

Impact of digital twin adoption on food supply chain performance: a system dynamics approach

Ying Huang, Abhijeet Ghadge  and Nicky Yates

Centre for Logistics, Procurement and Supply Chain Management, Cranfield School of Management, Cranfield University, Cranfield, Bedfordshire, UK

ABSTRACT

Digital Twin (DT) technology provides a promising solution to challenges within the food supply chain (FSC) due to its unique characteristics. While existing literature highlights the potential of DTs to enhance real-time monitoring, predictive analytics, and operational efficiency, a quantitative assessment of the overall impact of DT implementation on FSC performance is missing. This study bridges this research gap by integrating experimental and analytical approaches. Empirical data were collected through questionnaires from food industry practitioners, combined with literature to develop a mental model for capturing the interrelationships among DT-relevant technologies, FSC operations, and supply chain performance. Later, by deploying systems thinking and system dynamics (SD) modelling approaches, the impact of DT adoption on FSC operational metrics is evaluated. The findings indicate that the DT positively impacts inventory levels, actual delay (lead time), and unfulfilled orders in the short term, while contributing to cost reduction and food waste in the long term. The SD models not only highlight the impact of integrative technology adoption on the operations of FSCs but also provide a comprehensive framework for modelling and assessing SC systems under the influence of technology. This study contributes by providing quantitative evidence of DT's impact on the FSC.

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1. Introduction

Food supply chains (FSCs) are complex in nature and involve a series of interconnected processes and activities in the sourcing, manufacturing, processing, distribution, and consumption of food products (van Beusekom-Thoolen et al. 2024; Yadav et al. 2022). This makes them prone to disruptions and, on occasion, can lead to irreversible collapses, such as food recalls and scandals (Song et al. 2017; Stranieri et al. 2021). FSCs are characterised as fragmented, complex and constantly changing systems, along with specific food product attributes such as perishability, seasonality, and the need for controlled temperature and humidity conditions (Annosi et al. 2021; Shukla and Jharkharia 2013). Furthermore, FSCs are confronted with various challenges in terms of monitoring and maintaining food quality, safety, authenticity and ensuring the traceability and visibility of the food industry (Gokarn and Kuthambalayan 2017; Yadav et al. 2022). These can become costly and complicated issues for FSC stakeholders, affecting the efficiency of the SC, food product safety and quality, as well as having broader impacts on people's health, economic fluctuation, and societal stability (Brooks et al. 2021; Zhang et al. 2016). For example,

FSC participants in a food network may be reluctant to share data with others, which can hinder their ability to achieve real-time visibility of different food supply chain stages, potentially leading to food safety or food waste incidents (Qian et al. 2023). Effective real-time process coordination and visibility through information sharing are among the possible ways to alleviate some of the food network challenges (Ding et al. 2014; Viet, Behdani, and Bloemhof 2020).

With the extension of Industry 4.0, developing DTs provides promising technology solutions to alleviate challenges in managing and improving supply chains (Ivanov and Dolgui 2021). Recognising the potential of DTs, practitioners and academics have explored their characteristics and applications for improving food industry operations and management (Huang, Ghadge, and Yates 2024; Maheshwari et al. 2023a). DTs' visibility and real-time simulation can ensure information sharing and transparency, assisting supply chain managers in making informed decisions (Patil et al. 2024). Furthermore, as an integrative concept, DTs integrate different technologies such as IoT, cloud computing, and big data analytics (Ivanov 2024), which provides an innovative

CONTACT Abhijeet Ghadge  abhijeet.ghadge@cranfield.ac.uk  Centre for Logistics, Procurement and Supply Chain Management, Cranfield School of Management, Cranfield University, Cranfield, Bedfordshire, UK

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solution to achieve food traceability, transparency, safety, and security (Maheshwari et al. 2023b; Tozanli and Saénz 2022).

DTs can be categorised into four main types based on their scope and level of abstraction: component twins, product twins, process twins, and system twins (Bao et al. 2019; Huang, Ghadge, and Yates 2024; Sharma et al. 2022; Tao et al. 2019). Process twins model and synchronise the flow of activities, data, and decisions within a specific operational process, such as production, logistics, or quality control (Bao et al. 2019; Schilling and Seuring 2024). In contrast, system twins operate at a higher level of aggregation, capturing interactions among processes or organisational units across an entire supply chain or organisations (Machacek et al. 2025; Melo et al. 2025).

This study explicitly adopts and investigates the process-level perspective of DTs within the FSC context, focusing on how DTs are applied to monitor, simulate, and optimise key processes such as production, logistics, storage, and quality control across the FSC rather than individual components, assets or entire systems (Agrawal, Fischer, and Singh 2022; Ivanov and Dolgui 2021; Tao et al. 2018). Here a process-level DT is a dynamic virtual model that synchronises data and decision rules to support the analysis of operational performance within specific FSC operations, such as inventory management and logistics (Aretoulaki et al. 2024; Schilling and Seuring 2024). Importantly, this distinction clarifies the scope of this study, while the literature acknowledges ongoing challenges relating to DT architecture design, technological integration, and adoption decision-making; these implementation-focused issues fall outside the remit of our study. We assume the presence of an adopted, functional process-level DT and focus on evaluating its post-adoption implications.

Existing industry applications of DTs focus primarily on the enablers and barriers of implementing DTs in SCs and other industry fields, such as manufacturing and healthcare (Ivanov and Gusikhin 2025; Semeraro et al. 2021; Tao et al. 2018). However, their implementation and impacts on the FSC are still in its infancy (Huang, Ghadge, and Yates 2024). Some studies demonstrated the potential of DTs' characteristics corresponding to FSC challenges (Huang, Ghadge, and Yates 2024), but there is a lack of research focusing on how to evaluate the impacts of DTs for the FSC (Ivanov and Dolgui 2021). Most research on DTs is either conceptual or only focuses on identifying drivers or barriers to their successful implementation within different industry settings (Ivanov 2024; Perno, Hvam, and Haug 2022; Semeraro et al. 2021). Furthermore, limited studies evaluate the impact of DTs within the FSCs, as the current literature primarily studies only demonstrative uses of DTs'

cases (e.g. Burgos and Ivanov 2021) and lacks in determining the overall effect of DTs' adoption on the supply chain system. For example, the study by Maheshwari et al. (2023a) developed a DT model of a food process industry manufacturing ice cream. They found that the DT model enhances the existing system's efficiency, but they only focused on a specific individual performance metric (efficiency) rather than capturing the holistic view or the overall view of SC performance. Ivanov and Gusikhin (2025) demonstrated DTs can improve operational performance and be used for resilience stress testing. However, there is an evident lack of research in the extant literature assessing the wider impact of DTs on SC performance. Thus, it is necessary to understand and evaluate the broader process-level implications of DTs within FSC operations for SC performance from a holistic perspective. To address this gap, the system dynamics model developed in this study operationalises the process-level DT perspective by explicitly modelling the dynamic interactions among key FSC processes, namely production, inventory management, distribution, and demand fulfilment, rather than focusing on individual assets or system-wide architectures. Systems thinking is a theory attempting to understand how different dimensions interact and how they can be brought into an appropriate relationship for improved results (Sterman 2000), which is a suitable lens for investigating an unstructured situation and providing a theoretical perspective for analysing DTs' implementation, impacts, and supply chain performance within the FSC. Furthermore, this study aligns with calls for systems-thinking approaches to analyse the complexity of supply chain management (Rebs, Brandenburg, and Seuring 2019).

The primary objective of this study is to assess the impact of process-level DT adoption in the FSC by evaluating supply chain key performance indicators, including operational cost, lead time, service level, inventory levels, and food waste (Er Kara et al. 2021; Vu, Ghadge, and Bourlakis 2025). These metrics are suitable for evaluating the performance of SCs when influenced by interventions such as the introduction of a new technology or a disruption in the SC (Ghadge et al. 2022; Kumar and Nigmatullin 2011). In addition, the objective of this study is to highlight the opportunities and relative performance improvements that may arise from process-level DT adoption, rather than to provide concrete numerical predictions for practices. As DTs play an important role in information sharing and are likely to influence operational activities within the FSC, it becomes essential to examine their broader implications on performance outcomes. Thus, the following research question is proposed: ***How does process-level DT adoption impact food supply chain performance?***

The rest of the paper is structured as follows. Section 2 provides a theoretical background on systems thinking and system dynamics, followed by a review of the relevant literature on DT in the FSC. A detailed research methodology is discussed in Section 3. The findings from the empirical data and analytical modelling are presented in the subsequent sections. Section 8 presents a discussion of key findings, and the paper concludes with contributions to research and practice, along with limitations and future research directions.

2. Theoretical background and relevant literature

2.1. Systems thinking and system dynamics

This study adopted systems thinking to extract DT's impact on SC performance. Systems thinking is 'the ability to see the world as a complex system, in which we understand that you cannot just do one thing and everything is connected to everything else' (Sterman 2000, 4). Systems thinking theorises that systems' behaviour results from the interactions of their parts and that change in one part of a system invariably impacts other parts and the system as a whole (Sterman 2000). This is particularly suitable for investigating unstructured, complex situations, which remain a valuable foundation for considering and characterising the different disciplines explored (Alem Fonseca, Tsolakis, and Kittipanyangam 2024). Furthermore, systems thinking provides an appropriate theoretical perspective for understanding and mapping the fundamental cause-and-effect interrelations within SC operations (Mingers and White 2010). A system view allows for capturing positive and negative cause-effect links in the form of feedback loops, i.e. circular sequences of causes and effects that can be either balancing or reinforcing (Sterman 2000). Systems thinking recognises two main approaches: soft systems thinking and hard systems thinking (Bititci and Spanellis 2023). The soft systems thinking approach is recommended in complex, dynamic, and interlinked contexts (Wilson and Van Haperen 2017) to establish causal relationships. On the contrary, hard systems thinking, based on simulation and modelling, is suitable for analysing quantitative data (Flood and Carson 2013; Ghadge et al. 2013).

In the context of this study, dynamic interactions exist between different technologies of DTs and supply chains, such as DTs, which can change how information flows and decisions are made. Such dynamic interactions are best understood through the lens of soft systems, which can account for these complexities and feedback loops. Thus, systems thinking is a primary methodological approach for the given problem and, therefore, adopted in this study.

