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Review

Analyzing the Implementation of Digital Twins in the Agri-Food Supply Chain

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Abstract: *Background*: Digital twins have the potential to significantly improve the efficiency and sustainability of the agri-food supply chain by providing visibility, reducing bottlenecks, planning for contingencies, and improving existing processes and resources. Additionally, they can add value to businesses by lowering costs and boosting customer satisfaction. This study is aimed at responding to common scientific questions on the application of digital twins in the agri-food supply chain, focusing on the benefits, types, integration levels, key elements, implementation steps, and challenges. *Methods*: This article conducts a systematic literature review of recent works on agri-food supply chain digital twins, using a list of peer-reviewed studies to analyze concepts using precise and well-defined criteria. Thus, 50 papers were selected based on inclusion and exclusion criteria, and descriptive and content-wise analysis was conducted to answer the research questions. *Conclusions*: The implementation of digital twins has shown promising advancements in addressing global challenges in the agri-food supply chain. Despite encouraging signs of progress in the sector, the real-world application of this solution is still in its early stages. This article intends to provide firms, experts, and researchers with insights into future research directions, implications, and challenges on the topic.

Keywords: digital twin; agri-food supply chain; contributions; integration level; challenges

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1. Introduction

In recent decades, various technologies have been implemented to improve the efficiency of the agri-food supply chain. New challenges are arising that require the use of innovative solutions due to evolving market demands, regulations, and cost-effectiveness. As a result, increasing efficiency through effective, integrated smart technologies and approaches like digital twins (DTs) has been actively addressed in recent years. A DT is a new notion that has emerged alongside the advancement of Industry 4.0. It provides virtual representations of physical systems during their lifecycle using real-time data from sensors, thereby enhancing decision-making processes. The DT can represent both living and non-living objects, as well as processes that can be analyzed and simulated to interfere with the course of evolution [1]. The use of reliable DTs could be one of the most crucial techniques for monitoring supply chain processes in a real-time. As a result, the ability to simulate multiple operations and predict critical situations in advance enables rapid response and process modification, as well as enhancing resilience.

A DT is a virtual copy of a physical system, including its environment and processes, that is kept up to date by sharing information between the physical and virtual systems. It is a tool that has a continuous link between its physical and virtual counterparts (the twin) [1,2]. It consists of three components: a digital definition of its counterpart derived from CAD, Product Lifecycle Management (PLM), etc.; operational and experiential data of its counterpart gathered primarily using Internet of Things (IoT) data and real-time telemetry; and information model (dashboards, HMIs, etc.) that corresponds to and displays the information to facilitate decision-making. A DT is continuously learning and updating itself by using sensor data or external entities. All aspects of human activity, including the livestock sector, logistics, the petrochemical industry, and manufacturing, can profit greatly from DT systems [3]. The design, management, maintenance, development, and all industrial aspects related to goods, services, equipment, operations, and activities, as well as human resource management, can all be optimized with the use of these tools. Moreover, it enables users to remotely manage and control components and systems, as well as assess and predict resource- and process-related changes through "what if" analysis. Thus, firms would be able to assess information regarding service quality, new product development [4], and timely delivery. Furthermore, the DT is used to aid in the identification of control parameters to meet target KPIs and enhance the existing operation in terms of increasing energy efficiency and savings, reducing the number of off-target end products, improving process consistency, and reducing downtimes during maintenance [5].

In the context of the supply chain, the DT is a simulation model of an actual supply chain that forecasts supply chain dynamics using real-time data and snapshots [6] and that can send and receive data in both directions in real-time [7]. Supply chain DTs differ from conventional simulation models in terms of update frequency, powerful analytics capability, and simulation capability, allowing for deep synchronization and dynamic interaction between the physical and virtual worlds [8]. Supply chain analysts can use its output to assess supply chain activity, predict unforeseen events, and implement corrective measures. It is also used to monitor and forecast real-time changes in orders, supply, demand, approvals, and so on. As a result, firms can effectively evaluate their supply chain and adapt to changes more swiftly.

Despite the importance of DTs in improving agri-food supply chain activities, from the literature review conducted, it has emerged that the scientific community does not have a common understanding of the concept. As a result, DTs have been presented in a variety of ways in the articles. In certain cases, distinguishing DTs from digital models and digital shadows has become more challenging [9–14].

The adoption of DTs in agri-food supply chains is crucial because it enables the early detection of risks and the quality monitoring of food items using statistical, data-driven, or physics-based models [15]. Given the rising concerns about monitoring real-time activities, the agri-food supply chain continues to struggle with assuring traceability.

Despite promising advances in the field, DTs are still in their early stages of use in agri-food supply chains [16–18]. This is due to issues such as education (which causes management change and knowledge transfer), accurate representation, data quality, costs, intellectual property protection (data ownership concerns, identity assurance methods, and user access control), digital security, and interoperability [19], as well as ethical concerns and potential societal and safety consequences [1].

