Digital Twins in Business Logistics

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While decision-making can be difficult, digital twins offer an effective solution by bridging the gap between reality and digital modelling through virtual duplication of the real world. Despite their potential, digital twins are still relatively new in business logistics, leading to uncertainty in supply chain management. This paper focuses on the use of digital twins in supply chain management, seeking to offer information about their functionality and applications. Through a systematic literature review, this study goes more in-depth into the function of digital twins in improving decision-making processes, efficiency, and sustainability in supply chain operations.

Additional Key Words and Phrases: Digital Twins, Supply Chain Management, Business Logistics.

1 INTRODUCTION

In a world of uncertainty, making decisions in our lives can be difficult. The future is unpredictable and unclear, leaving us with questions and what-if scenarios. However, there is a glimpse of hope, the possibility to foresee the unforeseen. Introducing the digital twin, an alternative virtual world that replicates all the physical objects precisely [1]. It uses real-time data to create an accurate environment that can help with decision-making.

A current ongoing project is the implementation of digital twins in a transportation network to improve the resilience of the supply-chain logistic processes using the Twente canals [2]. Led by researchers at the University of Twente, the goal is to improve resilience against difficulties brought on by severe weather conditions. With the help of digital twins, circumstances can be simulated, and predictions can be made that prevent disasters and improve responsiveness. By creating virtual environments of the transportation network, decision-making processes can be improved, by locating potential problems more efficiently, and therefore reducing future disruptions. This project is an example of how digital twin technology can be used to minimize risks and improve the general reliability and efficiency of transport systems. Although digital twins have been out there for a while now, they continue to evolve and change fast. With new technologies constantly being added, the landscape of digital twins is becoming increasingly complex, which creates an overflow of possibilities and alternatives [13]. This rapid growth can be a challenge to understand existing digital twins and how they can support business logistics. This research problem forms the basis for creating an overview of the complex digital twins' landscape on supply chain management.

In this research, I conduct a systematic literature review regarding the use of digital twins in business logistics. By examining and identifying different articles and reports, this research deepens the understanding of the application of digital twins in supply chain management and logistics to improve strategic operations in a company, which leads to better decision-making. In consequence, this study contributes to the aforementioned project involving the Port of Twente [2], since based on this systematic literature review, the project's researchers can develop a digital twin based on the latest developments in this area.

2 RESEARCH QUESTION

To complete this research, the following main research question needs to be answered:

How do existing Supply-Chain Logistics' Digital Twins (DTs) support business logistics (DT functionalities)?

This can be answered with the following research questions:

1. In which logistic processes and for which purpose are organizations across different industries adopting digital twins?
2. To what extent can digital twins assist in predicting and mitigating risks related to supply chain disruptions?
3. How can digital twins in business logistics be considered to increase resilience and sustainability?

3 RELATED WORK

Digital twin was first introduced in 2003 [5] by Dr. Michael Grieve through a lecture on Product Lifecycle Management (PLM) [9]. When it was first introduced, it was not more than a concept. As time continued, the concept turned into an actual virtual product. The concept of digital twins holds the existence of both the physical and the virtual systems in one digital environment [8]. With this, digital twins can simulate virtual reality with real-time data and can predict upcoming events.

In 2016 [6], the approach to predict the future of logistic processes with the use of machine learning was suggested. This approach would have two stages: firstly, creating a system model and ontology for logistics, followed by planning, and predicting future logistical processes. Subsequently, in 2017 [7], the infrastructure for a digital shopfloor management system enabled by digital twins was implemented in the ESB Logistics Learning Factory. Although machine learning was used as a building block, technical IT expertise was required for the communication between the software and the product.

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Over subsequent years, the development of digital twins continued to progress even more [10]. Building on the progress of digital twins in supply chain management [11], this study addresses a gap in the literature by presenting a methodology for digital twin design, thereby leading the use of digital twins in supply chains and providing a comprehensive tool for decision-making.

Mapping the knowledge and different aspects of Digital Twins (DTs) can be quite difficult. Marmolejo-Saucedo and Hartmann [37] discuss how DTs impact supply chain management by gaining visibility and improving decision-making; however, they did not present sustainability in the supply chain. In contrast, this paper will delve deeper into the sustainability aspect. Furthermore, Le and Fang [38] focus more on the technical side of DTs, resulting in different research questions and conclusions compared to this research paper. Nguyen, Duong, Zhu, and Zhou [36] talk about the trends in DTs, leading to different findings and presenting a different focus of investigation in the area, for example focusing on physical internet-based supply chains. Although many studies about digital twins have been carried out over the years, this paper aims to bridge the gaps between them.

