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DIGITAL TWINS FOR SUPPLY CHAINS: MAIN FUNCTIONS, EXISTING APPLICATIONS, AND RESEARCH OPPORTUNITIES

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ABSTRACT

In recent times, manufacturing industries and their related supply chains have faced growing internal and external pressures. Due to the complex nature of global supply chain networks and the increased frequency of disruptive events, there is a pressing need to implement digital tools to support these industries. Digital twins have gained significant interest from industry and research communities due to their ability to provide valuable services in the short term. While there have been many contributions on digital twin-based methodologies for system design and production planning and control, the use of digital twins in supply chain management still needs to be improved. This paper presents an overview of the existing contributions on digital twins for supply chains. Starting from a preliminary literature review on the topic, relevant works are selected and used to identify insights on the current development level and future research opportunities.

1 INTRODUCTION

Global supply chains recently faced significant disruptions caused by both internal and external factors. The demand for customized products and pressure on prices has led to a shift towards more flexible production systems and logistics networks. At the same time, unpredictable events such as pandemics and lockdowns have highlighted the importance of stress testing and risk-averse planning approaches (Simchi-Levi and Simchi-Levi 2020). Consequently, production and logistics enterprises are increasingly investing in digitization (Belhadi et al. 2022). Recent studies have emphasized the significance of *digital twins* as decision support systems that rely on predictive modeling of the behavior and dynamics of a supply chain (Arshad et al. 2022; Marmolejo-Saucedo 2020). To achieve this objective, a simulation or optimization engine is commonly integrated with the digital shadow, which enables dynamic interaction with the physical system. This feature facilitates the addition or expansion of functions while providing interactive feedback (Busse et al. 2021; Martin and Oger 2022). Moreover, it is crucial for both the virtual and physical system to continually exchange information, hence a bidirectional data link is needed.

Among others, one of the most inclusive definitions of digital twin identifies it as *"a set of adaptive models that emulate the behaviour of a physical system in a virtual system getting real time data to update itself along its life cycle. The digital twin replicates the physical system to predict failures and opportunities for changing, to prescribe real time actions for optimizing and/or mitigating unexpected events observing and evaluating the operating profile system"* (Semeraro et al. 2021). Recent literature has introduced the term *Digital Supply Chain Twin* (in the remainder indicated as DT for the sake of simplicity) to differentiate it from the ones applied to other fields. This terminology refers to a DT that fulfills the requirements and specifications of supply chain management and reflects a growing trend in recent articles. Indeed, by integrating sensors and other data handling technologies (e.g., Internet-of-Things) to several critical phases

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of supply chains (e.g., orders arrival timestamps, shipping tracking), DTs can offer real-time insights into the performance of a physical supply chain and identify potential issues or bottlenecks (Wang et al. 2022). Also, the integration of DTs within supply chain management phases promises a multitude of advantages, including the optimization and improvement of customer service, reduced costs, and increased profits. By leveraging DTs, businesses can identify and eliminate inefficiencies, reduce risks, and monitor and track the supply chain's performance to identify opportunities for improvement. Another advantage of DTs is the real-time monitoring of supply chain performance, where sensors and other data sources can be integrated into the DT to provide a real-time view of the supply chain. This feature can enable managers and operators to quickly identify and resolve issues, preventing costly delays and disruptions, and ultimately enhancing the overall performance of the supply chain. For instance, DTs can be used to simulate various scenarios and test different strategies for managing the supply chain from a particular state. This can aid managers in making more informed decisions about resource allocation in the short-term and adjusting the supply chain to meet the customer expectations.