System dynamics is a tool or approach for modelling this complex system and predicting its behaviours over time (Mingers and White 2010; Rebs, Brandenburg, and Seuring 2019; Sterman 2000). System dynamics (SD) methodology is part of the hard systems thinking approach, helpful in modelling and analysing the behaviour of SCs (Disney and Towill 2003; Machuca and Barajas 2004; Ovalle and Marquez 2003). Supply chain processes often involve several variables and non-linear dynamics (Surana et al. 2005). Obtaining a model that explains such complex dynamics and behaviours is often difficult or unfeasible. Due to this fact, the system dynamics approach is an appropriate tool for modelling complicated key relationships among multiple variables to draw holistic observations (Langroodi and Amiri 2016).

2.2. DT in the food supply chain

FSCs have been an influential area of research among practitioners and academics in recent years (Kumar and Agrawal 2023). Perishable products account for over USD 36 billion of losses in the food and grocery sector, making it difficult to ignore the effect of perishability. Currently, the FSC confronts different challenges, such as maintaining food quality, reducing food losses and waste, ensuring food safety, and information asymmetry (Despoudi 2021). These challenges came from the FSC's complexity and uncertainty, which consisted of different stakeholders and activities (Gokarn and Kuthambalayan 2017). DTs are a promising solution to help the FSC overcome these identified challenges. The characteristics of DTs include monitoring, real-time simulation, enhanced monitoring, and provision of supply chain visibility for some FSC stages (Huang, Ghadge, and Yates 2024; Semeraro et al. 2021). Subsequently, DTs can bring improvements to the food industry's operations and processes, such as real-time monitoring, traceability, and food quality control (Maheshwari et al. 2023a). Recent reviews further emphasise that DTs in SCs enable real-time monitoring, predictive analytics, and integrated decision-making, therefore enhancing transparency and fostering resilience (Guo and Mantravadi 2025; Ivanov 2026; Monteiro and Barata 2025).

Furthermore, through real-time monitoring and data feedback, DTs can provide visibility across different stages of the SC (Zhao et al. 2021). DTs improve collaboration efficiency among stakeholders involved in the SC through visualisation and data sharing. For example, SC stakeholders (suppliers, manufacturers, distributors, and retailers) can share real-time data to reduce information asymmetry and improve response speed and decision-making accuracy (Maheshwari et al. 2023b).

There are some use cases of DTs' applications in the food industry (e.g. Tozanli and Saénz 2022). Some of the food and beverage companies, such as Kraft Heinz (2022), use DT technology to integrate real-time data from sensors, human interactions, and various operational and financial sources. This helps them monitor warehouse inventory fluctuations, manage item locations, and enhance demand forecasting for customers and distribution channels. This approach allows for more precise demand predictions and ultimately improves the overall experience for stakeholders. Similarly, Philip Morris International deploys DTs to simulate thousands of what-if scenarios, reflecting the long-term outcomes of strategic decisions (Ashcroft 2022).

3. Research methodology

To answer the defined research question, systems thinking was established as a suitable theoretical lens, as FSC can be regarded as a complex and dynamic system. Furthermore, the DT technology is considered an intervention in the FSC system. SD modelling is perceived as an efficient tool for varying scenarios (Kazancoglu et al. 2021).

Currently, there is no widely accepted approach for modelling the DT-enabled supply chain system. Thus, the proposed research design for this study was established and divided into three stages, as shown in Figure 1. In the first stage of this research design, primary data was obtained through the questionnaire survey (part of the previous research) and secondary data from relevant SC modelling studies, industrial reports, and case studies. The empirical, primary data was collected through the questionnaire survey to gain practitioners' insights about the key stages of FSCs, the benefits of DTs for the FSC, and the relevant technologies of DTs. This, combined with the above-mentioned secondary data sources, identified the impacts of different technologies of DT on SC operations and their complex interactions, along with the identification of relevant SC variables. The outcome of this phase on data collection is the identification of Digital Twin (DT) relevant technologies, key supply chain performance metrics, and boundary conditions for the model.

The second stage developed a mental model based on insights generated using collected data on SC operations, performance metrics, and the integrative technologies of DTs. Brainstorming sessions with the research team helped develop the mental model, integrating the impacts of different technologies associated with DT on SC operations and performance. The mental model helps to translate the collected data and knowledge into a conceptual model (Er Kara et al. 2021). The relationships and

dependencies among FSC operations, DT technologies and SC performance captured through a mental model provide the foundation for dynamic modelling by identifying causal relations and feedback loops for the third stage.

The third stage focused on modelling the system dynamics. Insights from the mental model were used to develop a causal loop diagram (CLD), which captures the key variables and their interactions under the influence of DT. Stock and Flow diagrams were modelled and compared with the conventional FSC and DT-enabled FSC. These SD models quantitatively analysed the interrelationships among identified interactions of different DT technologies on SC operations and their impact on SC performances. By simulating developed SD models and comparing them, this study assesses the impacts of DT on the SC system. Each phase feeds into the next, with outcome being simulation results that help generate useful insights into the DT-FSC interactions.

4. Insights from survey and secondary data

The questionnaire survey was distributed to practitioners from different stages of the food industry, such as manufacturing, transportation, processing, retailing, and IT service providers. To ensure that the respondents have relevant knowledge and experience with DTs, screening questions were adopted to test whether they can assess this survey. Respondents were asked to evaluate different determinants related to DTs' implementation from technological, organisational, and environmental aspects using a seven-point Likert scale (1 is 'Strongly disagree' and 7 is 'Strongly agree'). The demographic profile of the 260 respondents for the survey collected data as part of the earlier stage of this research. In this survey, 64.51% of the respondents were from different stages of the food industry, including raw food producers, food processors, distributors and food retailers. Since the DT integrates different technologies, IT service providers and food or technology consultants provided highly relevant insights into the type and characteristics of DTs for addressing FSC challenges. Furthermore, 80% of respondents worked in managerial roles and had significant industry experience within their organisation. This evidence shows the robustness of the primary data collection following the questionnaire survey.

Several valuable insights from the survey highlighted DT's characteristics and the benefits it brings to the food industry through order processing, inventory management, and information sharing (part of the earlier research study). Respondents also agreed to a certain extent that DTs can help to improve the efficiency of

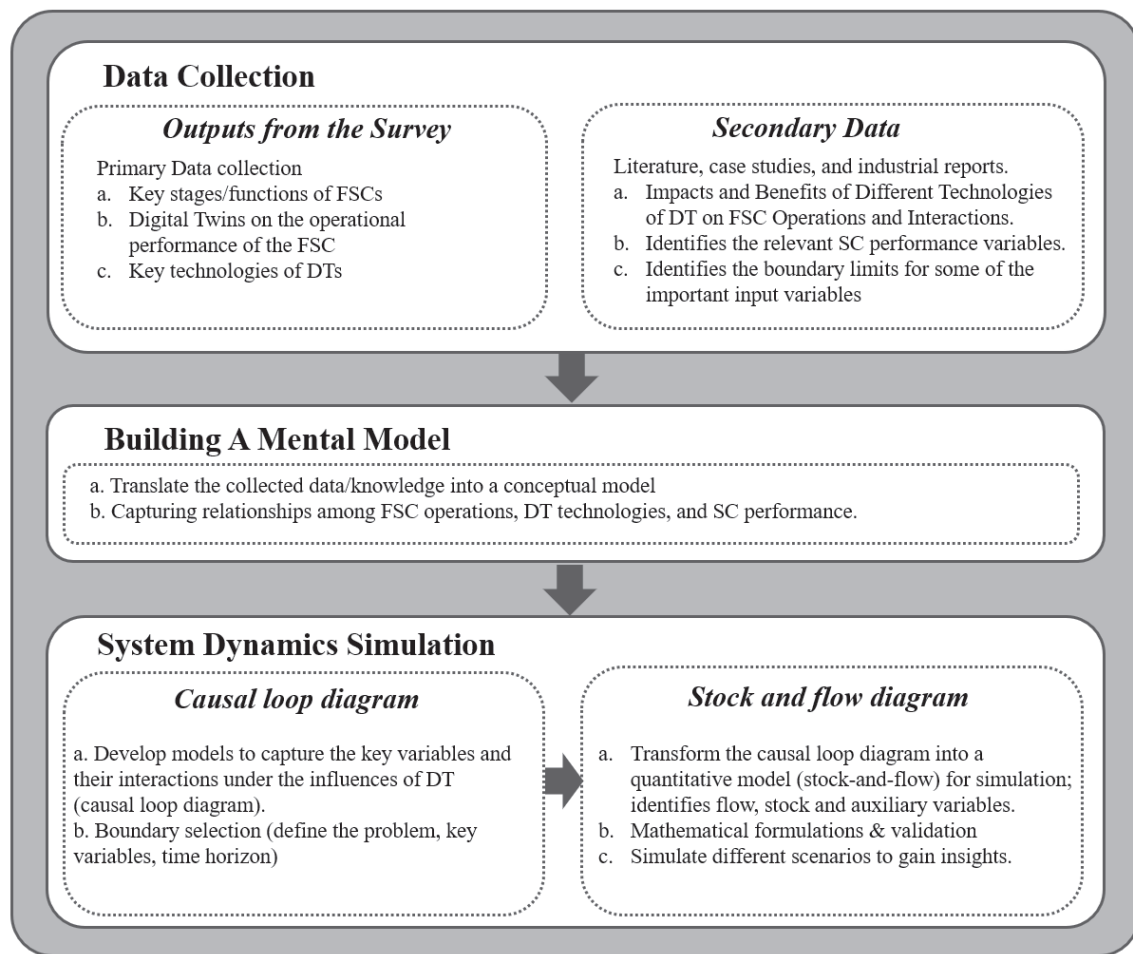


Figure 1. Research design.

processes in the FSC. They also firmly believed that collaboration and compatibility with existing IT and technological architectures are important for the adoption of DTs. Furthermore, the respondents somewhat agree that DTs can help enhance the company's risk management capabilities and reduce transaction/operational costs. Broad highlights on the benefits of DTs in FSCs are presented in Appendix D.

This questionnaire survey also collected the respondents' views on DTs' relevant technologies. Several insights into the importance of different technologies for integrating, developing, and operating DTs are presented in Appendix E. Considering the development and relevance of DTs, among all relevant technologies for DTs, most respondents thought that IoTs were far more crucial for the DT than any other technology, as indicated by the IoTs/sensors' mean value of 5.86. IoTs enable the data collection and connectivity of the supply chain operations processes in the real world (Ben-Daya, Hassini, and Bahroun 2019; Wang, Ghadge, and Aktas 2024). Cloud computing, which supports scalability and data

storage, was identified as the second most important technology for integrating, developing, and operating the DT. AI/ Machine Learning/BDA for data analysis and improved decision-making is the third most important technology for integrating, assessing, and operating the DT. AI/BDA are essential for predictive and prescriptive analytics within the DT, which helps forecast potential future states of the system by analysing historical and real-time data (Tao and Zhang 2017). BC/Distributed ledger is also used to ensure that data is securely shared between stakeholders and that changes are auditable and secure within the DT environment (Kamble et al. 2022). These insights into key benefits and integrated technologies obtained from the survey are used later in developing a mental model. Survey insights were used qualitatively to shape the mental model by identifying perceived operational constraints, information-sharing challenges, and DT-related benefits. These insights informed the selection of system variables, causal relationships, and boundaries rather than being directly converted into numerical parameters.