Currently, DT applications are more focused on sectors such as the manufacturing, construction, automotive, and aerospace industries [3]. Only a few studies have focused on DT applications in food and agriculture. In this case, there is an initial trend toward the implementation of DTs, and more clarity and insights are needed for the scientific community and industries interested in the implementation of this technology. To the best of our knowledge, despite being a hot topic that has caught the interest of many businesses and academics, DT implementation in the agri-food supply chain is still not well investigated, and no detailed study analyzing the current state of the art has been found. In particular, the benefits, types, levels of integration, key aspects, implementation processes, and challenges related to the adoption of DTs in the agri-food supply chain remain unclear. Therefore, this study aims to provide a first contribution to the topic by responding to the following research questions (RQs): how does the use of DT applications contribute to the agri-food supply chain? (RQ1); what are the key elements of implementing a DT? (RQ2); what types and levels of integration exist within the DT in the agri-food supply chain? (RQ3); what are the steps for implementation? (RQ4); and how challenging is it to adopt DTs in the agri-food supply chain? (RQ5).

The remaining sections are arranged as follows: the background is described in Section 2, and the method used in the study is described in Section 3. The fourth section of the paper goes into detail about the descriptive analysis and discussion of research questions. Finally, the summary, implications, and limitations of the study are stated in Section 5.

2. Theoretical Background

2.1. Challenges in the Agri-Food Supply Chain

The agri-food supply chain is a complex network of stakeholders who share common goals such as ensuring food quality, food security, food safety, and sustainability. It is subject to greater uncertainty and risk than other supply chains, raising serious issues concerning its impact on the environment, society, and the economy [20]. Additionally, unprecedented occurrences such as the COVID-19 pandemic and Ukraine's prolonged war, as well as economic sanctions, have highlighted the vulnerabilities of global supply networks [21,22]. These factors can result in problems related to unexpected delays, cost management, collaboration, data synchronization, rising freight charges, demand forecasting, digital transformation, port congestion, and the perishable nature of products [23].

The agri-food supply chain is one of the sectors that use advanced tools to evolve into a data-driven, intelligent, agile, and autonomously connected system [4]. Recent technology breakthroughs in cloud computing, IoT, big data, blockchain, robotics, and AI provide smart connected systems [20], allowing for the automation of this industry. Automation approaches are essential for developing supply chain DTs, which can lead to scalable and sustainable growth in the industry.

2.2. Supply Chain DTs

A DT is a dynamic, real-time depiction of the different agents in the supply chain network that forecasts supply chain dynamics using real-time data and snapshots. In logistics, the supply chain DT maps the data, state, relationships, and behavior of the system, mimicking its behavior using dynamic simulation capabilities [21,24]. Four areas of DT application have been identified in the supply chain, including network level (network management and transportation), site, manufacturing, warehousing, and cargo handling [24]. Network management is concerned with managing and monitoring valuable networks, while the transportation domain includes use cases involving the network-level transportation of products and commodities. Manufacturing is the most common application area on the site level, involving tasks related to the production of goods. Warehousing covers applications related to facilities that store, ship, and return goods and materials.

Supply chain optimization through DTs adds value to businesses by lowering costs and boosting customer satisfaction [25]. To do this, all aspects of the supply chain must be upgraded, including material flows, financial flows, and information flows. By simulating alternative scenarios and identifying risks and opportunities, DTs enable businesses to optimize levels of inventory, reduce costs, enhance collaborations, and improve supply chain efficiency [26,27]. Additionally, supply chain management based on DTs does not require physical proximity, meaning that actual product movement from source to the consumer is no longer dependent on the location of the parties performing control and collaboration [28].

DTs are becoming increasingly popular in the agri-food supply chain due to their benefits, such as improved product quality, resource utilization, maintenance, production planning, reduced losses, improved logistics, energy savings, and increased visibility [18,19,22,29–31]. They enable supply chain actors to control demand, understand demand patterns, monitor food quality and marketability, track goods during transportation, ensure traceability, and monitor environmental conditions [26,32,33]. In agriculture, the use of such tools can provide information on fertilizers, chemicals, seeds, irrigation management techniques, environmental protection, pests, climate, crop monitoring management solutions, market demands, and business changes [34]. In general, DTs in the agri-food supply chain provide simulation and optimization, livestock tracking and health management [2,35–37], collaborative planning and collaboration [8], crop monitoring and management [38,39], supply chain visibility and traceability [40,41], and predictive analytics and decision support [42] to help farmers and supply chain managers identify patterns and generate actionable insights.

3. Methodology

This study used a systematic literature review (SLR), which uses a list of peer-reviewed research to identify, evaluate, and synthesize ideas using strict and well-defined criteria. SLR seeks to address RQs, test hypotheses, and theories, or produce new arguments [43]. SLR was chosen for this study because of its ability to reduce bias and improve the accuracy of exploring and analyzing related studies. Thus, the methodology ensures a detailed analysis of relevant works, thereby offering a key foundation for the evolution of traceable information.

3.1. Data Sources and Keywords Definition

In this review, the Scopus and Web of Science databases have been used as a data source with the keywords (“digital twin” OR “digital model” OR “digital shadow” OR “simulation model”) AND (“post-harvest” OR “agri food” OR “agrifood” OR “agri-food”). Because many publications on this topic have been published without consistent use of terms, the search was carried out with considerable care, using a wide range of keyword combinations. When choosing keywords, several elements related to digitization in the agriculture and food supply chain were considered.

