autonomous decision-making. CDT is distinguished from conventional DTs by its enhanced perception capabilities, including standardized object representations, goal-oriented attention, memory through information storage, problem-solving, reasoning, and learning [110]. Several research topics relating to this concept could be investigated. First, CDTs must autonomously connect and communicate with other CDTs or intelligent systems using standardized protocols and semantic technologies. Ontology, a Semantic Web solution, supports abstraction and conceptualization through formal, explicit, and shared vocabularies. For example, semantic-enhanced DTs improve the visibility of urban parking resources and allow real-time monitoring and resource allocation [45]. This aligns with the Web of Things concept, which emphasizes integrating operable and controllable objects across IoT platforms and applications. Second, CDT can incorporate problem-solving capabilities through a Knowledge Graph (KG). KGs are used to describe and enhance ontology-provided knowledge about entities, relationships, properties, and events within a domain, infer new facts by reasoning, and support the evolution of CDTs. Recent studies have explored combining DTs and KGs for resource allocation in manufacturing systems, accounting for real-time spatiotemporal constraints and requirements [109]. Similar composite studies are likely to be applied in other LSCM areas, such as intralogistics and last-mile delivery, especially for self-organizing or autonomous systems.

4.2.3.2. Self-organizing system. The evolution of DT towards cognitive abilities creates new research opportunities in self-organizing systems. Self-organizing systems are advanced smart systems, capable of functioning autonomously with minimal external intervention [8]. Most research has focused on smart manufacturing, arguing cognition is a prerequisite for self-organizing systems, particularly at the object level, enabling context awareness, information analysis, decision-making, and reasoning. These capabilities facilitate self-configuration, self-optimization, and self-healing [47]. Few studies have applied this concept to LSCM, a more complex domain that involves both open and closed systems (e.g., global logistics, intralogistics), while manufacturing systems are typically seen as intralogistics. In open systems, effective system-wide control is hypothesized to be necessary to prevent chaos or other unexpected outcomes, even when agents are self-controlled. Pan, Trentesaux, and Sallez [61] suggested that a self-organizing logistics system (SoLS) must exhibit intelligence, openness, and decentralized control for efficiency and effectiveness, recommending a rule-based decentralized control approach. Similarly, van Duin et al. [88] proposed algorithm-based control for a self-organized parcel delivery system. These studies consider that agents operate under system-wide control rules predefined by humans during system design. However, little discussion has focused on how cognitive agents would behave in such systems. It can be hypothesized that if cognitive DTs possess reasoning and self-evolution capabilities, SoLS performance could improve continuously, as cognitive DT-based agents refine predefined rules and algorithms. Investigating the role of cognitive DTs in SoLS, and their potential to revolutionize current LSCM practices, presents a significant research opportunity.

4.2.3.3. (Generative) Artificial Intelligence-Assisted DT. (Generative) AI can enhance LSCM by improving learning, perception, prediction, interaction, adaptation, and reasoning capabilities [30]. Generative AI extends learning beyond structured data to encompass implicit knowledge and practical human experiences. By processing natural language, it enables intuitive communication with humans, seamless task collaboration, and the ability to learn from human expertise, particularly in managing anomalies and incidents. The combination of reasoning and prediction shows potential for enhancing supply network robustness. Kosasih et al. [36] use machine learning with Knowledge Graphs to predict hidden supply relationships and develop a comprehensive supply network representation, thereby enhancing risk management. Mapping the global supply network is a key prerequisite, a necessity highlighted during the pandemic due to widespread supply chain disruptions and significant resulting losses. Pichler et al. [66] suggest using value-add-tax (VAT) and trade data to map the global supply network at the firm level, covering 20 % of the global Gross Domestic Product (GDP) within the network representation. Machine learning can subsequently be employed to identify firms with potential for both physical trade (materials and merchandise) and digital trade (data exchange). In a Multi-agent system (MAS), each digital twin operates as an agent with specific objectives, taking actions to accomplish defined goals. Multi-Agent Reinforcement Learning (MARL) can be utilized to determine the actions of each digital twin within the system. This system functions in a dynamic, non-stationary environment, capturing real-time states and changes across digital twins. Each digital twin adapts to others, pursuing individual rewards while simultaneously contributing to the system's global objectives for greater collective benefit.

5. Conclusion

This paper investigated the state of the art of DT research and applications in logistics and supply chain management from three perspectives: Application areas, Service types, and Technology Readiness Level. A Systematic Literature Review was conducted using this framework, yielding 70 relevant papers for in-depth analysis. Statistical results revealed that intralogistics, including smart manufacturing and warehousing, is the primary application area for DT, reflecting its origins in closed systems. Digital transformation and resilience have also received significant research attention. Eight DT-enabled services were identified from the perspective of service innovation. Technological maturity, measured by TRL, varies across services and application areas. This study offers a comprehensive overview of the research landscape of emerging DT technology in LSCM, highlighting key insights and gaps. Based on the findings, several promising future research directions are suggested to advance the field. Finally, this review is limited to academic peer-reviewed publications, excluding grey literature, industry reports, government documents, and project deliverables. Additionally, due to the novelty of DT technology in LSCM, the TRL assessment was simplified into three stages: low (research), medium (development), and high (deployment). As DT technology and research rapidly evolve, future reviews could benefit from more refined assessment methods.