4 METHODOLOGIES

This research is carried out with the guidance of Kitchenham's procedure for Systematic Literature Reviews [3]. In an SLR, many papers are gathered, and the paper set is then narrowed down to a collection that is relevant to answer the research questions. To find the papers, a query is elaborated. Consider, for this work, the following query:

(supply chain management OR business logistic* OR logistic*) AND (organization* OR department* OR compan* OR business operation*) AND digital twin*

The queries will be applied to Scopus, Science Direct, IEEE Explorer, and Web of Science. Furthermore, to come up with the final collection of papers, it is important to define inclusion and exclusion criteria.

For the inclusion criteria (IC) we have:

1. The language of the report can be in either Dutch or English.
2. The report was published after 2003 (the year in which the term 'Digital Twins' was first introduced [5]).
3. The work is published in a peer-reviewed scientific venue.
4. The report is relevant to this research study.

For the exclusion criteria (EC) we have:

1. The report is incomplete.
2. The report is a duplicate of another article. In case of duplicates, the most complete version will be selected.
3. The report must be paid for.

After collecting the data, the backward snowballing method is applied, as explained by Wohlin [4]. In this process, additional papers in the reference list of the collected papers are added to the collection. After this step, the reports are narrowed down to a certain number that is eligible enough for this research paper. Figure 1 shows how many papers were selected and excluded through the application of the criteria.

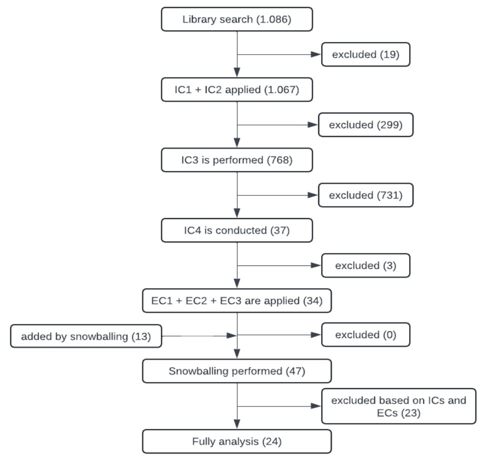

Figure 1. Research selection process.

5 ANALYSIS OF THE SLR RESULTS

In this section the analysis of the SLR results will be presented, addressing research questions regarding the application of digital twins in supply chain management and business logistics. 5.1 will talk about the adoption of digital twins in supply chain operations (RQ1), 5.2 will talk about the prediction and risk mitigation of digital twins (RQ2), and 5.3 will present the resilience and sustainability of digital twins (RQ3):

5.1 DTs Adoption in Supply Chain Processes and Purposes

Supply Chain Management (SCM) extends to various industries such as food, healthcare, manufacturing, retail, and even more. It involves the management of integrated networks to boost competition, accessibility, and maintenance throughout a product's whole life cycle with the help of newly developed technologies that allow organizations to engage in better operations [12]. Digital Twins (DTs) can be integrated into the activities of SCM, such as management, product development, planning, customer services, and marketing [13]. A digital twin adopted in the supply chain is called a Digital Supply Chain Twin (DSCT). It is defined as a real-time, bidirectional data exchange digital simulation model of a logistics system. It functions as a digital representation of network circumstances at any given time, enabling businesses to simulate real-world resources and interactions at different levels of complexity [14]. Optimization of a continuous cycle is made possible by the merging of both virtual and physical world links since possible physical states are predicted in the virtual environment and optimized for a particular goal [22].

5.1.1 SCM Requirements and DTs Functionalities. There are some requirements for supply chain management to apply a smart simulation for their strategy [14]. These requirements need to align with the management and strategy of a supply chain. According to Wang et al. [14], the main requirements are:
Connectivity is the capacity to link all businesses, goods, buildings, and other important items in the supply chain. This allows for the provision of complete information as well as the monitoring of marketing conditions, internal business processes, and interactions between businesses.
Visibility is the capacity to monitor the movement of goods, money, and information along the supply chain. To determine where and how products are stocked as well as when and how they are sold to customers, supply chain managers need to have access to real-time data about production, inventory, logistics, and marketing.
Agility is the capacity to recognize changes quickly, gather relevant information, assess possibilities and dangers, come to the best conclusions, carry them out, and adapt operations as sufficient for the company.
A supply chain that is **integrated** exchanges information and collaborates to make decisions at various supply chain levels.
An **intelligent** supply chain employs predictive analytics to shield the chain from potential threats and make large-scale, optimal decisions.