Figure 1 compares the number of publications on DTs in manufacturing with respect to logistics and supply chains. The papers have been obtained as a result of two separate queries which have been done on 2023-01-10 on the Scopus database, respectively: (1) ”Digital Twin” AND (”Logistics” OR ”Supply Chain”), resulting in 528 papers, and (2) ”Digital Twin” AND (”Manufacturing” OR ”Production”), which provides 3687 results. The figure shows that while in manufacturing there has been a significant increase in publications following 2017, the number of publications on DTs for supply chains has not experienced the same increase. We may infer that the generation and management of DTs for supply chains may reveal to be more challenging than building DTs of manufacturing systems. Literature has provided successful DT implementations that focus on specific supply chain processes, such as manufacturing (Kritzinger et al. 2018), retail (Kümpel et al. 2021), logistics (van der Valk et al. 2022), and healthcare (Rivera et al. 2019). Despite these succesfull applications, literature still lacks of a widely accepted methodology and framework for building DTs for supply chains. This is likely due to the complexity of supply chains, which involve numerous stakeholders and intricate processes that require both precise modeling and frequent manual interventions. The complexity may further increase if the value chain spans across the globe and involves various transportation modes. Additionally, supply chains are highly dynamic and frequently subject to disruptions such as pricing pressures, customer and supplier issues, and transportation delays. These disruptions cause significant structural changes in both material and information flows that are not easily reflected in digital models, which are often designed for lower-frequency uses. Furthermore, structural changes necessitate continuous adjustments to data sources, which can pose a challenge in generating and updating accurate digital representations.

This paper aims to gather insights from the available literature and summarize the main features that must be provided by DTs applied to whole value chains. Existing literature reviews are listed and exploited to gather useful insights on the technological enablers, barriers, and research challenges. The rest of the paper is organized as follows: Section 2 summarizes the existing literature reviews and frameworks on DTs for supply chains; Section 3 discusses on the common features and functions of DTs. Section 4 summarizes the main applications; Section 5 lists the research opportunities; Final remarks can be found in Section 6.

2 LITERATURE REVIEW

In this section, we gather insights from existing literature reviews on DTs for supply chains. The papers have been selected by executing the query *”Digital Twin” AND (”Logistics” OR ”Supply Chain”)* on the SCOPUS database without date restrictions (Lugaresi et al. 2023). From the 528 results, a subset of papers has been selected based on the following criteria applied to the title and the abstract: (1) the publication must be in English, (2) the publication must regard the application of DTs to provide benefits to supply chains, (3) the publication aims to provide a comprehensive literature review on the subject. As as result, the 15 papers listed in Table 1 have been selected and are summarized in the following.

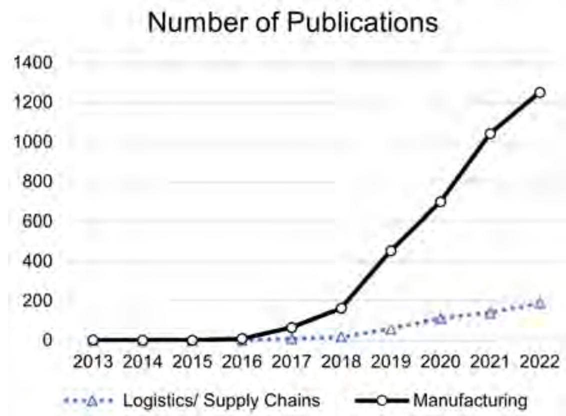

Figure 1: Comparison in the number of publications on digital twins in manufacturing with respect to logistics and supply chains in the last ten years (from Lugaresi et al. 2023).