A critical academic literature review established key variables influencing SC operations and performance indicators. As a result, inventory management, order processing, information sharing, waste management, customer satisfaction and operational efficiency are considered critical variables in SC operations. Adjustments for low inventory levels, time for inventory adjustments, order fulfilment, production capacity, manufacturing cycle time, waste management, and demand forecast accuracy were established as key activities for SC operations. Demand variability, information sharing, backlogs, and unfilled demand were established as key variables influencing SC operations. Whereas raw material costs, production costs, inventory costs, profit/revenue, fill rate, lead time, and customer response time were identified as key performance indicators. More details on these key variables and the relevant justifications for the SC operation model are provided in Appendix A. Also, identified key SC performance indicators and their corresponding definitions obtained from the academic literature are illustrated in Appendix B. Insights obtained from relevant case studies and practitioner/industry reports were used for gathering insights such as choice of input variables and assigning corresponding values for SD modelling, along with cross-validating established impacts on the FSC system.

5. Development of mental model

A mental model approach was deployed to comprehensively represent the interrelationships among SC operations/key activities, different DTs' relevant technologies, and SC performance. Brainstorming sessions with the research team facilitated the mental model's development. Three important aspects were considered in the development of the mental model: SC operations, performance metrics and DT integrative technologies. The cognitive map visually illustrates this mental model. Such mental models are generated by an individual or group of experts for a given system, capturing variables, entities, and causal linkages/relationships based on available knowledge, following an iterative process (Er Kara et al. 2021; Mital, Del Giudice, and Papa 2018).

Figure 2 illustrates how DT-relevant technologies such as IoT, CC, BDA/AI, and BC/Distributed Ledger strengthen information flows and sharing by facilitating real-time data exchange, accurate demand forecasting, and traceable transactions (Chan 2003; Hader et al. 2022; Hoshimova, Mahdavisarifa, and Cagliano 2021). Figure 2 also showcases that implementing DT-relevant technologies benefits supply chain operations, including inventory management, order processing, and demand

variability. At the operational level, this enhanced information sharing is important in boosting data accuracy and visibility across SC, which assists SC stakeholders' decisions and reduces uncertainty (Kembro, Selviaridis, and Näslund 2014). For example, real-time inventory data from IoT and analytics allow firms to adjust their inventory and production levels to meet demand fluctuations, optimise reorder points, reduce holding costs, and minimise stockout and mitigate backlog risks (Ben-Daya, Hassini, and Bahroun 2019; Weißhuhn and Hoberg 2021).

Similarly, BDA/AI strengthens demand forecasting, allowing inventory and production levels to dynamically adjust to fluctuations, reducing waste and improving service responsiveness. Blockchain further ensures traceability and trust in transactions, while CC supports scalable data storage and seamless integration across partners. Figure 2 also reflects feedback loops between DT-technologies and supply chain performance. For example, improved demand forecasting enhances production scheduling, which stabilises inventory levels and reduces waste, ultimately improving customer satisfaction and profitability. Conversely, reduced lead times and improved order fulfilment reinforce delivery performance, which positively affects revenue and overall supply chain reliability.

In this mental model (Figure 2), several SC performance metrics are linked to SC operations, such as profit/revenue, inventory level, customer satisfaction, overall cycle time and fill rate. Also, the influences of DT-relevant technologies, namely IoT, CC, BDA/AI, and Blockchain/Distributed ledger, on SC operational variables and performance metrics are considered. This systemic representation showcases how DT adoption extends through operational processes to deliver measurable improvements to supply chain performance.

6. SD model development

6.1. Causal loop diagrams (CLDs)

Utilising insights from the mental model, causal loop and stock-and-flow diagrams are developed in system dynamics to conceptualise the system structure of FSC operations interacting with DT technologies. These diagrams often serve as a transition between mental models and formal simulation models (Stave and Kopainsky 2015). In this study, we employed CLDs as the conceptual modelling tool to illustrate the feedback structure and enhance a better understanding of a conventional FSC's behaviour. We adopted Sterman's (2000) stock management structure and referred to the food chain system dynamics modelling framework proposed by Georgiadis, Vlachos, and Iakovou (2005) to create

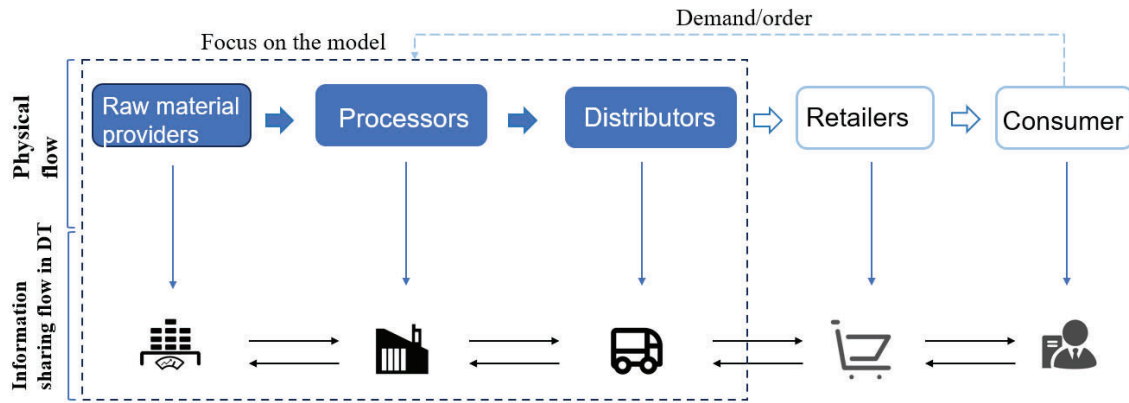


Figure 3. Structure of FSC system and focus of the research.

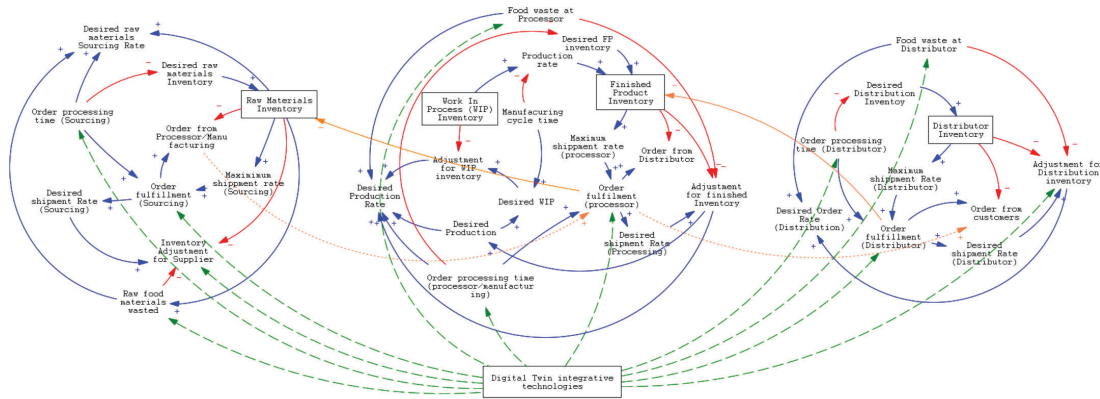


Figure 4. Causal Loop Diagram capturing the impacts of DT on FSC.

and provide real-time insights into stock levels, delivery performance and average demand, improving inventory adjustment and reducing food losses. In the model, distribution inventory, order fulfilment, food product waste and their links with the processing stage are considered. The green dashed arrows in Figure 4 highlight the influence of DT-integrative technologies (IoT, CC, BDA/AI, and Blockchain). DT affect information sharing, inventory adjustment times, and order processing efficiency, therefore reinforcing positive loops (e.g. better demand forecasting improving production-distribution alignment) and balancing negative loops (e.g. excess inventory triggering adjustment to reduce overstock). DT adoption reduces food waste at sourcing, processing, and distribution stages by improving decision-making under uncertainty. Thus, Figure 4 conveys a systemic view of how DTs reshape the causal relationships within the FSC. Reinforcing loops drive improvements in responsiveness and efficiency, while balancing loops mitigate risks of

overproduction and waste, together demonstrating the dynamic benefits of DT adoption.

By considering the impacts and potential of DTs from questionnaire surveys and previous research, Figure 4 reveals how DTs are involved in the three main stages of FSC as important information technology, by influencing conventional FSC information-sharing activity (highlighted by green lines). DTs can influence raw materials/food product waste at the sourcing, processing, and distributing stages because food is wasted or lost through the FSC (Maheshwari et al. 2023a; Sengupta and Dreyer 2023). DTs can impact order processing time and fulfilment rate from a time aspect due to their characteristics, such as real-time tracking and simulation. From an inventory management aspect, DTs impact the inventory adjustment level or time in the sourcing, processing, and distribution stages.