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 [15]. DTs provide certain features that can be modified to meet the requirements of various value chains. One of the functionalities is visualization and monitoring. DTs can help with *visualization and monitoring data* (status of assets, inventory, and products in real-time), however, continuous data exchange is needed for this process. A second functionality is *advanced analytics*. DTs have three systems to rely on predictive analytics, reactive analytics, and prescriptive analytics. Predictive analytics are frequently used for predicting potential occurrences or results. Reactive analytics include real-time analysis of occurrences as they happen and the establishment of proactive recovery plans shortly after failure is identified. Prescriptive analytics are methods used in DTs to test various supply chain setups. Another functionality is the *simulation and optimization*. Simulations can be used to examine different situations and boost the optimization of the supply chain by finding areas that could use improvement.

Digital Supply Chain Twin (DSCT) can be applied on three different levels: asset level, site level, or network level [15, 19, 20, 25]. With the **asset level**, DTs are concentrated on one physical part, like a machine, container, or truck. On a **site level**, several physical twins are integrated at a location or construction, like a warehouse or a production facilities and cargo handling. The **network level** is about combining multiple locations or facilities into a single DTs, which is useful for logistics visibility and risk management, which both will be further discussed in section 5.2.

Digital twins improve various management capacities, including visibility, transparency, cooperation, and traceability [16]. These capabilities can be used for a wide range of tasks, from the development of new management concepts based on end-to-end visibility and digital collaboration to basic process monitoring (e.g., containers and their physical locations).

The data exchange between the logistics system and its DSCT are characterized by three attributes: bidirectional, timely, and long-term [20,25]. Both directions are involved in the data exchange (*bidirectional*). As a result, modifications to the digital model result from modifications to the logistical system. In the same way, the logistics system makes decisions or takes actions based on the knowledge gained from the digital model. It is stated clearly that a DSCT does not require a certain level of automation in the data transmission. Data is exchanged rapidly (*timely*). The precise frequency is determined by the use case. A DSCT does not explicitly need to provide constant updates in real time unless the application case dictates otherwise. Moreover, data exchange is intended for continuous, long-term use, which thus extends the lifetime of the DSCT (*long-term*). DSCTs are specifically not defined as digital simulation models produced for one-time usage or as a component of project operations.

5.1.2 Integration DTs on Specific Department of SCM. Integrating digital twins into different supply chain departments provides a great strategy to improve operational efficiency. Businesses can gain relevant insights in production, manufacturing, management, planning, and design through the use of digital twin technology.

Smart resource planning involves using advanced technologies to assign tasks to human and non-human resources, thereby enhancing operational efficiency [12]. Digital twins (DTs) assist engineers in monitoring and extracting data on normal or excess production and inventory [18]. When applied to *factories and warehouses*, DTs continuously detect and upload real-time production and inventory levels, along with contextual data indicating their status. As this data accumulates, DTs provide detailed insights into the *production and inventory* of each factory or warehouse under many conditions. Additionally, DTs extract important assessment parameters such as cost, productivity, inventory levels, and ratings from employees and customers. DTs also help engineers in distributing supplies across different areas. When engineers make plans for supply distribution to normal production, excess production, and inventory, DTs present corresponding parameters related to production, cost, inventory level, and risk. This information guides engineers in the continuous re-planning of supply distribution. Furthermore, DTs help engineers *verify their planning*. Enabled by data and modeling technologies, the *virtual representation* (VP) of each unit integrates into the VP of the entire supply chain. As DTs enhance the quality of virtual modeling, the simulation results in the VP become more accurate, allowing plans to be generated in the previous step to be verified through virtual simulation. DTs collect inventory data from the DTs of warehouses, products in inventory, and other interacted DTs within the supply chain. Once sufficient data has accumulated, DTs assist engineers in *validating inventory planning*, ensuring more accurate and efficient resource management.