Agalianos et al. (2020) investigated the literature on the integration of discrete event simulation and DTs in the management of warehouse systems. The work highlighted the trend of including real-time capabilities in simulation experiments, for instance for scheduling capabilities. Barykin et al. (2020) attempted to address the link between DTs and risk management. The authors concluded that there are no available approaches to build the conceptual model of a supply chain DT. Krajcovic et al. (2018) used a case study to demonstrate the phases with which an enterprice can adopt intelligent logistic planning methodology, and identified how different technologies can aid in specific inventory strategies. Marcucci et al. (2020) explored the DT concept and its potential role in urban freight transport policy-making and planning. The authors emphasized the importance of having a thorough understanding of the connections between real-world context and choice/behavior. The paper claims that the use of both behavioral and simulation models is crucial in creating a DT that can facilitate effective participatory planning processes and forecast both behavior and responses to structural changes and policy implementations. Vilas-Boas et al. (2023) provided an overview of the use of DTs in food logistics, outlining the key requirements for technologies to be applied in each stage of the logistics process. The paper also discussed potential research opportunities in the fresh food supply chain and highlighted the challenges that must be addressed when integrating these technologies. Taghipour et al. (Taghipour et al. 2022) emphasized the impact of digital enablers in enhancing the performance of various entities within a supply chain, and investigated how digitization can influence the profitability of these activities both individually and collectively. The authors underlined the importance of collaboratively managing supply chain processes that are autonomous and decentralized. Kamble et al. (2022) conducted a systematic literature review to examine the relationship between various dimensions of supply chain DT and sustainable objectives. The authors concluded that technological advancements in Internet-of-Things (IoT), cloud computing, and blockchain have expanded the potential applications of DT in supply chain management. Also, they suggested that a comprehensive supply chain DT should encompass all entities, including people and things, throughout the entire supply chain, rather than solely local manufacturing systems. Further, the paper proposes a sustainable DT implementation framework for supply chain management to assist future practitioners and researchers. Bhandal et al. (2022) identified four clusters of values and one cluster of enablers for DTs in operations and supply chain management. The value clusters include articles that demonstrate how DT implementation can improve supply chain activities at the level of business processes and supply chain capabilities. The authors identified the supply chain resilience and risk management value cluster as a newly emerging cluster and situated on the periphery of the primary literature network. van der Valk et al. (2022) did a liteature review by classifying papers on the basis of use cases, purposes, and technological readiness. The authors highlighted the challenges for DTs development and identified five main research directions: (1) the

Table 1: Existing literature reviews on digital twins for supply chains (from Lugaresi et al. 2023): • = full, (•) = partial coverage.

Reference	**Domains**	**Framework**	**Barriers**	**Enablers**	**Challenges**
Agalianos et al. 2020	Unspecific	-	-	-	-
Barykin et al. 2020	Unspecific	•	-	(•)	-
Krajcovic et al. 2018	Automotive	•	-	-	-
Marcucci et al. 2020	Urban Logistics	-	(•)	-	-
Vilas-Boas et al. 2023	Food	-	-	(•)	•
Taghipour et al. 2022	SC Management	-	-	•	-
Kamble et al. 2022	Sustainability	(•)	-	(•)	-
Bhandal et al. 2022	Risk Management	-	-	•	-
van der Valk et al. 2022	Unspecific	-	-	-	-
Zahra et al. 2022	IoT	-	-	-	-
Dy et al. 2022	Unspecific	-	-	-	•
Kulaç et al. 2022	Unspecific	-	-	(•)	-
Uhlenkamp et al. 2022	Unspecific	(•)	-	-	-
Jeong et al. 2022	Unspecific	(•)	-	-	-
Aguilar-Ramirez et al. 2022	Blockchain, IoT	-	-	-	-

integration of different information system tasks within a single digital object, (2) the derivation of further DT-driven services, (3) the development of of industrial use cases, (4) the extension of DT capabilities toward additional domains besides classical production, and (5) the direct control of supply chains. Zahra et al. (2022) highlighted the role of digitization in supply chains and the enabling technologies to achieve DT capabilities. Dy et al. (2022) examined the uses of DTs in different industrial sectors. Their literature review also focuses on the application of DTs for supply chain risks. The authors revealed the current advancements of DTs in the mentioned industries and their application to risk management. Its purpose is to aid supply chain practitioners and researchers in recognizing challenges and areas of potential research related to DTs. Kulaç et al. (2022) presented enabling technologies and application sectors of DTs for supply chain operations. The authors suggested the value of DTs can be divided in three main functions: (1) descriptive, which means providing end-to-end visibility of the supply chain status; (2) analytical and predictive, which exploits capabilities of simulation models for scenario analysis; (3) diagnostic, which exploits big data analytics and machine learning algorithms to detect patterns, hidden relationships, and abnormalities. Uhlenkamp et al. (2022) developed a maturity model of DTs that includes seven categories: context, data, computing capabilities, model, integration, control, human-machine interface. The goal is to assess the effectiveness of existing solutions and identify opportunities for improvement or adaptation to new use-cases. The method provides a comprehensive framework for evaluating DTs and represents the first step towards a systematic evaluation and a structured development of new applications. Jeong et al. (2022) provided a comprehensive overview of the evolution of DTs since the introduction of the term in 2002. The authors presented implementation layers to guide the practical application of DTs, and suggested technology elements for each layer that can efficiently facilitate the creation of new DT models. The technology elements are also defined and applicable across various domains. Aguilar-Ramirez et al. (2022) identified how DTs and blockchain technologies can collaborate to meet the requirements of supply chains. The authors identified the advantages and disadvantages that should be thoroughly evaluated before implementing blockchain-based DTs in any business.