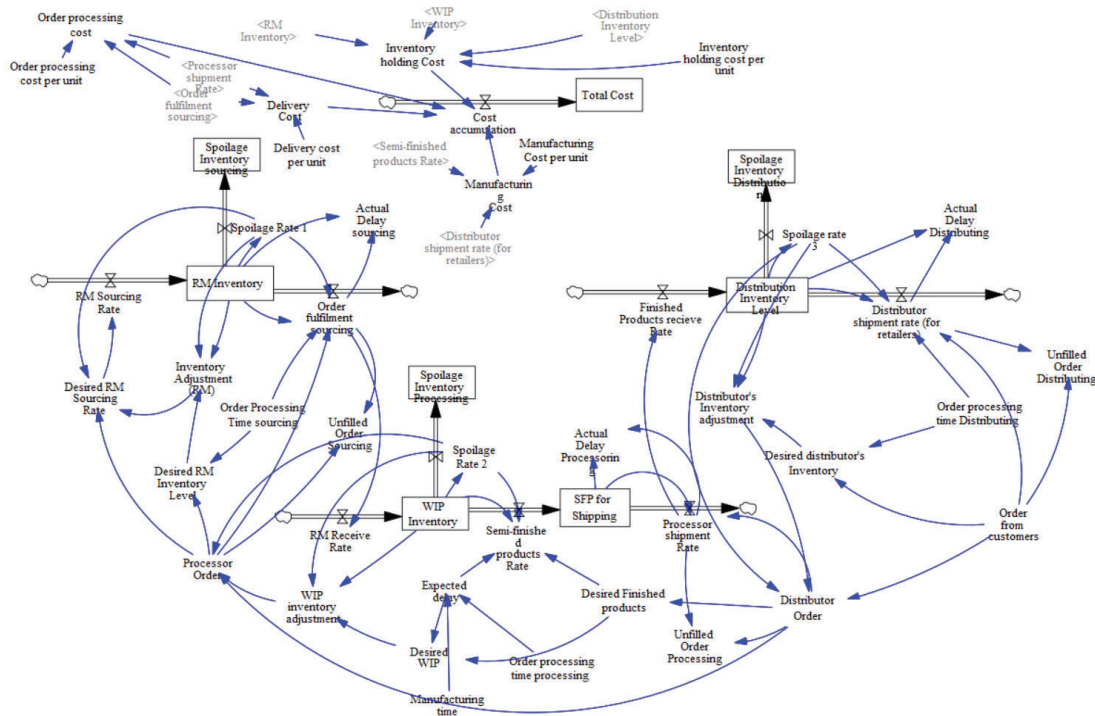


Figure 5. Stock and flow diagram for conventional FSC.

6.2. SFDs' development

Developing stock-and-flow diagrams (SFD) based on the designed CLD is the next step of this modelling. SFDs will be used to run simulations to evaluate the system changes brought by DT adoption in the SC. Two SFDs were developed to present the conventional and DT-enabled scenarios, as shown in Figures 5 and 6. Given the diversity of food products and supply chain contexts, several parameters were necessarily represented in the aggregated form. Their use provides a high-level approximation of FSC characteristics but does not capture product-specific operational dynamics. The key inputs and parameters used for simulation are demonstrated in Appendix F, which includes findings from secondary sources such as industry reports, case studies and academic literature, along with a few assumptions (primarily used to define some of the demonstrative values) for the simulations. For example, according to FAO (2011), approximately 9% of food is wasted as raw products during post-harvest and storage, 25% of food is wasted as processed foods at the manufacturing stage, and 10–17% of food is wasted in the distribution stage. Recently, a few industrial reports indicated that DT could reduce waste or spoilage by 20% to 50% (Attaran and Celik 2023; McKinsey & Company 2024; Sengupta and Dreyer 2023). Thus, we assumed the different spoilage rates in the conventional and DT-enabled cases accordingly (e.g.

Vu, Ghadge, and Bourlakis 2025). This is an acceptable approach in SD modelling (e.g. Er Kara et al. 2021; Kochan et al. 2018; Vu, Ghadge, and Bourlakis 2025) due to the lack of direct and available data on DT impacts in the FSC or companies unwilling to share confidential information. To further clarify the translation between data sources and SD structures, Appendix C complements Appendices A and B by summarising how each questionnaire survey item, literature insight, and industrial report informed the choice of variables, parameters and feedback loops, thereby providing a complete and transparent account of how secondary evidence was operationalised in the mental model and causal loop diagram.

The SC operation process typically begins when a customer places an order; the distributor checks the inventory status and sends the order for processing. When an order is received from the distributor, the processor orders from the food providers with enough raw food material providers to cover the desired inventory and future orders. The subsequent assumptions were established for modelling a conventional FSC and the DT-enabled FSC.

- All the orders will be dispatched or shipped promptly if the products are in stock.
- The processor/production order is assumed to be unconstrained by capacity and workforce, simplifying

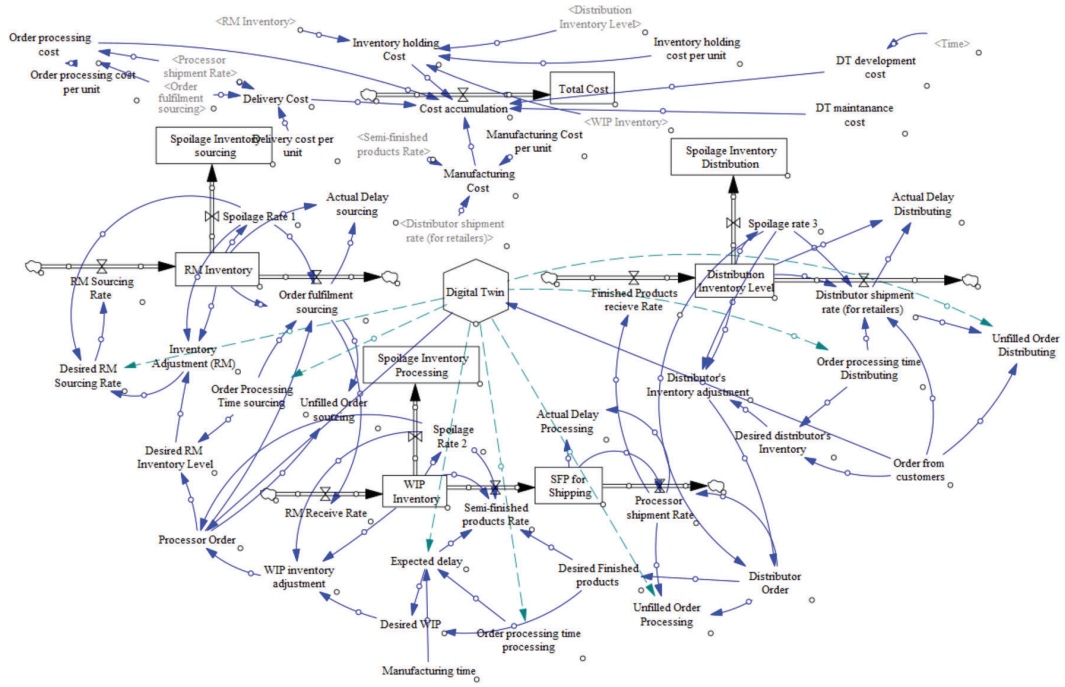


Figure 6. Stock and flow diagram for DT-enabled FSC.

the model's complexity. No capacity constraint exists in the supply chain network (Kochan et al. 2018).

- There are no backorders for the food processing stage. In the FSC, the unavailability of food products frequently results in decreased sales, as consumers can easily get alternatives. The SD modelling for the food system, thus, generally excludes the backorder variable. (Kumar and Nigmatullin 2011; Stave and Kopainsky 2015).
- The impacts of DT's visibility and communication improvements influence the spoilage rates in the different stages of SC (McKinsey & Company 2024; Sen Gupta and Dreyer 2023).

7. Model assessment and findings

7.1. Model validation

In system dynamics, model validity is typically assessed through structural validity, behavioural validity, policy/scenario validity, and sensitivity analysis (Barlas 1996; Sterman 2000). Given the exploratory nature of this study, the validation efforts focused on structural validity checks and sensitivity analysis, which are appropriate for evaluating the internal logic, conceptual consistency, and robustness of a hypothetical system dynamics model of FSC operations and performance under DT influence.

Structural validity was achieved through several procedures. First, boundary adequacy assessment was

conducted to ensure that the model captures the essential components and interactions relevant to FSC operations and performance under DT influence. Model variables were identified through structured triangulation of questionnaire survey results, relevant academic literature, and industrial reports. Second, the causal loop diagrams and stock-flow structures were reviewed and refined through multiple rounds of expert consultation with specialists in food supply chain management and digital transformation, helping to confirm that the feedback loops and causal linkages are conceptually appropriate and reflected real-world processes. Third, causal relationships were verified by cross-checking model equations and structures against relevant empirical studies. Finally, extreme condition tests were conducted to examine how the model behaves under limiting or boundary conditions and to verify that the structure produced reasonable results. Including boundary adequacy assessment was used to capture the essential components and interactions of FSC operations and performance under DT influence. This assessment was informed by an extensive review of relevant literature, industrial reports, and questionnaire survey. Sensitivity analysis examined how variations in key parameters affected model outcomes (details in Appendix H).

In addition, numerical sensitivity analysis was performed to evaluate the robustness and reliability of the established SD models (Sterman 2000) and for understanding the influence of parameter variations on the

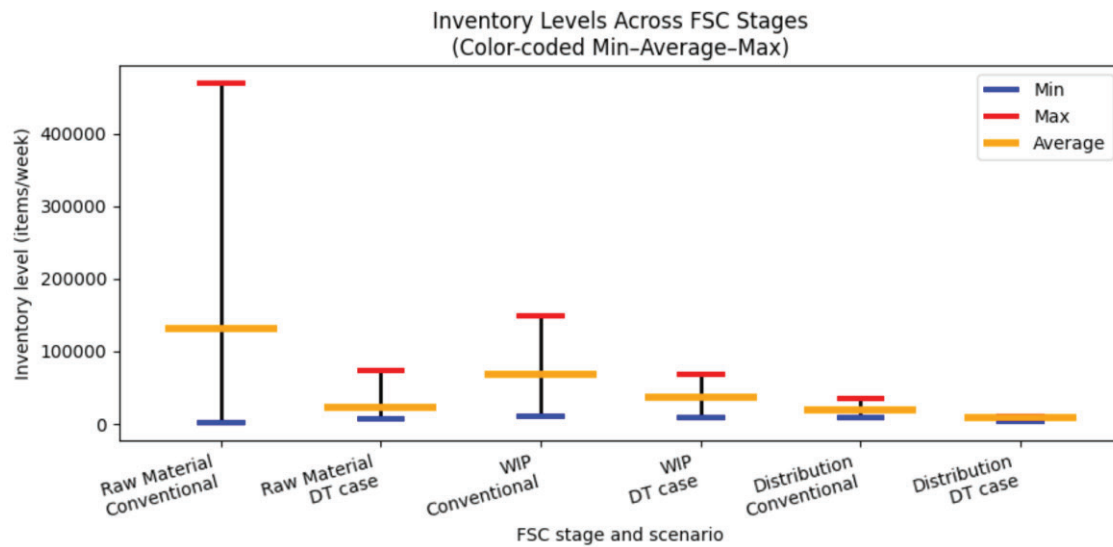


Figure 7. Inventory levels across FSC stages under conventional and DT scenarios.

overall system behaviour. Three sensitivity categories exist: numerical, behaviour model, and policy sensitivity (Sterman 2000). Here, numerical sensitivity for the current SD models was studied in Appendix H. Numerical sensitivity occurs when a change in assumption or input variables changes the numerical values of the results. No exponential growth, sudden collapses, or periodic oscillations were observed indicating that the model is relatively stable and ready for assessment.