In *additive manufacturing*, digital twins predict parameters like cooling rate, temperature, and hardness and outcompete conventional approaches by quickly responding to real-time variabilities [21]. They can forecast faults and crack patterns before failure occurs, improving system upgrades and encouraging sustainable production. Digital twin technology greatly helps product manufacturing and services by allowing management to meet demand across the product's life cycle.
Synchronization of the physical and virtual environment in real time increases competitiveness and flexibility in manufacturing processes. Smart products involve digital twins in on-demand manufacturing that includes smart factories, humans, and robots. They encourage data exchange to foster the creation of system architecture and integration of cyber-physical systems at the operational, sensor, and services layers. In this way, the performance metrics make digital twins useful for the optimization and strategic development of autonomous manufacturing.

In *manufacturing*, digital twins for predictive maintenance enable companies to have an instant view of the faults and variations in the structures and dynamics of their operations. Predictive maintenance will be further elaborated on in 5.2.1. Digital twin technology provides a level of visibility into the assets and production that was not possible before, allowing one to see the inefficiencies and make changes to improve operations and redesign the product [23]. Digital twins can be used to optimize *factory layout and design* in terms of productivity and resource efficiency [12]. To implement outbound designs in an operating environment, the digital twin machine gathers and verifies the designs and provides an overview of the product's contributions. Integrating physical supply chain assets with real-time digital representations of those assets improves the planning, management, and measurement of logistical processes [21]. However, using digital twins in different supply chain contexts is not without challenges, especially in terms of data, models, and related information security and privacy and ownership issues. Table 1 provides a summary of the main functionalities and departments which are mentioned in section 5.1.

Departments	Functionalities
Smart resource planning	Visualization and monitoring
Factories and warehouses	Advanced analytics
Production and inventory	Simulation and optimization
(Additive) manufacturing	
Factory layout and design	
Management	

Table 1. The main functionalities and departments in which DTs are used.

5.2 Predicting and Mitigating Risk in Face of Disruptions

Data collection, analysis, interpretation, and decision-making are the sequential steps in a data-driven decision-making process. DTs with predictive functions can help mitigate the risks that come along.

An example of the integration of DSCT showcases supply chain nodes, transportation operations, and other dynamic activities at ports and terminals [25]. With the use of data feeds and feedback loops that direct all stakeholders and decision-makers, it seeks to operationalize and synchronize the system in real-time. Based on traffic patterns and infrastructure developments, the DSCT can simulate the near future and predict asset locations in the future. Depending on the situation, the decision-maker can decide to reroute freight, evaluate modal shift, or modify load factors and vessel speeds. As a result, the decision-maker is better able to deal with disruptions.

5.2.1 DTs in Prediction and Decision-Making. Digital twins can be viewed as 'digital assistants' to managers, which can help in decision-making by using real-time data and predicting the consequences of certain decisions [16]. For example, they can compare different recovery plans after a disruption or measure the consequences of supply chain redesign on the environment. Furthermore, it can improve decision-making skills, for example, determining the best time to place an order in an inventory management system. In essence, digital twins are used to support decisions in real-time based on data. This technology can support decision-making in various fields such as planning, inventory management, production, maintenance as well as resilience and sustainable development. Resilience and sustainable development will be discussed in 5.3.

There are several techniques for predicting [18]:

- **Qualitative Methods**: In these scientific methods, engineers can make decisions based on their knowledge, feelings, and past experiences.
- **Casual Methods**: These hypothetical approaches indicate that demand is positively associated with many different types of factors and their changes.
- **Time Series Methods**: These analytical approaches involve prediction based on trends and patterns observed in past data and situations.
- **Simulation Methods**: Computer software is applied to model possible situations in different contexts and provide options to be considered in Supply Chain Planning (SCP).

Digital twins can offer decision support at all levels [19]. At the *operational and tactical levels*, DTs assess the changes in demand and supply that affect network locations and systems, which in turn helps to control fluctuations in product demand or supply disruptions. *Strategically*, DTs help in expanding or reducing networks by simulating the integration of new nodes or identifying which resources should be reduced to cut down expenses while maintaining the quality of services. Furthermore, DTs can perform *tradeoff analysis*, which means that they can compare different decisions made in the current period to the future years. This helps in achieving a good balance between cost, service, risks, and sustainability while at the same time satisfying the customer.

The digital twin framework offers five categories of value in the decision-making capabilities of digital twins in supply chain management [19, 21, 28, 30, 31].