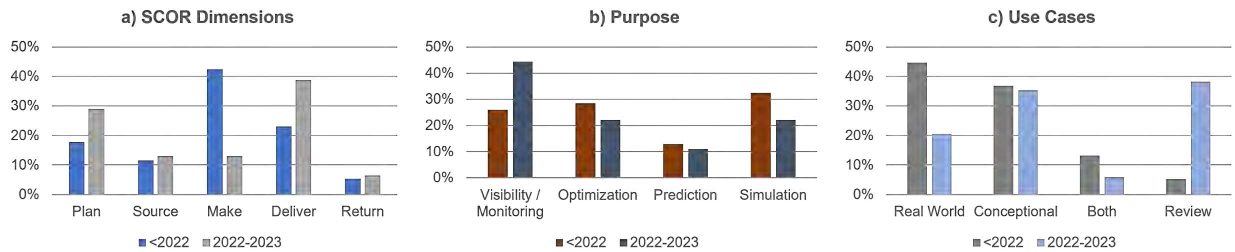

Figure 2: Trends identification based on the classification proposed in Van der Valk (2022): a) SCOR model dimensions, b) DT purpose, c) DT use cases. The indicators are expressing the relative number of papers that fall into each category.

2.1 Current Trends

van der Valk et al. (2022) conducted a literature review using the same query shown in Figure 1. They classified papers published until the end of 2021 according to use cases, purposes, and technological readiness. Since their study, 189 additional papers have been published. Therefore, it is relevant to identify current trends by analyzing how the new papers would be classified within the same categories, which are the (1) Supply Chain Operations Reference Model (SCOR) dimensions, (2) DT purpose categories, and (3) DT use cases.

Figures 2a, 2b, and 2c present the results of this trend analysis, providing useful insights into current research trends. Figure 2a shows the trends in the SCOR processes dimensions. Until 2022, there was a tendency to focus on the ”make” phases. This is coherent with Figure 1, as DTs for production phases were developed before those for supply chain processes. Recently, there has been a significant increase in papers focusing on planning (i.e., mostly risk assessment) and delivery phases (i.e., resilience, recovery phases). This shift indicates a focus on the entire supply chain, moving away from the factory level. Figure 2b shows the distribution of DT functionalities. Until 2022, there was a relatively even distribution among the DT functions, but more recently, there has been a significant increase in visibility and monitoring applications. This trend is supported by the fact that system state mirroring is one of the first steps in DT development, both in terms of implementation and application interests (Jeong et al. 2022). However, despite the focus on a particular service, the existing contributions remain at a general, conceptual level, without proposing practical insights on DT architecture building or diving deeper into quantitative methodologies. Figure 2c compares existing literature trends with respect to DT use cases. There has been a significant increase in the number of literature reviews, indicating a growing maturity of the topic.

Starting from the papers identified in the literature, we have selected significant contributions with the aim to highlight the main application frameworks, the functions of DTs in supply chains, and relevant applications, which are described in the next sections.