Since this review aims to investigate how DTs have been used in recent years in the agri-food supply chain, the search includes published papers from 1 January 2019 to 20 August 2022. After eliminating duplicates, the authors evaluated each article to determine whether it met the inclusion criteria.

3.2. Screening and Eligibility Check

Only works that have been peer-reviewed and published in journals, conferences, and book chapters were considered during the preliminary screening stage. All the articles collected from the two databases (Scopus and Web of Science) were checked for duplication using the reference management tool (Mendeley), followed by reading the abstracts and full texts of the selected articles.

The final screening and eligibility assessment were done based on the following criteria.

Screening Exclusion Criteria (SEC):

- SEC1—Is it a peer-reviewed journal article, a book chapter, a review, or a conference paper?
- SEC2—Does the document illustrate the use of DTs in the agri-food supply chain?

Eligibility Exclusion Criteria (EEC):

- EEC1—Is the full document available for reading?
- EEC2—Does the paper discuss digital models, digital shadows, or DTs in the agri-food supply chain?
- EEC3—Does the paper answer at least one of the research questions that have already been set?

4. Analysis and Discussion

4.1. Descriptive Analysis of Selected Studies

Following the initial screening and checks to ensure eligibility, 50 papers were selected for further analysis (Figure 1). This descriptive analysis began by examining the current trend of research development in the agri-food supply chain.

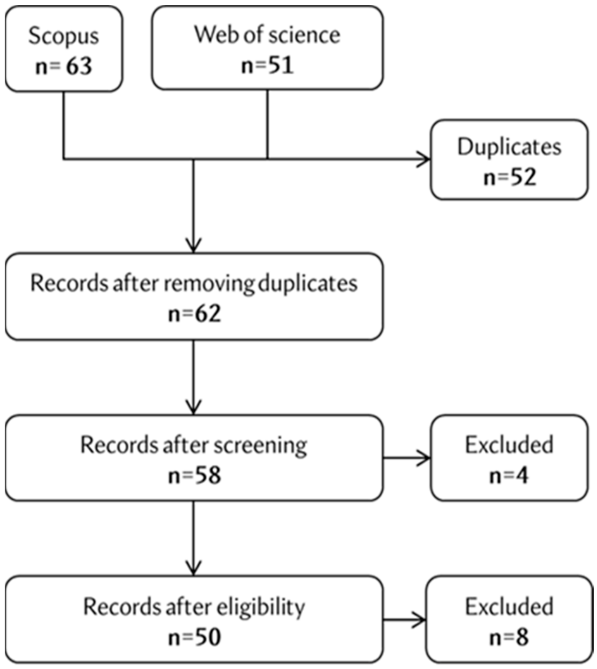

Figure 1. Stages for literature review.

Accordingly, the research trends on the implementation of DTs in the agri-food supply chain have recently attracted the interest of numerous scholars (Figure 2). The data for 2022 are not complete, and it looks like fewer papers were published in 2022 than in 2021. This is because the study only looked at papers that showed up in the search until 20 August 2022.

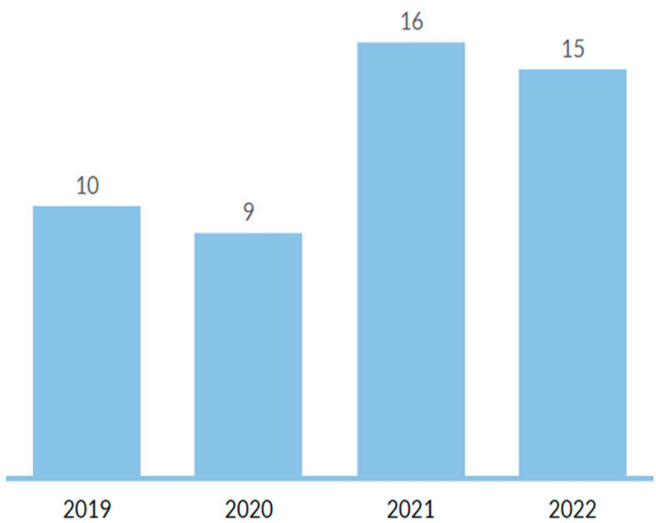

Figure 2. Distribution of papers over the years.

In total, 66% of all contributions are in the form of articles published in peer-reviewed journals. The remaining documents are review articles (6%), conference papers (26%), and book chapters (2%), as shown in Figure 3.

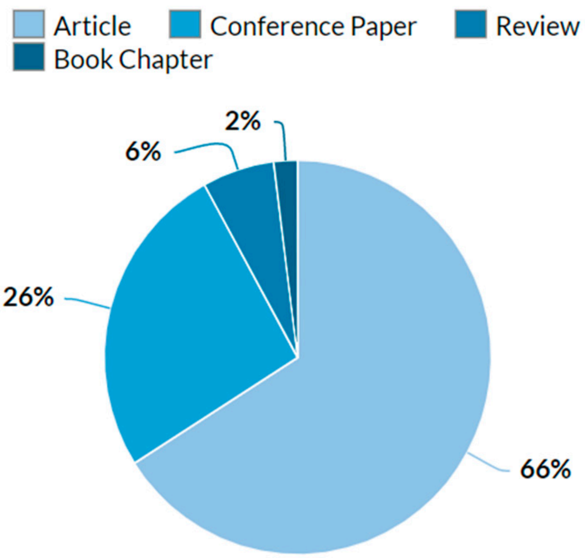

Figure 3. Contribution of selected papers.