1. The **Descriptive Value** is very helpful for high-value or remote items since it provides a real-time visual representation and description of the state of the systems, assets, or processes.
2. The **Analytical Value** uses advanced data analytics to simulate and give weights to data that is relevant, providing insights that cannot be assessed directly on the physical entity.
3. The **Predictive Value** enables the strategic analysis of network designs, sourcing options, and customer priority by anticipating future states of physical entities and logistics behaviors in different situations.
4. **Diagnostic Value** combines analytics and machine learning to identify links based on past data or corporate norms to find the underlying causes of logistic-specific states or behaviors.
5. **Prescriptive Value** makes decisions and acts on physical entities by predicting potential issues and implementing solutions, aligning with the prescriptive capabilities of DTs.

Machine learning algorithms such as supervised learning, unsupervised learning, and reinforcement learning can predict the need for maintenance based on the state of an industrial asset, its equipment, and its subsystems [27]. In order to integrate ML in DTs to develop maintenance strategies, also called *Predictive Model Development,* the next stages need to be executed. These maintenance strategies are explained in Table 2. The first stage, *Access and Explore data*, discusses the locations of the project's data access points. In the second stage, *Data Preprocessing/Fusion*, the data is being prepared. This includes data cleaning, formatting, organizing unprocessed data, etc. Pre-processing data is crucial for the Machine learning processes. *Visualization and Model Development* is the third stage where data is translated into readable plots and studied for data-driven decisions. The last stage is *Integrating* the predictions with a system. In this stage, dashboards are provided to give real-time prediction updates and an overview of components with the help of machine learning algorithms that are programmed using machine metadata and telemetry data. In conclusion, *predictive maintenance* is important for increasing productivity by preventing problems and minimizing delays due to unexpected breakdowns. The use of a digital twin can predict and warn failure, thereby increasing the lifespan of components and mitigating risks.

Maintenance strategies	Definition
Run to failure or reactive maintenance	This maintenance strategy involves allowing the equipment to keep running until it fails before fixing or replacing it if visible problems occur. This strategy often lacks in a practical maintenance plan. While it can be effective in businesses where equipment shutdowns have no impact on the output and material costs are minimal, using this strategy can lead to eventual detrimental of a business.
Time-based or preventive maintenance	The preventive maintenance approach is considered a cost-effective and simple strategy. It involved scheduling maintenance tasks at regular intervals to repair or replace damaged parts before any noticeable failure occurs. This method is effective for equipment parts that do not need to operate continuously.
Condition based or predictive maintenance	This maintenance strategy focuses on scheduling maintenance operations only when mechanical or operational conditions occurs. Whenever a condition reaches a specified unsatisfactory level, the machine is stopped to replace defective parts to prevent even more costly failure. Condition monitoring data, OEM, recommendations, and maintenance logs are used to create algorithms for predicting equipment failures. This method is great for effective performance
Pro-active or prescriptive maintenance	This strategy is the most advanced approach and goes beyond prediction failure. The algorithms used in this methos will not only predict failure, but also provide solutions.

Table 2. Maintenance Strategies.

5.2.2 Supply Chain Risk and Visibility. Risk management of supply chain (SC) disruption has expanded over the years and in the last decade and many model-based studies have been developed. *Analytical methods* can be used to evaluate disruption effects by changing the SC elements or parameters, which assist in strategic decision-making [30*]. Dynamic simulation models* fill these gaps by examining SC behavior through time and providing recommendations for the construction of more robust structures based on comprehensive, real-time information. *Analytical and simulation methods* are integrated into hybrid models that improve the recovery policy considerations. To support SC modeling, data on pre-disruption (risk exposure and other design options), disruption (elements impacted and capacities available), and recovery (monitoring of capacities and material flows in real-time) are needed. Real-time control technologies and analytics are needed for collecting this information.