2.2 Existing Frameworks

The implementation of DTs lacks a standard architecture, leading to confusion in terminology in the literature. Different approaches to defining DT architecture have been proposed. The manufacturing field originated the first approach, which identifies five dimensions of a DT: physical system, virtual system, data integration, service system, and connections between the dimensions (Zhang et al. 2021). This framework has been later extended to six dimensions with the addition of a decision support system (Jones et al. 2020). The second approach, commonly used in simulation studies, focuses on the components of the simulation within the DT (Arshad et al. 2022; Wang et al. 2022) and describes its architecture as the functional relationships between real-time input data, simulation experiments, and output results. In Martin and Oger (2022), the environment in which the reinforcement learning agent is trained is referred to as a DT, leading to the concept of DT being conflated with that of digital simulation or optimization. A modular framework proposed by Perez et al. (2022) divides the DT into three modules: (1) the *system identification module*, which renders an accurate model of the supply chain business processes using embedded data and parameters; (2) the *simulation engine*, that uses discrete-event simulation to explore different scenarios; (3) the *optimization engine* optimizes the system, its parameters, and functions using either heuristic algorithms or linear programming. Despite the aforementioned framework propositions, it remains complex to classify existing works under a limited set of framework types. Indeed, each contribution has characteristics that remain highly influenced by the chosen approach and application field.

3 DIGITAL SUPPLY CHAIN TWIN FUNCTIONS

DTs offer specific functionalities that can be tailored to the needs of individual value chains. In the following is provided a summary of the most cited functions that are expected from DTs to the aid of supply chain operations.

3.1 Visualization and Monitoring

To ensure that the DT always reflects the physical system and responds to environmental changes, it should be updated in real-time. The frequency of data exchange depends on the specific use-case, but it is widely agreed in the literature that continuous optimization and improvement cannot be achieved without a constant connection (Busse et al. 2021). Given the real-time connection, a DT allows organizations to visualize and monitor the status of assets, inventory, and products in real-time. This capability also grant the needed information to make on-time and undistorted judgements. Even unprocessed data can suffice for this function, which differs from analytics described in the next section.

3.2 Advanced Analytics

All DT systems rely on descriptive analytics to gain insights into the performance of the physical system, identifying patterns and trends based on historical data. In the following, the main types are summarized.

- *Predictive analytics* are commonly used to forecast future events or outcomes, and it is employed in several use cases, such as in the classification of products according to their quality (Min et al. 2019) or estimating the delivery failure probability of suppliers (Abideen et al. 2021). Using data from both the physical systems and the DTs, predictive analytics can be used to identify issues such as potential bottlenecks or inventory deviations, as well as to forecast both demand and supply. Differently from the traditional approaches, DTs can provide the capability to perform predictions based on data that do not represent any historical situation.
- *Reactive analytics* involve real-time analysis of events as they occur and the development of reactive recovery policies immediately after failure is observed. This approach is commonly used in risk management studies (Cavalcante et al. 2019; Ivanov and Dolgui 2021; Martin and Oger 2022). This function may also involve the use of sensors and real-time IoT data to monitor events and trigger automated responses.
- *Prescriptive analytics* are approaches used in DTs to test different configurations of the supply chain (Lepenioti et al. 2020). Other contributions used reinforcement learning to generate recommendations for prescriptive analytics. For example, Wang et al. (2022) trained an agent to make supply chain decisions regarding route optimization. Similarly, in (Burgos and Ivanov 2021), an agent is trained to make supply and delivery decisions. The agent is fed with different data such as warehouse data, orders, and truck route information until it determines the best action to take based on available data.

3.3 Simulation and Optimization

A DT can be used to analyse different scenarios and optimize the supply chain performance. For instance, the impact of changes to transportation routes, inventory levels, or suppliers can be tested and optimized in the virtual world before designing operational procedures. Pan et al. 2021 simulated different inventory policies using discrete-event-simulation in Anylogic and different what-if-scenarios to determine optimal inventory policies. The simulation capabilities can also be exploited to identify opportunities for continuous improvement (Marmolejo-Saucedo et al. 2020).

3.4 Adaptation

A DT must accurately represent the physical system in all its complexity and variability so that its outputs can be effectively used (Burgos and Ivanov 2021). The literature is rich with applications covering a wide range of DT scopes. Gerlach et al. (2021) proposed to simplify them in three main categories: (1) *asset level* focuses on a single physical component, such as a machine or device. However, asset DTs are atomic and are not compatible with the definition of digital supply chain twins. (2) *site level* involves the integration of multiple physical twins within a site or facility, such as warehouses or production facilities. Such a DT can be used to monitor interactions and dependencies between physical assets and optimize the entire site, including inventory management and production planning aspects. (3) *network level* involves the integration of multiple sites or facilities into a single DT. It enables coordination and optimization across the entire supply chain, including logistics and demand planning.