The search conducted on Scopus and Web of Science revealed that the publications drew their data from a total of 36 different journals. The International Journal of Production Research got the most citations (229), followed by the IEEE Transactions on Industrial Informatics with 103 citations, Animal Production Science with 51 citations, and the Journal of Resources, Conservation, and Recycling with 51 citations each (Figure 4).

Figure 4. Top 20 journals based on their citations.

The United States contributed 16.7% of the studies that were conducted on the application of DTs in the agri-food supply chain. This was followed by Switzerland, which contributed 15.6% of the studies, and China, which contributed 6.1% of the publications (Figure 5).

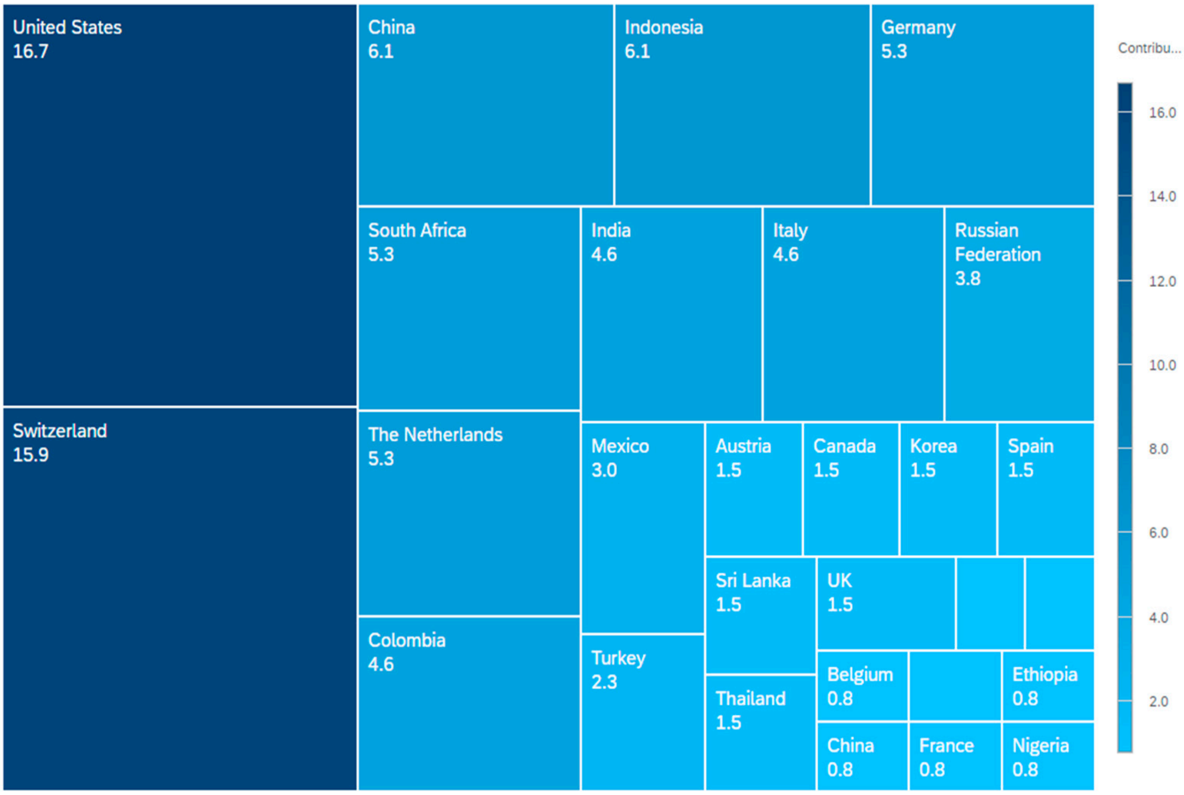

Figure 5. Treemap of contributing countries.

This analysis demonstrates the increasing interest among researchers from all over the world. In the coming years, there may be an increase in the number of publications that explore the contexts in which DTs might be leveraged in the agri-food supply chain due to the increasing need to digitalize the sector.

4.2. Discussion of Results with Respect to the Research Questions

Based on the framework shown in Figure 6, this section highlights recent scientific studies on DT applications in the agri-food supply chain, with an emphasis on the benefits (RQ1), key aspects of implementation processes (RQ2), types, integration levels (RQ3), implementation steps (RQ4), and challenges (RQ5).

4.2.1. Contributions of DTs to the Agri-Food Supply Chain (RQ1)

Several researchers contend that the adoption of digital technology had a significant impact on the supply chain's visibility, and the monitoring of processes [19,22,29–31]. Visibility is transparency in real-time over the entire transport network, including information on available capacity, interruptions, and operational status [7].