The *ripple effect* occurs when a disruption, rather than remaining localized or being contained to one SC part, causes downstream and impacts the performance of the SC [29]. In order to maintain SC's basic properties, it should be well planned enough to be stable, robust, and resilient as well as be adaptable in behavior in case of changes to achieve planned performance. *Resistance and recovery* are two essential functions for the ripple effect control in SC. **Resistance**, or the SC's ability to protect itself from disruptions and minimize their impact once they happen, requires some redundancy, such as backup sourcing, risk mitigation inventory, or capacity flexibility that must be implemented at the proactive stage. For **recovery**, this redundancy must be combined with reactive contingency plans for risk mitigation inventory, capacity flexibility, and backup supplies. Supply chain risk can be reduced by using big data analytics in a descriptive and predictive way, which improves visibility and forecast accuracy, reduces information disruption risks, and improves contingency planning. *Advanced trace and tracking systems* can minimize supply and time risks by enabling the real-time, coordinated activation of contingency plans. *Blockchain digitization* could help lower risk as well as prevent expenses, given there is a record of actions and data needed for recovery that helps synchronized contingency planning. Furthermore*, additive manufacturing* can reduce the need for risk mitigation inventory and capacity reservations, as well as the reliance on expensive backup contingency suppliers. *Decentralized control in Industry 4. 0, along with big data analytics and blockchain*, helps to improve risk diversification and disruption management. Moreover, the *application of additive manufacturing* can help prevent disruption propagation by decreasing supply chain complexity and improving the overall supply chain resilience. At *the proactive level*, optimization and simulation models, combined with big data analytics and advanced tracking systems, provide managers insights in predicting and planning for disruptions. Digital technology can also provide new challenges for developing resilient supply chains, such as those presented by additive manufacturing. At *the reactive level*, these technologies help with real-time interruption management, impact assessment, and simulation of recovery plans. Adaptation processes benefit from feedback and adaptive control approaches. Integrating simulation models with digital technology can help increase supply chain agility and visibility in the context of disruptions.

Supply chain visibility, given in Table 3, is important for effective decision-making and operational efficiency, especially in a globalized market [15, 31]. It ensures reliable and current information about supply chain processes through effective data sharing among stakeholders. Implementing Digital Twins in a company's logistical supply chain improves supply chain visibility through the use of modern digital technology. DTs can improve the four organizational visibility aspects (sensing, learning, integrating, and coordinating) by providing real-time data on internal and external activities. However, deploying Digital Twins is resource-intensive and does not guarantee complete visibility. Ivanov and Dolgui [29] propose a Low-Certainty-Need Supply Chain (LCN SC) framework dealing with supply chain disruption risk by combining efficiency and resilience. This framework reduces the need for uncertainty in planning decisions and recovery coordinating activities. There are three key elements:

1. **Structural variety and complexity reduction.** Reducing structural complexity through product line-based segmentation and using low-risk consolidation points can improve both lean and resilient supply chain designs, therefore lowering disruption propagation. 2
2. **Process and resource utilization flexibility.** Flexibility in process and resource usage, supported by Industry 4.0 technologies like as additive manufacturing, Big Data analytics, and blockchain, improves supply chain resilience by increasing adaptability and planning.
3. **Efficient parametric redundancy.** Non-expensive parametric redundancy seeks to effectively manage capacity, inventory, and lead time for both everyday operations and disruptions. This happens with research potentials in network redundancy optimization and the use of additive manufacturing to reduce risk mitigation requirements.

The research on ripple effect control for supply chain (SC) disruption management focuses on three principles: 1) Integrated modeling for resilient network structures; 2) Proactive planning and optimization of network redundancy for robustness and resilience; and 3) Situational proactive control through simulation and analytics to provide an effective transition from disruption to recovery. These concepts aim to develop decision-support systems to create efficient and resilient SCs.

Supply chain visibilities	Definition	DTs in SC visibility
Learning	How new knowledge and information from internal and external processes can be collected and absorbed by the enterprise.	Digital Twins increase learning visibility by collecting, articulating, and defining new information from both internal and external sources.
Coordinating	How experienced the company is at coordinating different aspects of the supply chain and making decisions	Digital twins improve coordination by giving accurate representations of logistical operations. This helps in strategic decision-making and efficient management in supply chain.

	affecting multiple participants in the system with long-term consequences.	
Sensing	How quickly an organization can gather current information on internal and external operations and react to market changes.	Digital Twins improve sensing visibility by quickly collecting and analyzing real-time data.
Integration	How successfully a company can implement and incorporate new strategies and technology to get a competitive advantage.	Digital Twins make integration easier by synchronizing processes and technologies throughout the supply chain, creating a collaborative environment between stakeholders.

Table 3. Supply Chain Visibility.