Behavioural validity and policy/scenario validity were not assessed in this study due to the hypothetical and abstracted nature of the model, which was developed for exploratory and comparative analysis rather than a real-world case study. Behavioural validity typically requires comparison of simulated results with reliable historical data (Sterman 2000); however, such data do not exist for the system examined, as the model does not correspond to an empirically observed system. Additionally, DT applications in FSCs are still at an early stage; there are very few empirical cases from which to derive quantitative validation. Similarly, policy/scenario validity could not be assessed, as the policies examined are exploratory and have not yet been implemented in real systems. Without empirical implementation or observable outcomes, it is not possible to compare simulated policy effects with real-world results.

7.2. Model assessment

To evaluate the impact of successful DT adoption in the FSC, this study used five SC performance metrics, including inventory level, unfulfilled orders, lead time, cost, and food waste. These SC performance indicators

were derived from the previous SC studies (Er Kara et al. 2021; Kochan et al. 2018; Singh et al. 2024; Vu, Ghadge, and Bourlakis 2025) and used to compare system behaviour under conventional FSCs and DT-enabled FSCs scenarios. While information availability, visibility, and quality are critical characteristics of DTs, they are inherently embedded in the way DT improves operational performance across these metrics. For example, enhanced visibility and information availability support better inventory coordination and improve responsiveness to demand fluctuations. Thus, although not separately quantified, these information-related characteristics of DTs are integral to the improvements captured in the operational performance measures presented in this study. Similarly, DT-enabled traceability facilitates better handling of quality issues and indirectly supports recall management, which is reflected in reduced waste and cost. Furthermore, this comparison enables a clearer understanding of how DT adoption can influence efficiency, responsiveness, and overall performance in the FSC.

7.3. Impact on inventory Level

Optimal inventory level at different stages of FSC is a good indicator of supply chain efficiency (Aramyan et al. 2007). Thus, changes in raw materials inventory, WIP inventory, and distribution inventory were captured under the conventional FSC and DT-enabled FSC scenarios. In the conventional FSC scenario, the raw materials inventory (green) is volatile, with inventory levels changing rapidly (between 10,000 and 470,000), exhibiting clear peaks and valleys that indicate a delayed response

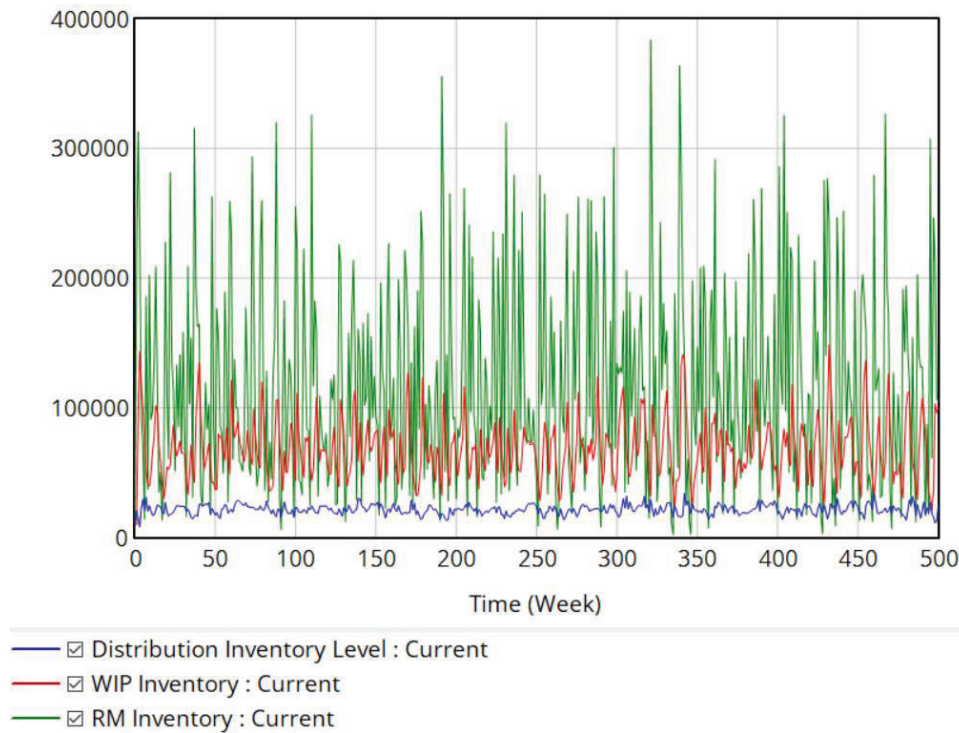


Figure 8. Inventory level for conventional FSC (items/week).

from SC stakeholders, as observed in Figure 8. Compared with raw material inventory, work in progress (red) is less volatile, but still has high inventory levels. Distribution Inventory (blue) is less volatile, with more stable inventory levels, possibly due to an adequate buffering strategy in the downstream distribution network. From the results, raw material inventory levels are the highest among the three stages, followed by work-in-progress and distribution inventory (Figures 8 and 9). The conventional FSC inventory strategies rely more on high-safety stocks and large reserves of raw materials. In summary, the results of this study support the established view that high volatility and high inventory levels are associated with increased operational costs, reduced flexibility, and responsiveness to demand fluctuations (Aramyan et al. 2007; Rong, Akkerman, and Grunow 2011). This was evident in the model outputs, which showed cost increases and performance decreases under demand and excessive inventory levels. As shown in Figure 7, the DT-enabled case is associated with lower average inventory levels across all FSC stages and exhibits lower observed minimum and maximum values compared with the conventional FSC. Compared with the conventional FSC, the DT case shows reductions in average inventory levels of approximately 44% for raw material inventory, 46% for work-in-process (WIP) inventory (e.g. reduction in average WIP inventory = (Conventional – DT) /

Conventional * 100%), and 44% for distribution inventory. In addition to lower mean inventory levels, the DT case displays narrower observed minimum–maximum ranges across all FSC stages, suggesting reduced dispersion in inventory trajectories over the simulation horizon. These patterns are indicative of more stable and responsive inventory dynamics under DT-enabled information sharing, rather than evidence of statistically significant differences.

Compared to the conventional inventory level, the average volume of the three inventory stages, raw materials, WIP, and distribution inventory level, has dropped significantly under the DT-enabled case (Figure 9). DT helps determine appropriate inventory and replenishment strategies, ensuring that inventory is served correctly and in a timely manner, hence facilitating an efficient supply chain with optimal customer service levels. Due to the strong data analytics capability of DT, the average raw materials inventory has been observed to drop by 43.6%. The fluctuation of raw materials inventory (green) is also significantly reduced with stable inventory volume. This indicates that DT's optimisation feature minimises the risk of overstocking or understocking. This control over inventory levels highlights DT's ability to adapt to demand and supply variations, a key factor in controlling SC fluctuations. Similarly, for WIP inventory and distribution inventory, the inventory level and fluctuation are

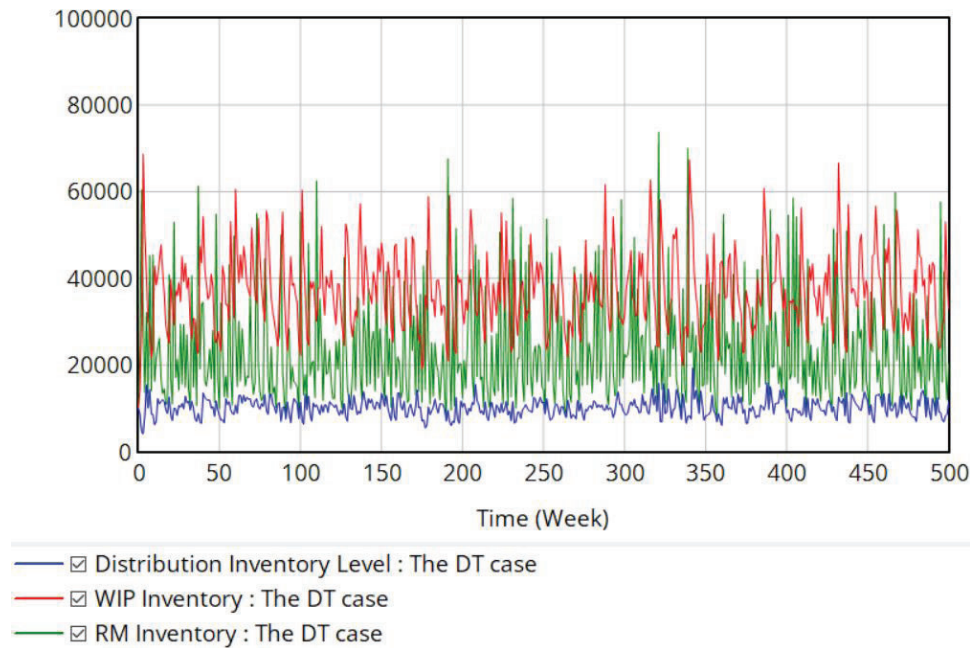


Figure 9. Inventory level for DT-enabled FSC (items/week).

significantly reduced, and the curve is much smoother than the conventional FSC.

7.4. Impact on unfulfilled orders (service level)

Unfulfilled orders directly impact customer satisfaction when the current inventory level cannot fulfil an order (Pham and Ahammad 2017), increasing unfulfilled orders and, thus, poor customer service. Furthermore, approximately one-third of all food produced is wasted, partly due to inefficiencies in supply chain logistics (FAO 2011), which helps reduce unfulfilled orders and minimise food waste to some extent. Unfulfilled orders are an important SC performance metric for evaluating the performance of the FSC. Figures 11–13 demonstrates the unfulfilled orders across three stages of the FSC – sourcing, processing and distribution under conventional and DT-enabled scenarios. The unfulfilled order shows high variability and frequent peaks, reaching values of approximately 80,000 units (Figure 11), primarily due to a lack of real-time demand visibility and slower supply chain responsiveness under the conventional FSC.