Due to the short shelf life of many agri-food products in the supply chain, excellent forecasting and monitoring tools are needed to eliminate the mismatch between shortages and surpluses [26]. A DT continuously controls demand, can better comprehend demand patterns, and allows for the connection of sensor data in a real-time to monitor the quality of food and marketability [44]. Furthermore, it has significant potential for use in determining food quality and the design of personalized foods [16,30]. Retailers might use this tool to assess how the temperature difference between the packhouse and their store impacts the overall quality of their products [45,46]. Similarly, the use of DTs for tracking goods, traceability, and monitoring the environmental conditions, weight loss, and overall quality loss in the postharvest supply chain has also attracted the interest of the food industry [32,33,47]. This would enhance system integration and product or system visibility and knowledge, as well as help predictive capabilities, perform scenario analysis, and continuous improvement. Table 1 summarizes case studies of agri-food DTs.

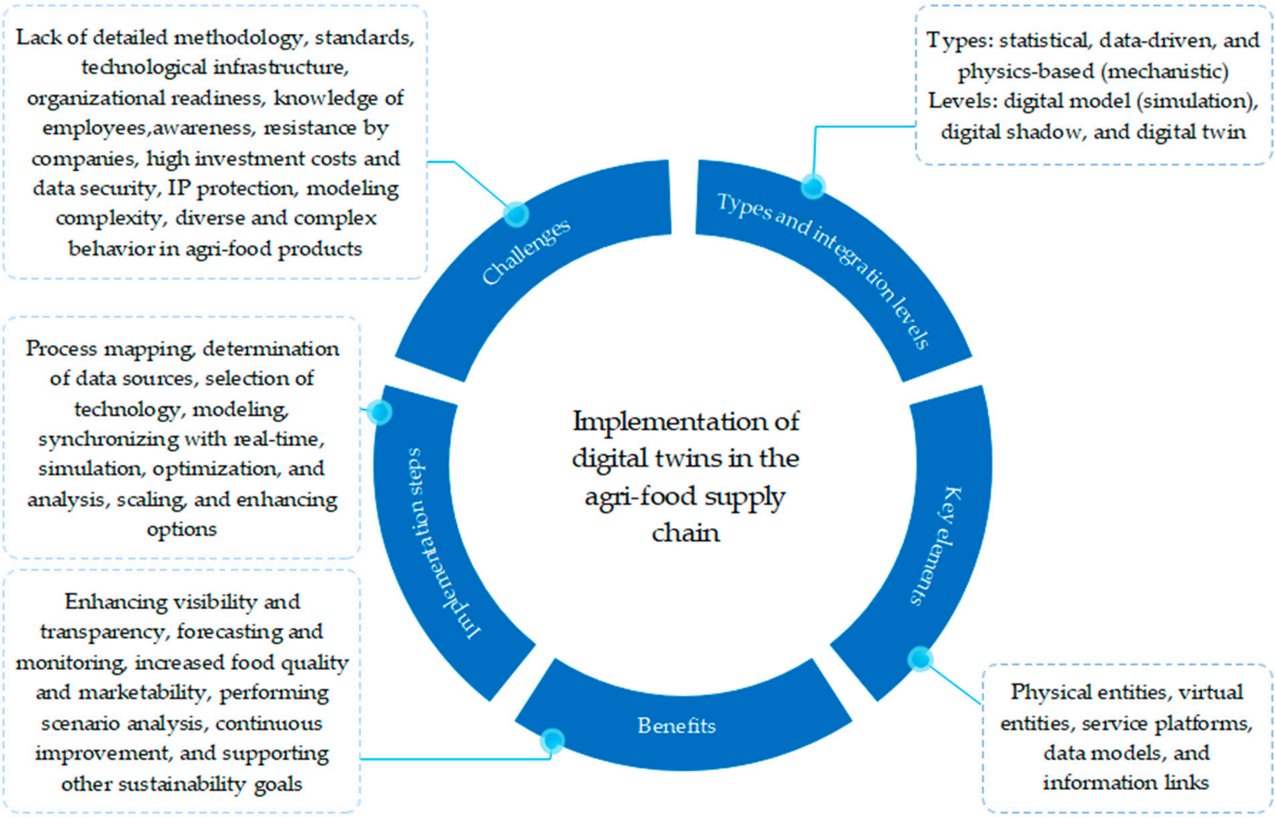

Figure 6. Highlights of the results discussed in the paper.

Table 1. Identified use cases of agri-food supply chain DTs.