Ivanov and Dolgui [30] provide approaches for using data-driven decision support systems (DSS) and information technology to control supply chain (SC) disruption risk. These ideas are based on information control theory and cybernetics, with SCs considered to be Systems of Systems (SoS). Cybernetics, the study of information control and communication, is important in SC disruption risk modeling because it focuses on control, self-adaptation, and self-organization in open systems. They have the ability to improve SC resilience by quickly identifying and responding to disruptions using real-time data analytics. This proactive strategy promotes successful risk management and fast execution of recovery measures. Three fundamental elements from cybernetics that apply to SC risk management are:

1. **Requisite Variety.** Variety is a measure of the number of different system states.
2. **Viable System Model (VSM).** This model focuses on the ability to sustain the system's identity in the face of environmental dynamics through management, operation, and interaction with the environment.
3. **Second-order Cybernetics.** Focused on proactive planning and control, this principle involves modeling both the environment and the control object as one. It focuses on adaptive and feedback control with online data updates.

Given the fundamental elements, the formulated methodological principles of data-driven DSS for SC disruption risk management contain four principles. The first principle focuses on *decision support as an applicable system model*, which is divided into pre-disruption, disruption, and post-disruption phases. This classification offers a clear guide on how to design effective SC and prepare for emergencies. The second principle focuses on *the synchronization of physical and cyber data with online SC modeling.* This principle emphasizes the need to integrate data from different sources including ERP systems, RFID, and blockchain in improving the assessment of resilience and simulation of recovery. The third principle of the framework calls for *the consideration of supply chain models as a combination of physical and cyber systems.* This approach based on second-order cybernetics recognizes the integration of the physical and the digital within SC systems. The fourth principle is about the use of supply chain risk analytics systems for learning and identification of disruption patterns. The identified disruption patterns can improve the resilience analysis and the decision-making process by using historical data and the developed systems. In summary, data-driven SC risk analytics systems, embodied in digital twins, facilitate decision-making by enabling historical data analysis, predictive optimization, real-time recovery control, and continuous learning from disruptions.

5.3 Resilience and Sustainability with DTs in Logistics

Supply chain resilience is defined as the capability of the supply chain to prepare for unknown events, react to disruptions, and bounce back from them while maintaining operational continuity within expected levels of connectivity and control over structure and function [32]. Resilience is the ability to predict, identify, and protect against risks as well as the ability to prevent and recover from problems. Its techniques involve proactive planning and network redundancy management to predict interruptions and respond efficiently, including backup and inventory capacity, security measures, supplier relationship building, and demand forecasting.

Although visibility is a crucial factor in risk management, as discussed in section 5.2.2, it is also very important in improving resilience. Visibility and data analysis improve resilience towards complexity and disruptions, and provide the opportunity to improve reliability and sustainability, while especially extensive decision support provides the opportunity to improve efficiency [20].

Longo, Mirabelli, Padovano, and Solina [26] talk about a framework, Simulation-Based Decision-Making, for enhancing resilience and sustainability. The proposed framework is designed to help supply chain managers and can be utilized to mitigate disruption in its performance. It refers to a series of processes that must be performed in a cyclical way in order to continually improve the supply chain over time. The first step is *Data Management.* This step involves understanding the supply chain's structure, including products, nodes, transport modes, inventory policies, demand characteristics, costs, and revenues. The manager must conduct a risk analysis to identify potential disruptions at different levels of the supply chain. The second step is to define *performance indicators* that measure the performance of the supply chain in various scenarios. In this framework, the indicators are on two main domains: sustainability and resilience. The next step is to develop one or more possible *strategies.* For each identified disruption, there must be a solution provided to mitigate its impact. After this step, the *digitalization* phase of the supply chain is executed. A digital twin of the supply chain is created. This digital twin simulates the scenarios to help understand the impact of different strategies on sustainability and resilience without actual implementation, thereby saving costs and minimizing errors and waste. Once the most effective strategies are chosen, they are applied and conducted in the real supply chain. The phases can be *repeated* for continuous improvement. This results in greater performance and resilience. An agricultural case study has been conducted regarding this framework. This study showed the framework's potential to improve resilience and sustainability indicators, however, more research is needed to identify the best strategy.

DTs can help with measuring the network's efficiency and sustainability, as well as explaining how design factors influence the organization's carbon footprint and CO_2 emissions while achieving sustainability goals without incurring extra costs and services [19]. Digital twins can improve product design, manufacturing, and service by combining real, virtual, and networked data, resulting in improved sustainability [21].

Data-driven learning takes an active part in improving resilience by helping organizations generate disruption scenarios for designing and planning resilient supply chains [30]. This process helps in risk assessment, supplier analysis, and real-time monitoring, allowing continuous business operations.