Compared to DT-enabled FSC, unfulfilled orders are significantly reduced (rarely exceeding 20,000 units); the peaks are less frequent and have less volatility, reflecting DT as the technology supporting improved forecasting, real-time inventory tracking, and faster response to demand fluctuations. Figure 10 shows notable reductions in the variability of unfulfilled orders. The most

pronounced improvement is observed at the raw food provider stage, where the standard deviation decreases by approximately 64%. These reductions indicate that DT adoption substantially stabilises order fulfilment dynamics, mitigating extreme shortages and reducing volatility across upstream supply chain stages. At the distributor stage, the standard deviation of unfulfilled orders decreases by approximately 32% under the DT-enabled scenario compared to the conventional case. At the processor stage, variability is reduced by about 56%. Across all stages (See Figures 11–13), DT-enabled FSC demonstrates a considerable reduction in unfulfilled orders compared to the conventional FSC, reflecting enhanced SC efficiency. The most significant improvements are observed in the raw materials and processor stages. Thus, DT technology is observed to improve FSC performance by minimising unfulfilled orders.

7.5. Impact on lead time

Lead time (or actual delay) is a key performance indicator for evaluating the impact of technology on the SC. The DT's ability to provide real-time visibility, predictive analytics, and optimisation aligns with reducing delays and improving SC efficiency (Ivanov and Dolgui 2021; Maheshwari et al. 2023a). Lead times are affected by poor forecasting, leading to the bullwhip effect. Such fluctuations in lead times necessitate maintaining high inventory levels to effectively respond to orders and

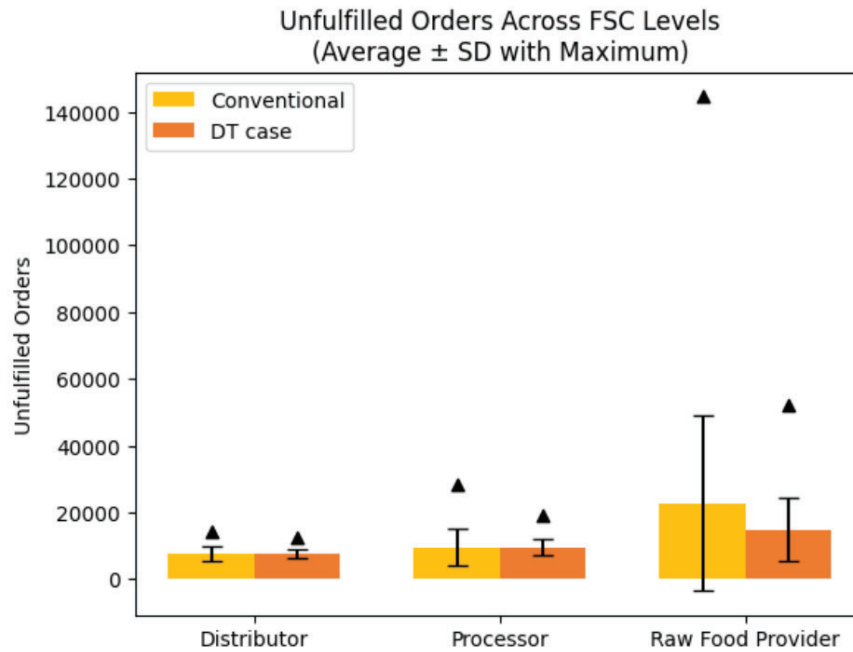


Figure 10. Unfulfilled orders across food supply chain levels under conventional and DT-enabled scenarios.

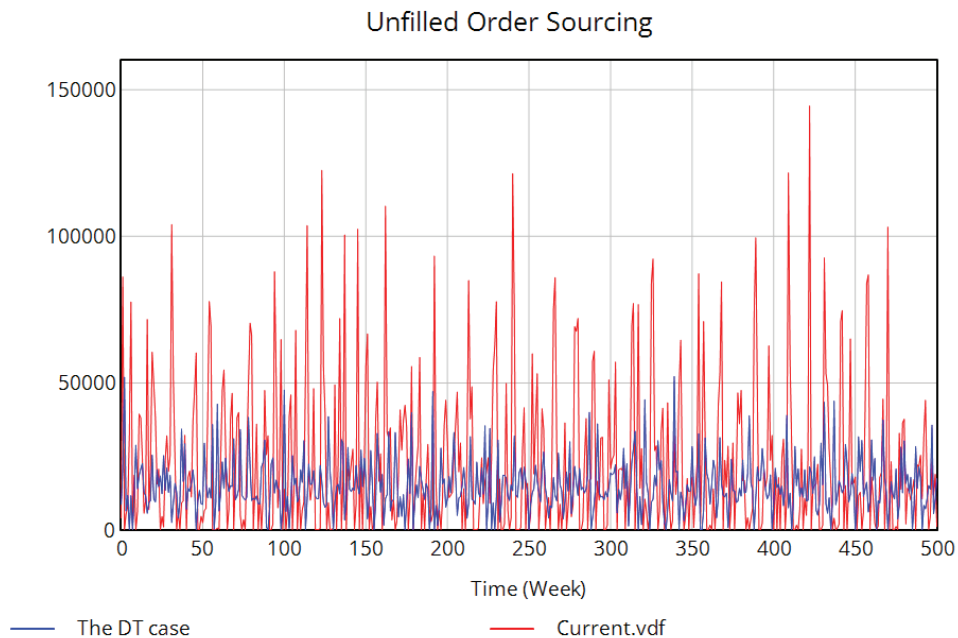


Figure 11. Scenario comparison of unfulfilled orders in the sourcing (Items/week).

ensure service levels. However, reducing lead time variability provides some advantages, including lower inventory levels, reduced order delays, and improved service levels (Kochan et al. 2018). A notable observation is that DT helps stabilise lead time variability. DT achieves this by reducing lead time for processing activity in the SC, improving information visibility and providing more accurate demand forecasts (Ivanov and Dolgui 2021;

Kamble et al. 2022). These enhancements collectively contribute to better SC efficiency. The details of the actual delay in weeks for product movement across different stages of the SC are demonstrated in Figure 14. Under the DT case, the sourcing delay is 1.68 weeks, which is higher than the conventional case (the sourcing delay is 1.23 weeks); sourcing takes longer, possibly due to DT implementation complexities in resources or changes in

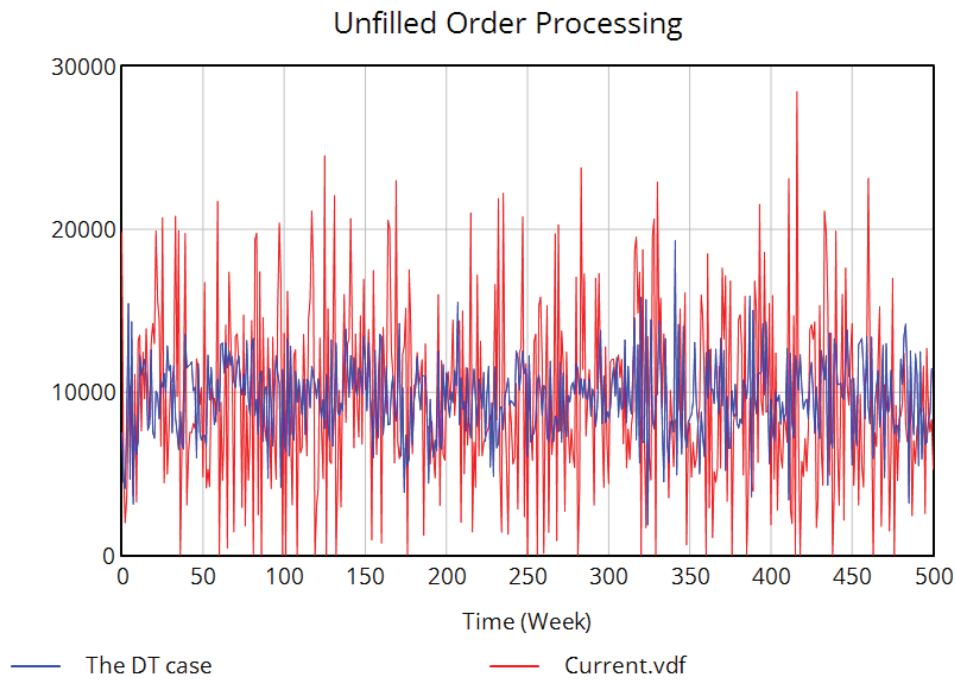


Figure 12. Scenario comparison of unfilled orders in the processing (Items/week).

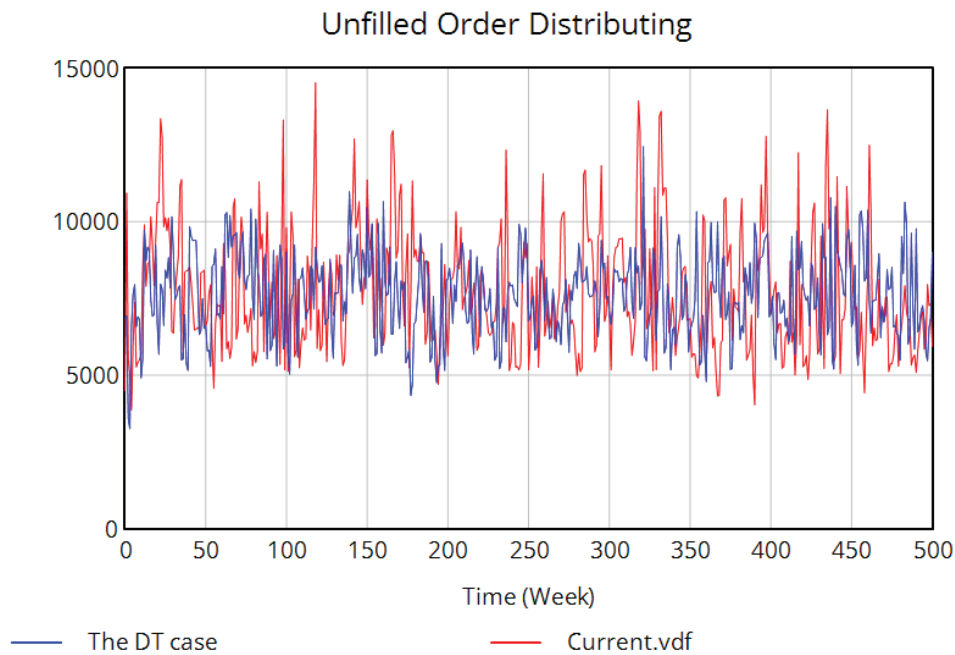


Figure 13. Scenario comparison of unfilled orders in the distributing (Items/week).

supplier integration. The conventional case has higher delays, especially in processing and distribution, and is more unpredictable. However, the DT case significantly improves efficiency, reducing processing and distributing delays while maintaining consistency (DT improves processing efficiency, reducing processing time by nearly 48% compared to the conventional case).