Application Area	Implementation Purpose of DT	References
Transportation and storage of fruit	To provide insights regarding the thermophysical behavior of fruit	[48]
Food retail supply chains	To enhance end-to-end visibility and resilient management of demand, inventory, and capacity	[22]
Postharvest supply chains	To provide insight with actionable data and aid in detecting and predicting supply chain issues	[15]
Refrigerated transport and cold storage	To optimize the cooling process for a variety of fruits and vegetables with complex shapes and compositions	[46]
Cold chain	For cold chain optimizations in the design process	[45]
Food industry	To enhance food quality and traceability, and design personalized foods	[16]
Refrigerated supply chain	For monitoring food quality and marketability	[44]
Fruit retail	For monitoring the quality of fruit during storage	[31]
Food supply chain	To replicate the dynamic evolution of a system over time	[49]
Agriculture	To collect and analyze fruiting body growth in farming	[50]
Meat and livestock	To replicate the value chain	[51]
Smart farm	To enhance farm management	[52]
Food processing plant	To enhance pasteurization and predict processing conditions in beverage processing	[53,54]

Recently, agricultural sectors such as controlled environment agriculture, open-field agriculture, and animal farming have started using DTs [48,55,56]. As the next phase of the digitization paradigm, DT technologies can help farmers by enabling continuous and real-time monitoring of the physical world (the farm) and updating the status of the virtual environment [57]. Digital farming methods can supply information regarding the use of fertilizers, chemicals, seeds, irrigation management techniques, environmental protection, pests, climate, crop monitoring management solutions, market demands, and business changes [34]. In addition, it can be used to monitor greenhouse activity and predict crop growth [1]. Besides this, these systems allow growers to monitor the health of their crops and receive real-time notifications regarding pests, diseases, and climate change. This helps farms decide what to do with the actual crop and how to use fertilizers, as well as determine the effects of these activities.

4.2.2. Key Elements in DT Implementation (RQ2)

More broadly, the top five essential components of DTs have been identified in physical entities, virtual entities, service platforms, data models, and information links [16,58]. The identification of physical entities is the first essential component of DT implementation. The physical entity is a relative term that refers to the actual product or system that a virtual DT mimics in the real world. This may include "vehicle", "component", "product", "system", "artifact", etc. For instance, in the agri-food supply chain, it is common to find the DTs of fruits, farms, and supply chain networks. To build a virtual entity, one must create a digital model with the same appearance, properties, behaviors, and rules as the real entity. In addition, service platforms are essential components for the execution of models. Additionally, the virtual entity needs to have access to cloud applications, data, and knowledge for it to work properly. In the supply chain DT development, experts are increasingly seeking real-time data such as demographic data collected from various supply chain participants or stakeholders that can be used to get information regarding the location of truck routes, fulfillment centers, retail outlets, consumers, etc., to better understand logistics. These data can be directly entered into databases like the Enterprise Resource Planning (ERP) database and the production system to build a DT with a simulation tool [59]. Furthermore, DTs can utilize data from transportation management systems (TMS) and customer relationship management systems (CMS) [7]. It is also possible to combine internal data from the systems of the actors with external data sources (e.g., weather, traffic, competitors' prices). These lay the groundwork for the DTs of the supply chain to construct a model that is as realistic and accurate as possible to conduct analysis and simulations based on high data quality. Smart analysis and the quality, quantity, and integration of data are fundamental requirements for the optimal usage of supply chain DTs. In addition, basic requirements for supply chain DT adoption include visibility and transparency, update frequency, data collection, data analysis, simulation capabilities, decision support capabilities for planning, and the ability to handle disruptions.

4.2.3. Types and Levels of DT Integration (RQ3)

In the agri-food supply chain, DT models can be statistical, data-driven, or physics-based (mechanistic) [15,44,45,47,55]. Multiphysics modeling and simulation are used in physics-based approaches to model and simulate the relevant physical, biochemical, microbiological, and physiological processes, including the CAD geometry of the fruit, material property data, and the physical model's beginning and boundary conditions [45,46,48]. This is accomplished by employing a mathematical definition of the relevant biological processes, such as biochemical processes, that affect fruit quality parameters [48]. In the case of a data-driven model, AI techniques, including machine learning, are utilized for model building, calibration, verification, and validation. Machine learning models can be trained in a variety of ways, including through supervised and unsupervised learning. The model training data could include horticultural-product storage conditions as well as the measured biological response of fresh horticulture products over time.

Recent applications of DTs in the agri-food supply chain, mostly in the fruit supply chain, have emphasized physics-based DTs [15,16,29,30,44,45,47,48,55,60,61]. Because of advancements in prediction accuracy and computational performance, the adoption of a physics-based DT is growing rapidly [5]. Using mechanistic models (e.g., heat and mass transfer) and kinetic models (quality deterioration), a DT can forecast when food will change its quality over time, including during storage and shipment. With such models, more emphasis has been placed on monitoring fresh fruits and vegetables, contributing to product loss, particularly during transcontinental shipments.

In comparison to statistical and data-driven DTs, which determine how fresh horticultural products end up losing their quality by looking for patterns in the data, physics-based twins provide a better description of the physiological, biochemical, microbiological, and physiological processes that are taking place, which explains why this quality loss occurs [15]. In response to specific temperatures and other environmental conditions, they can assist horticulture items in communicating their history as they move from the field to the consumer. By connecting real-world products to sensors, DTs help determine how the quality of products changes over time. Similarly, machine learning-based techniques are used to build biophysical DTs comprising process and raw material data to replicate a food product and process [16].