6 SUPPLY-CHAIN LOGISTICS' DIGITAL TWINS SUPPORTING BUSINESS LOGISTICS

In the field of supply chain management, the use of DTs is one of the key technologies in the modern world. These virtual copies of physical resources and operations help organizations to optimize their logistics by increasing the levels of visibility, productivity, and control. Digital twins help in making and planning decisions in real time by using real-time data and advanced simulations. In this section, we will answer the research questions to answer the main research question.

In which logistic processes and for which purpose are organizations across different industries adopting digital twins? Organizations across various industries adopt digital twins in supply chain management (SCM) for processes such as management, product development, planning, customer services, and marketing [15]. The main objective is to create a real-time, bidirectional data exchange digital simulation model that supports supply chain visibility, risk management, and disruption handling [20, 25]. Digital Supply Chain Twins (DSCTs) enable businesses to simulate real-world resources and interactions, optimizing their supply chain operations for better decision-making and efficiency [16].

To what extent can digital twins assist in predicting and mitigating risks related to supply chain disruptions? Digital twins serve as 'digital assistants' to managers by using real-time data to predict the consequences of decisions, compare recovery plans after disruptions, and measure the impact of supply chain redesigns. They offer advanced analytics for predictive, reactive, and prescriptive decision-making for the future states of logistics behaviors and assess risks [30]. These capabilities enable supply chain managers to prepare for disruptions more effectively and respond to them more quickly, thus improving overall supply chain resilience [15].

How can digital twins in business logistics be considered to increase resilience and sustainability? Digital twins increase resilience and sustainability in business logistics by offering real-time monitoring and simulation capabilities that help in decision-making. They allow businesses effectively manage the supply chain in a sustainable manner by simulating various scenarios and determining the best and most sustainable solution [19]. Through the application of DT at asset, site, and network levels, organizations are better placed to have enhanced visibility, transparency, and traceability of their supply chains hence making them more resistant and sustainable [21].

Existing Supply-Chain Logistics' Digital Twins (DTs) support business logistics by enhancing decision-making, efficiency, and sustainability. They are used in processes such as management, product development, planning, customer services, and marketing to simulate real-world resources and interactions for optimized operations. DTs predict and mitigate risks related to supply chain disruptions by using real-time data to simulate various scenarios and assess potential impacts. Furthermore, they improve resilience and sustainability by enabling real-time monitoring, optimization, and transparent operations across supply chain networks. This integration leads to more resilient and efficient supply chain systems, capable of adapting to unforeseen challenges and reducing environmental impact.

7 CONCLUSION

This paper offers an analysis of the use of Digital Twins in business logistics, with a focus on supply chain management. By conducting a systematic literature review (SLR) [3], the gaps in DTs are being targeted and a framework is provided by addressing the research questions.

In section 5.1, we talked about how digital twins are being adopted across different logistics processes, providing a clear understanding of their functionalities in other departments. Furthermore, in section 5.2 we discussed the predictive and risk mitigation capabilities of DTs, demonstrating their effectiveness in predicting and managing disruption. In section 5.3 we focused on how DTs contribute to increasing resilience and sustainability in supply chains, with a focus on real-time monitoring and decision-making for optimal operations.

This research serves as a basic subsidy for the development of the digital twin currently being developed in the Twente Canals project [2]. By integrating existing knowledge and identifying gaps, this work provides a solid foundation upon which the project's digital twin can be built. The insights gained from this SLR will be useful in directing the development and implementation phases, ensuring that the project leverages the most recent advancements in DT technology. The study can help emphasize the areas where the project should focus on to achieve its desired goal.

However, it is also important to recognize some limitations of this review, despite its broad scope. While the SLR was comprehensive, it cannot guarantee 100% coverage of all relevant literature in the field. New studies may have been published since the data collection or may not have been indexed in the digital libraries searched. Digital twins are quickly evolving, and new technologies or methodologies can be already developed that could influence future research and application.

For the future research agenda, this paper can set a framework to gain insights into the application of Digital Twins (DTs) in business logistics. It can be used as a basis for future projects, and it can even be used for investigation regarding supply chain management. In conclusion, while this study provides valuable insights into the application of digital twins in business logistics, it also sets the stage for future research to build upon these findings. The goal is to enhance the efficiency, resilience, and sustainability of supply chains through the strategic use of digital twin technology.

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