The DT case demonstrates a reduction in processing and distribution delays, highlighting improvements in overall efficiency and consistency due to the adoption of DT. Furthermore, sourcing delays are slightly higher in the DT case, which could be attributed to initial adjustments or challenges in adopting DT, particularly in the early stages of adoption.

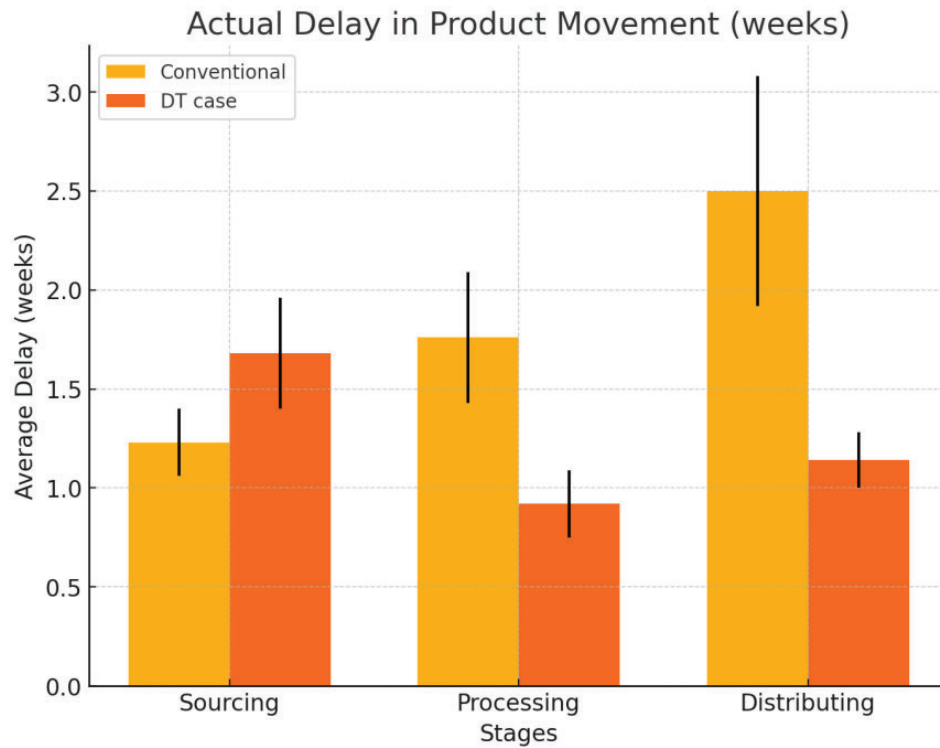


Figure 14. Actual delay in product movement.

7.6. Impact on operational costs

The operational cost for the two cases (the conventional FSC and the DT-enabled FSC) is evaluated to uncover the potential impacts of DTs on SC costs. In this case, operational costs include inventory holding costs, manufacturing costs, transportation costs, and order processing costs. The administrative and technology costs were excluded from this model to reduce complexity. The detailed calculation and modelling of the operational cost are presented in Appendix G, and the results of the operational cost are shown in Figures 15 and 16.

According to industrial reports, the estimated cost of adopting the DT range (for a fundamental asset DT with integration functionalities) is between \$79,000 and \$132,000 (Visartech 2024). The development cost of the DT technology can be divided into different expenses such as deployment, integration, and maintenance costs (Oetl, Eckart, and Schilp 2023); in total, the DT costs range from \$71.5k to \$114k. Thus, those technology costs in the model were considered as development and maintenance costs for DT, as outlined in Appendix G.

The costs for the two cases are evaluated to reveal DT's potential impacts on the operation cost of FSC operations. The basic operational cost of FSC consists of inventory holding costs (from raw materials, processing, and distribution), manufacturing costs, order processing costs, and delivery costs. Appendix G presents a detailed

calculation and modelling of the operational cost. The initial investment cost of DT will be higher (technology cost), and the total cost will appear relatively high. However, in the long run, using DT helps reduce the inventory holding costs of the supply chain, reduces waste, and thus positively affects the total cost level. DT's control over demand forecasts, combined with transparent and timely information transmission, will further help reduce order processing and transportation costs. For example, at 500 weeks (Figure 16), the cost advantage of the DT supply chain is observed compared to the short time horizon of 10 weeks (Figure 15).

7.7. Impact on food waste

When evaluating the effectiveness and sustainability of FSCs, food waste is a crucial performance metric, drawing attention to inefficiencies in production, processing, storage, transportation, and consumption to assess how effectively resources are utilised (Parfitt, Barthel, and Macnaughton 2010; Raak et al. 2017). Food waste is linked to unnecessary energy and water use and emissions of greenhouse gases generated by production and delivery operations. Food waste is not considered an isolated phenomenon, but rather an emergent outcome of several interacting factors within the FSC. For example, inventory dynamics such as overstocking from inaccurate demand forecasts or poor coordination increase the

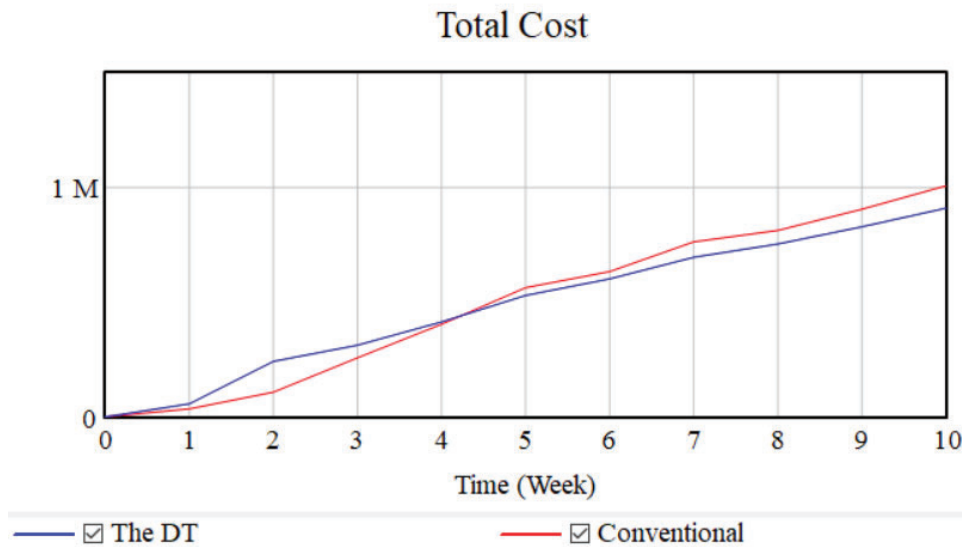


Figure 15. Total cost scenarios for conventional and DT-enabled FSC (10 weeks).

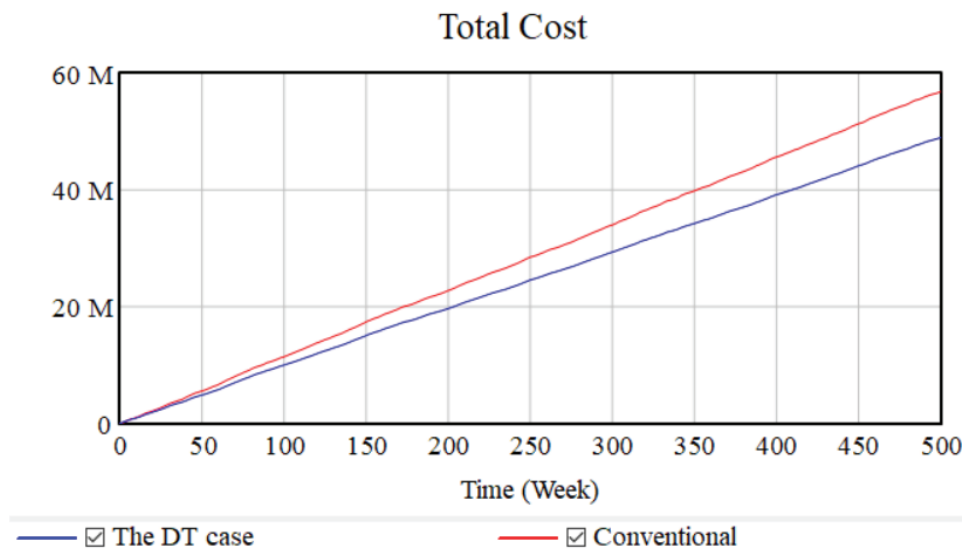


Figure 16. Total cost scenarios for conventional and DT-enabled FSC (500 weeks).

risk of food product expiration or spoilage. Similarly, long lead times and delays in information sharing develop a mismatch between supply and demand, resulting in either excess inventory or late deliveries, both of which increase food waste. Similarly, unfulfilled orders may trigger reallocations or additional production, leading to inefficiencies and surplus disposal.

By enhancing transparency, traceability, and real-time decision-making, DT provides an opportunity to minimise food waste and further support enhancing FSC performance. DT also reduces forecasting errors and improves inventory coordination (Guo and Mantravadi 2025). With end-to-end visibility and forecasting capabilities, DTs can better coordinate production and sales, reduce excess inventory and reduce waste (Monteiro and

Barata 2025). These improvements brought by the adoption of DT mitigate the drivers of food waste across the supply chain.

Figure 17 compares spoilage inventory levels in the processing stage of the FSC under two scenarios as an example. In the RM material spoilage inventory, the conventional FSC illustrated high variability in spoilage levels (which often exceed 30,000 units), with frequent peaks indicating inefficiencies. However, low spoilage and smoother fluctuations in DT-enabled systems suggest better control over inventory through real-time tracking or analytics. DT helps reduce delays and improve storage conditions for raw materials, minimising spoilage risks. The comparison of processor and distribution spoilage inventory indicated a similar pattern. Thus, DT-enabled

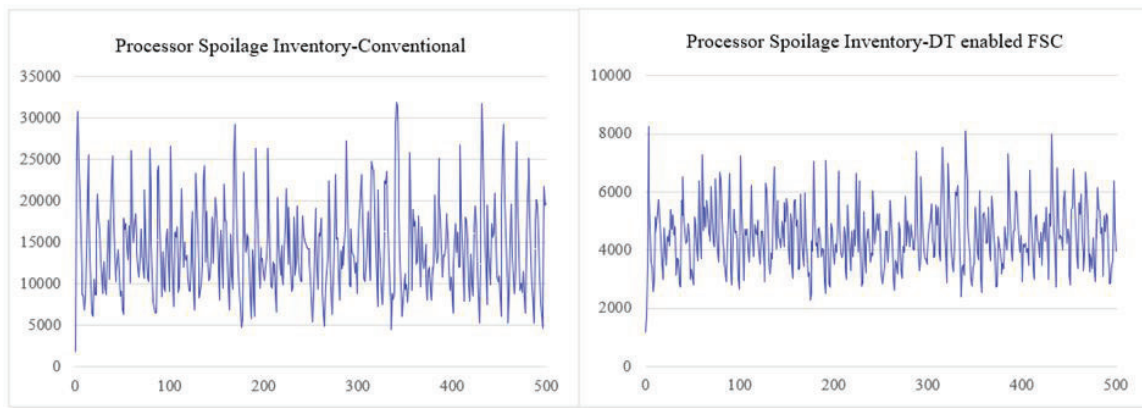


Figure 17. Cross-scenario comparison of spoilage inventory in the processing stage.