The scientific community has described DTs in a variety of ways in the literature. In some circumstances, it has become more difficult to distinguish DTs from digital models and digital shadows [9–14]. To precisely define a digital model, there must be no automated data exchange between the physical and virtual twins. These kinds of models are used by the industry to determine how a change to a digital entity's counterpart might be affected if implemented. A digital shadow is a unidirectional exchange between a physical and a digital object—not vice versa, whereby a change in a physical object creates a change in its digital counterpart. In this instance, data flow is automatic from the physical asset to its digital replica, but manual from the digital asset to its physical counterpart. It is typically employed for data collection and subsequent analysis [29]. The model is referred to as a "DT" if data flow between a physical object and a digital entity is entirely integrated in both directions. In other words, any modifications made to the digital item are mirrored instantaneously in its physical counterpart, and vice versa. The autonomy of the model is the primary distinction between digital shadows and DTs [62]. In the DT, interventions could be automatic, whereas, in the digital shadow, they must be deliberate (human-supported) decisions. A digital model (simulation) depicts what could happen to an item or supply chain system, but a DT depicts what is already happening. Table 2 presents the category of selected papers based on the level of integration.

Table 2. Category of selected papers based on the level of integration.

Level of Integration	References
Digital model (simulation)	[46–57]
Digital shadow	[56,63–67]
DT	[15,16,22,30,31,44–46,48–55,68,69]

4.2.4. Implementation Steps (RQ4)

The implementation of a DT entails several steps, including process mapping, determination of data sources, selection of technology, modeling, synchronizing into real-time, simulation, optimization, and analysis, as well as scaling and enhancing options [26] (Figure 7).

Compared to implementation in manufacturing or a piece of machinery, a supply chain DT requires the modeling of the entire supply chain supported by real-time or near-real-time operational parameters [70]. Various modeling methods can be used to manage the growing complexity and unpredictability of the agri-food supply chain. In the selected papers, modeling techniques such as agent-based modeling [71,72], system [63,73–75] discrete event simulation [30,56,66,76–80], and hybrid simulation [30,81,82] are commonly used. The application of these methods will provide answers to planning-related questions, such as the amount to be purchased, delivered, or produced. During the modeling process, the DT should be constructed with long-term plans in mind. Moreover, the framework should enable the modeling and analysis of alternative processes, asset performance optimization, and event forecasting.

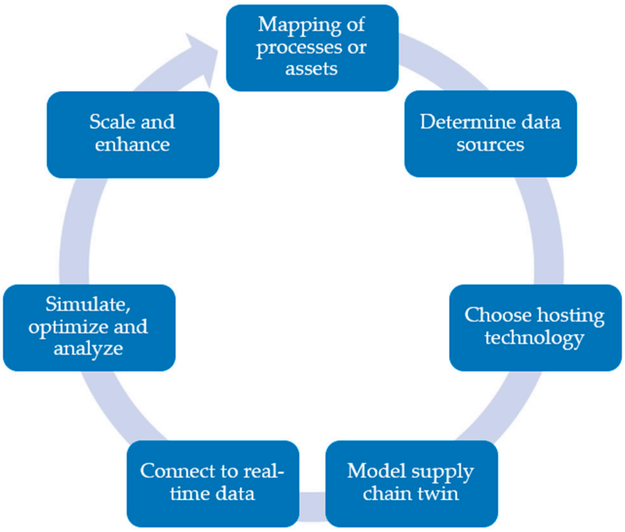

Figure 7. Steps to implement the supply chain DT.

Connecting to real-time data is yet another vital step for the agri-food supply chain's DT deployment. Although the time scale is goal-oriented, real-time data are essential for the use of DTs [26]. For instance, distributed control systems, predictive control models, online optimization, and process scheduling use seconds, minutes, hours, days, or weeks as time scales. Sensors are frequently linked to the IoT, which is unquestionably a requirement for DTs since real-time data collection is made possible by wireless connectivity between many objects located in the same or distinct physical areas. Sensor technology is available to monitor the agri-food supply chain; however, it is still challenging to apply in commercial supply chains [45]. Various types of sensors have been installed in the agri-food supply chain to date to execute DT scenarios. In the case of post-harvest activities, for instance, temperature and gas sensors are reported to be used to monitor the status of a fresh product during the logistics and storage phases [15,45,46,48,55,56,83], as well as to depict inventory and grain quality as it flows across a plant [30]. Citrus shipments also employ sensors for temperature measurements [44]. Infrared thermal cameras are also proven to be an effective tool for detecting physiological changes in fruits [31,84–88]. In the case of DT-based smart farms, several sensors can be utilized to monitor the plant's nutrients, growth, and environmental conditions [52]. Among the sensors are environmental sensors that measure temperature, chemicals, light humidity, air velocity, lighting, ventilation, and movement, which allows for reporting their behavior, health, and condition [89]. Temperature and pressure sensors have been indicated for use in the proposed DT models in food processing [53,54]. Sensors and indicators time-temperature indicators, freshness indicators, gas indicators, and integrity indicators) are used in smart packaging to detect biological, chemical, or gaseous changes in packaged fresh produce [90]. Sensor-based RFID tags can detect corresponding attributes and chemical changes in fresh fruits and vegetables throughout the post-harvest supply chain [32].