3.5 Enterprise Systems Integration

Information system databases from tools such as enterprise resource planning (ERP), warehouse management system (WMS), material requirements planning (MRP), and customer relationship management (CRM) are typically identified as the main data sources for DTs (Coelho et al. 2021). Cloud-sharing and external data can also be exploited. The integration remains challenging as state of the art DTs imply a partial re-purposing of enterprise systems and migration to holistic data storage solutions (Marmolejo-Saucedo and Hartmann 2020). For instance, Min et al. (2019) illustrated a DT application in a petrochemical manufacturing industry where data is collected using industrial IoT systems with specific edge computing capabilities. The data is then retrieved using ad-hoc application programming interfaces to be further processed.

4 APPLICATIONS

The development of DTs for supply chain analytics is mainly aimed at providing decision support systems for increasing supply chain visibility, managing risks, and handling disruptions. In these applications, DTs can use the large volume of data they gather about the physical system and its functioning to detect anomalies in real-time, using information from the field as well as from enterprise information systems to identify critical areas and assess them.

4.1 Supply Chain Visibility

According to Moshood et al. (2021), the DT can contribute to four different dimensions of visibility: (1) Sensing visibility: the DT can detect real-time changes and interpret sensor data to gain insights into the supply chain flow. (2) Learning visibility: the DT has the potential to gain knowledge about the operations of the organizations, such as the transport of suppliers, through flows of data. This knowledge can be dynamic and used to suggest solutions and improve processes. (3) Integrating visibility: the DT can improve a company's adaptability and ability to incorporate new approaches by analyzing vital internal processes and aligning them. (4) Coordinating visibility: the DT allows for better decision-making through collaboration between different parties involved in the supply chain, including suppliers, manufacturers, and distributors.

4.2 Risk Management

The use of DT for risk management has gained attention in recent years, primarily because of the increasing complexity and interdependence of systems resulting from the industry 4.0 transformation. Furthermore, the demand for real-time risk monitoring and decision-making has contributed to this trend (Barykin et al. 2020; Gerlach et al. 2021). Indeed, in order to enhance agility and redundancy in supply chains, it is important to implement good practices such as diversifying suppliers and avoiding single points of failure. However, even with these measures in place, risks cannot be completely eliminated. DTs with predictive functions can help mitigate these risks. In the literature they are often referred as supply chain *"control towers"*. For instance, Wang et al. (2022) suggest that DT can simulate scenarios corresponding to the main identified risk scenarios, in order to recommend the best reconfiguration strategies for each scenario. Cavalcante et al. (2019) developed a DT in which data about suppliers' past delivery, such as deliveries on-time and late deliveries, are processed to predict the probability of each supplier delivering an order on time. This model creates a risk profile of each supplier, which can help in intelligent decision-making and shaping a more resilient supply chain through risk avoidance or risk reduction strategies such as removing high-risk supplier portfolios or combining them with more delivery-reliable suppliers. As more data becomes accessible, and quantitative and modeling methods continue to evolve, the usage of DT technology for risk management is expected to expand (Bhandal et al. 2022).

4.3 Disruptions Management

Disruption modeling using DTs in supply chain is a growing trend in recent years, although still considered a novel topic. In particular, the Covid-19 pandemic has led to studies exploring the benefits of using DTs to model and mitigate disruptions in the supply chain. Wang et al. (2022) discussed a case study of an online retailer in China, who created a cloud-based digital supply chain platform. The study aimed to validate the simulation model in the platform by calibrating its parameters to accurately reflect the current demand status in one of the areas with 96% accuracy. Different scenarios, such as changes in demand, supplier lead times, and transportation routes, were then tested to enable comprehensive improvements in the supply chain. Burgos and Ivanov (2021) explored the use of a DT-based approach to model and mitigate the impact of COVID-19 on a European food retailer's supply chain. They combined historical sales data, inventory levels, and supplier lead times to create a DT model using AnyLogic, and simulate different scenarios to assess the impact of certain disruptions on the supply chain. Their findings showed that increasing safety stock levels and using alternative suppliers can improve supply chain resilience in the face of disruptions such as a pandemic. The study highlights the potential of DT-based approach to provide real-time visibility and enable proactive decision-making, thus improving supply chain resilience.