CRediT authorship contribution statement

Yu Liu: Writing – original draft, Visualization, Software, Project administration, Methodology, Formal analysis, Conceptualization. **Shenle Pan:** Writing – review & editing, Supervision, Methodology, Funding acquisition. **Eric Ballot:** Supervision, Methodology, Funding acquisition.

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. Categorization of reviewed papers

Title	Service [1]								Areas of application [2]	Technology Readiness Level (TRL) [3]
	Monitoring	Optimization	Evaluation	Prediction	Control	System management	System Integration	Adaption		
[55]			✓	✓		✓			SN - digital transformation	H
[96]	✓		✓						IL - factory	H
[95]	✓							✓	IL - warehouse	H
[25]	✓	✓				✓			IL - warehouse	H
[74]	✓	✓							SN - digital transformation	H
[73]	✓		✓						SN - digital transformation	H
[15]	✓	✓							IL - factory	H
[109]	✓	✓							IL - factory	H
[68]						✓			SN - digital transformation	L
[67]			✓			✓		✓	IL - factory	L
[9]			✓						SN - resilience	L
[107]	✓						✓		IL - factory	L
[38]	✓			✓					FMT - road	L
[106]							✓		FMT - ITS	L
[71]				✓			✓		FMT - railway	L
[69]			✓	✓	✓	✓			IL - factory	L
[12]		✓	✓				✓		SN - digital transformation	L
[1]	✓		✓						SN - digital transformation	L
[27]	✓			✓		✓		✓	SN - resilience	L
[52]	✓		✓						CL - policy-making and planning	L
[11]			✓						SN - resilience	L
[20]						✓			SN - digital transformation	L
[78]	✓			✓		✓			FMT - pipeline	L
[28]	✓	✓		✓	✓				SN - digital transformation	L
[33]							✓		SN - resilience	L
[75]	✓		✓	✓	✓		✓	✓	SN - sustainability, resilience	L
[78]			✓	✓					SN - resilience	L
[2]	✓			✓		✓			FMT - ITS	L
[48]		✓					✓		SN - resilience	L
[41]	✓	✓		✓					FMT - road	L
[102]	✓		✓						SN - sustainability	L
[60]	✓		✓						Intra - factory	L
[86]			✓	✓					FMT - ITS	L
[99]	✓	✓	✓						CL - urban transport system	M
[16]	✓		✓						SN - digital transformation	M
[53]		✓							SN - sustainability	M
[94]	✓	✓							SN - resilience	M
[105]				✓					CL - crowdsourcing	M
[65]	✓	✓	✓	✓					SN - digital transformation	M
[13]		✓	✓						SN - sustainability	M
[64]			✓						SN - resilience	M
[100]			✓						FMT - ITS	M
[54]	✓		✓		✓				IL - factory	M
[22]	✓	✓							IL construction site	M
[44]	✓			✓	✓		✓		FMT - ITS	M
[24]		✓				✓			IL - factory	M
[21]		✓				✓			SN - digital transformation	M
[77]			✓						SN - digital transformation	M
[72]					✓				IL - airport	M
[94]	✓	✓							IL - factory	M
[46]	✓	✓	✓					✓	CL – urban transport system	M
[40]	✓	✓				✓			IL - warehouse	M
[37]	✓		✓			✓			FMT - road	M
[4]	✓	✓							IL - factory	M
[42]	✓	✓							FMT - ITS	M
[70]			✓						FMT - ITS	M

(continued on next page)

(*continued*)

Title	Service [1]								Areas of application [2]	Technology Readiness Level (TRL) [3]
	Monitoring	Optimization	Evaluation	Prediction	Control	System management	System Integration	Adaption		
[6]	✓	✓	✓					✓	SN - resilience	M
[5]							✓		SN - resilience	M
[18]	✓								FMT - pipeline	M
[87]	✓								IL - factory	M
[19]	✓	✓							IL - warehouse	M
[98]	✓		✓						FMT - ITS	M
[51]								✓	IL - warehouse	M
[101]	✓	✓			✓				IL - factory	M
[56]				✓					FMT - ITS	M
[39]	✓	✓	✓						IL - warehouse	M
[26]	✓							✓	CL - crowdsourcing	M
[23]	✓		✓			✓			SN - digital transformation	M
[50]				✓		✓			SN - digital transformation	M

[1] Eight types of services, please refer to Fig. 5.
[2] CL - City logistics, FMT - First-mile transportation, IL - Intralogistics, SN - Supply Network.
[3] L - Low, M - Medium, H - High.

Data availability

No data was used for the research described in the article.

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