Another key stage in developing a DT for the supply chain is the capacity to simulate, optimize, and analyze. Possibilities for applying prescriptive, predictive, and advanced analytics to influence decision-making through digital supply chain twins vary from strategic to operational [89]. Once integrated with models, operations, and assets can be simulated or optimized to obtain insights, test possible scenarios, or adapt to disturbances. The outcomes should be communicated throughout the enterprise to inform plans of action at all levels. The simulation module offered by cloud computing can predict future conditions of the real-world supply chain by applying different parameters to its DT. The DT's outputs could help optimize, monitor, or forecast supply chain behavior [30,45,48,52,55].

Ultimately, DTs should be scalable across enterprises to enhance end-to-end visibility across supply chains. They can even connect with suppliers and consumers outside of the enterprise. More real-time data points from internal sources, third parties, and industry groups can enhance the DT's performance.

4.2.5. Challenges for the DT Implementation (RQ5)

The adoption of DTs in the agri-food industry remains difficult [91]. For instance, deploying IoT-based agricultural systems still faces significant challenges due to the demand for continuous power supplies to operate. Although alternative energy sources such as solar and wind can be used to meet the energy demand, this will greatly increase the cost. In the countryside and village areas, the lack of a reliable internet connection is another challenge. The connection needs to have enough broadband to deliver data as needed by the service. In addition, farmers need instruction in using basic computers and tablets, as well as knowledge of how the IoT works.

In practice, mapping and obtaining a detailed real-time snapshot of the supply chain is challenging. The simultaneous validation of all model-output parameters is an additional barrier to the use of DTs in supply chain applications [44]. Moreover, the stakeholders in the cold chain, such as retailers, require specific evidence to demonstrate the benefits in shelf life that may be obtained with certain digital solutions. Unfortunately, pilot studies to derive such validations are sometimes costly and time-consuming. Further implementation issues include a lack of detailed methodology and standards, a lack of clear data governance, and difficulties gathering and storing massive datasets [20,92–94]. For instance, the lack of modeling standards for DT can lead to compatibility issues during the integration of models created separately [95]. Developing a data acquisition system, synchronization problems, the modeling of a complex system, lack of awareness, companies' resistance to adopting the technology [96], as well as difficulties in developing, understanding, controlling, and simulating real-time changes in the system, all pose challenges.

Combining multidisciplinary knowledge and providing enough data are the two most difficult aspects of implementing DTs [16]. Similarly, education (which causes management changes and knowledge transfers), accurate representation, data quality, costs, IP protection (data ownership concerns, identity assurance procedures, and user access control), digital security, and interoperability [19,97] can be considered obstacles to the implementation. Moreover, in agriculture, the implementation of the DT is hindered due to ethical concerns, as well as potential societal and safety consequences [1]. Due to product complexity and operational challenges, the deployment of DTs at the industry level remains difficult [5,47]. However, some recent studies show promising signs of progress [17,18,29].

5. Conclusions

This study explored the state of the art in the implementation of DTs in the agri-food supply chain and provides insight into the roles of the DT in improving supply chain performance, optimizing resources, facilitating collaboration, and sharing information. The benefits, types, integration levels, key elements, and implementation steps of a DT in the reviewed area, as well as the challenges to its implementation, were discussed. In this regard, DTs can improve efficiency and sustainability in the agri-food supply chain by providing visibility, minimizing bottlenecks, planning for contingencies, and improving existing processes and resources. However, the scientific community lacks a common comprehension of the DT concept, making it impossible to distinguish between a DT, a digital model, and a digital shadow. Furthermore, research advances and real-world implementations of DTs in agri-food are still in the early stages of development.

The findings of this study are intended to help researchers, policymakers, and the agri-food sector understand the potential and future possibilities of using DTs, including meeting sustainability goals. As a result, the current study could give researchers a clear understanding of the benefits of DTs in supporting the agri-food industry, as well as details on the current pattern of DT utilization. This research will further assist academics in identifying the capabilities of the solution along with the requirements during the DT development and implementation phases. Researchers and supply chain actors would benefit the most from an in-depth analysis of DTs to gain a common awareness of this emerging tool.

The literature search was conducted using the Web of Science and Scopus databases, which are commonly used data sources for literature analysis. Despite their large citations, these databases have limitations in terms of document availability and coverage. Many reports regarding the progress of DT implementation by the companies are documented in white papers and other publications that are not included in both databases. Despite our best efforts to assure inclusiveness, our study is limited to publications that have undergone peer review. So, additional related work that has been published in other databases or languages other than English might be missed during our analysis. As a result, scholars interested in DT applications in the supply chain could consult additional sources. Researchers might also focus on evaluating the solution's effectiveness in terms of sustainability and feasibility, which will boost confidence in industries within the agri-food supply chain to incorporate this technology into their business processes. Furthermore, studies might be directed toward the development of tools and standards for the use of DTs to ease implementation efforts. Future research should focus on practical applications and proving the technical and economic benefits of DTs, as well as exploring their deployment and operation from a technical and economic standpoint.

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