5 RESEARCH OPPORTUNITIES

Based on the literature review and discussion, preliminary types of research challenges have been identified by the authors.

5.1 Digital Twin Architecture Definition

Architecture challenges involve the creation of a comprehensive and commonly accepted DT architecture, which can benefit both researchers and practitioners. To enhance the performance of the entire supply chain, the management processes should be decentralized, autonomous, and collaborative, enabling each component to independently achieve its own objectives and constraints while simultaneously pursuing overall optimization (Taghipour et al. 2022). Therefore, it is crucial to design and establish a practical DT architecture that can support the development of general components, including data exchange interfaces, as well as application-specific services. Additionally, the structural design must consider the operational phases of DTs, such as life cycle management (Romero et al. 2020).

5.2 Digital Twin Generation

Some research directions remain unexplored in the supply chain domain, and similarities with the manufacturing domain can provide useful guidance. For example, supply chains could benefit from model generation approaches and methodologies for managing DT operational phases (Lugaresi and Matta 2021; Matta and Lugaresi 2023). Indeed, an investment in digitization feed the intuition that the increased amount of data can be used for the generation of supply chain material flow and information models. Such capability will be essential to guarantee the physical-to-digital alignment and to validate the logical structure of the digital models.

5.3 Interaction Challenges

Although the interaction between the physical and digital worlds is a crucial aspect of DTs, few studies have explored this topic in depth. Indeed, interaction challenges arise from the complexity of managing existing DTs once they are operational. Thus, there is a need to develop techniques specifically tailored to address the challenge of physical-digital alignment (Tan and Matta 2022). This is particularly important for achieving level 5 of the DT evolution framework, which involves building and managing DTs at the federated level. However, there is currently a lack of clarity on how this will be achieved (Jeong et al. 2022; Haße et al. 2022).

5.4 Application Challenges

Application challenges are specific to the implementation of DTs in supply chains. DTs have been implemented to improve various functions within the supply chain such as procurement, logistics, distribution, and retail, but they have not been widely adopted in a holistic approach, resulting in DTs that only address one or a few echelons of the supply chain (Valero et al. 2022). This approach overlooks the potential benefits of a comprehensive DT approach. Additionally, the multi-structural composition of supply chain networks and the organizational, financial, and informational changes necessary for successful DT implementation still need to be addressed. While most existing implementations focus on an asset-centric perspective, there is a lack of research on enhancing the sensing and adjusting capabilities of the entire supply chain environment. Although supply chain DTs can provide planning and controlling capabilities at both tactical and operational levels, their potential benefits on the strategic decision-making level for providing business intelligence and enhancing the business ecosystem are yet to be fully explored. Furthermore, devising and integrating DTs for small and medium enterprises within value chains present significant challenges. Indeed, according to Marmolejo-Saucedo and Hartmann (2020), there is a lack of a technological platform capable of modeling DTs in all of their complexity. Hence, some companies must opt to create their own platform. Additionally, a DT requires a significant amount of data to provide an accurate representation of the physical system, leading to extensive data management concerns such as privacy, quality, and security, as noted by Bhandal et al. (2022). It also requires significant computational capabilities or investments in licenses that may not be readily available to many companies.

6 CONCLUSIONS

The field of supply chain management experienced an increased interest about DTs. While there are relatively few applications, some case studies showed promising results exploiting specific functionalities of DTs. However, a lack of a comprehensive overview of DTs capabilities and frameworks remains. This study is preliminary. Future research should formalize the contributions of DTs through systematic literature reviews. For instance, specific DT functions can be applied to different processes within a supply chain, and requirements can vary extensively depending on the applications. The relationships between DT functionalities and requirements require deeper study. Future research should also include quantitative assessment of the impact and implications of using DTs for value chains, as well as developing standardized architectures and frameworks to facilitate their uptake in industry.

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