FSC outperforms the conventional FSC at different SC stages, reducing spoilage inventory and leading to lower food waste.

8. Discussion and contribution

This study examined how process-level DT implementation influences SC performance by enhancing information and data sharing among stakeholders across various stages. Using SD models, upstream FSC operations were simulated and compared under two scenarios: a conventional FSC and a DT-enabled FSC. Rather than reiterating widely accepted conceptual benefits of DTs (e.g. visibility, traceability, forecasting accuracy), this section focuses on specific operational mechanisms and managerial insights that emerge from the numerical results. To address a critical research gap, four key FSC performance indicators were assessed, namely inventory level, unfilled orders, actual delay (lead time), and food waste. Since the model is not calibrated against company-specific data, the numerical performance improvements should not be interpreted as transferable estimates for real DT implementations. The results instead illustrate relative differences between scenarios under controlled assumptions. The results revealed that indicators significantly improved under the DT-enabled system compared to the conventional counterpart, validating the positive role of DT in enhancing SC performance. Specifically, DT adoption led to notable reductions in raw material and WIP inventories (43% and 50%, respectively) compared to conventional systems, (these inventory reductions have a direct positive influence on operational costs and food waste) which not only reduced holding costs but also lowered the probability of food waste. These reductions demonstrated how enhanced information sharing and predictive analytics can mitigate unnecessary inventory buffers. Moreover, the finding confirms the prior conceptual understanding that DT adoption

significantly improves inventory levels, order fulfilment, and food waste reduction (Bhandal et al. 2022; Guo and Mantravadi 2025; Ivanov 2024).

More importantly, the numerical results reveal how DT-enabled information synchronisation changes operational behaviour. Earlier detection of upstream shortages enabled proactive adjustments to procurement and production activities. Real-time alignment between inventory levels and actual demand reduces the over-reactions observed in the conventional FSC scenario, resulting in fewer extreme shortages and smoother material flows. These behavioural mechanisms highlight why DT adoption yields measurable improvements across inventory levels, unfilled orders, and lead-time delays. From a managerial perspective, these mechanisms imply that DT adoption can support a shift from static, rule-based inventory planning to dynamic, demand-responsive decision-making. Managers may use these insights to refine replenishment policies and improve the timing of production adjustments.

While the impact on unfilled orders was moderate in this study, the overall effect on operational efficiency was substantial. It is also evident that DT-integrated technologies such as IoT, cloud computing, and BDA/AI enable seamless information sharing, fostering trust, collaboration, and operational continuity across the FSC. While conventional FSCs often suffer from isolated decision-making and excessive inventory buffers (Vlajic, Van der Vorst, and Haijema 2012), DT-enabled systems dynamically share order status and inventory levels, ensuring better demand alignment and reduced operational risks. The magnitude of improvements observed in the numerical results (e.g. 46.3% reductions in the inventory level indicator) also guides investment priorities. The most substantial performance gains stem from mechanisms that reduce information delay, improve upstream visibility, and synchronise production–inventory decisions. This suggests

that investment in IoT-enabled sensing, data-integration infrastructure, and predictive analytics capabilities may yield operational returns. Evidence from large-scale DT deployments (e.g. Ford Motor Company) demonstrates that the managerial benefits arise from improved visibility and forecasting (Ivanov and Gusikhin 2025). These insights reinforce the value of DT-enabled visibility and process synchronisation for investment decisions in FSCs.

The SD model further illustrates that DT adoption activates reinforcing feedback loops, such as improved demand forecasting leading to more accurate production scheduling, as well as balancing loops that stabilise inventory corrections. Managers can use the model as a policy-testing environment to explore alternative scenarios (e.g. demand shocks, capacity changes, or delay reductions) before committing to DT implementation. However, the numerical performance improvements illustrated by the SD simulations (e.g. reductions in inventory level, lead-time delays, and unfulfilled orders) reflect the dynamics of abstract system structures rather than guaranteed results of real-world DT implementations. These numbers should be regarded as directional insights showing how the DT-based feedback loop influences FSC behaviour rather than directly transferable performance benchmarks. The actual DT project will heavily depend on data quality, granularity, implementation scope, and product-specific constraints.

8.1. Contribution to theory

This study enriches the body of knowledge on DT adoption in SC contexts by offering insights into system behaviour, operational performance, and food system dynamics under DT-enabled transformation. It contributes to the technology adoption literature in FSC by integrating systems thinking with SD simulation to model and assess complex, interrelated supply chain processes.

The first contribution lies in extending the application of systems thinking within FSC research. Traditional static analysis methods often fall short of capturing the evolving and interconnected nature of SC operations. By contrast, systems thinking offers a holistic lens to analyse complex systems like the FSC, making it especially suitable for studying the dynamic impacts of emerging technologies. This study uses SD modelling to reflect these complexities, providing a more nuanced understanding of how DT adoption influences SC performance over time.

The second key contribution is the development of SD simulation models that capture the interdependencies between DT adoption and core supply chain processes, rather than applying SD in isolation, the modelling

integrates DT capabilities such as real-time visibility, traceability, and predictive decision support into the modelling of supply chain processes, including inventory management, order fulfilment, and sourcing. This integration enables a quantitative evaluation of how DT adoption mechanisms translate into improvements in the key performance indicators (cost, lead time, service level, and waste). By structuring scenarios for both DT-enabled and conventional FSCs, the study facilitates the exploration of feedback loops and dynamic interactions that shape SC behaviour, offering a robust theoretical foundation for examining adaptive decision-making in real-world dynamic environments. By quantifying the holistic impact of DT adoption, this study moves beyond conceptual claims found in much of DT literature and provides experimental evidence of systemic performance improvements in supply chains.

Finally, this research enhances the integration of soft and hard systems thinking within the domain of technology adoption. Previous studies have effectively employed SD simulation to evaluate technologies such as Blockchain and cloud computing (e.g. Kochan et al. 2018; Vu, Ghadge, and Bourlakis 2025). This study builds on those efforts by demonstrating that DT adoption is not a one-time implementation but an evolving process whose benefits materialise progressively. The findings highlight that digital transformations in supply chains demand a long-term, system-oriented perspective, as technology-enabled improvements do not emerge instantaneously but through sustained integration and adaptation.

8.2. Contribution to practice

This study provides several valuable contributions for practitioners in the FSC sector, as well as policymakers aiming to promote digital transformation in the industry.

First, the study offers a structured and empirically grounded methodology to assess and implement DTs within FSC operations. By integrating insights from questionnaire surveys and practitioner reports, supply chain managers will be able to systematically identify operational areas likely to be impacted by technology and evaluate targeted interventions accordingly. Second, the study demonstrates the practical utility of SD modelling and simulations as a tool for scenario analysis and strategic decision-making. Practitioners can utilise these models to evaluate various DT implementation strategies by comparing performance indicators, forecasting outcomes, and supporting more informed investment decisions. The ability to visualise and simulate complex interactions across supply chain processes enhances the managerial capacity to anticipate and manage operational and performance impacts resulting from technology adoption. Most importantly, this

highlights that investment in DT-enabled capabilities (e.g. IoT, cloud computing, and BDA/AI) not only supports operational continuity but also justifies the cost of implementation through measurable performance gains. Furthermore, the SD model can serve as a strategic experimentation tool for supply chain managers. By adjusting parameters such as demand variability, production delays, and capacity constraints, decision-makers can explore the consequences of alternative policies before implementing DT solutions. Although the model does not prescribe specific decision rules, it supports scenario exploration and helps managers understand the systemic impacts of their choices.

Third, the proposed approach is not limited to DTs but offers a flexible framework for evaluating the integration of other emerging technologies within supply chains. This extensibility allows decision-makers to proactively respond to technological advancements (such as Metaverse or Generative AI), thereby improving responsiveness, efficiency, and competitiveness in FSC operations. Finally, the findings offer important policy implications. By highlighting how DT adoption positively influences performance indicators such as efficiency, lead time, and service levels, the study provides a foundation for designing targeted policy interventions. Government agencies and industry regulators can use these insights to create supportive policies, such as adoption incentives, subsidy programmes, and strategic technology initiatives, that encourage digital transformation in the food industry. For policymakers, this evidence on the broader impact of DTs on food safety and system resilience strengthens the case for further promoting DT in the FSC to enhance efficiency and sustainability. Fourth, to avoid potential misuse of model outputs, we emphasised that simulation results are intended to support conceptual understanding and scenarios exploration rather than provide prescriptive quantitative expectations. Practitioners should consider specific product characteristics and operational and contextual data to calibrate DT models before using them for planning or making investment decisions.

8.3. Limitations and future research directions

The study has several limitations that provide potential opportunities for future research. For modelling and analysis, necessary simplifications and abstractions were made, leading to the omission of some influential factors, such as customer preferences, market competition, seasonality, and the characteristics of food products. These omissions may cause deviations between the model results and actual situations. Future research should consider additional influencing factors, such as customer behaviours, policy environments, and supply

chain risks, to develop a more refined model. In addition, the model has not been calibrated against firm-level operational data nor validated by reproducing historical behaviour. As a result, the numerical outputs should be interpreted as conceptual indicators of system behaviours rather than precise predictions of DT impacts. Future research should incorporate empirical calibration using time-series data from FSCs, triangulate assumptions through expert elicitation, and apply behavioural validation tests to strengthen model credibility. These changes ensure more transparent reporting of model limitations and align claims with the support that a stylised, exploratory SD model can provide.

The proposed method also has limitations. Specifically, this study relies on several overarching hypotheses derived from survey response across products and regions. Because food products vary in perishability, demand volatility, regulatory environment and technological readiness, aggregating these factors inevitably leads to simplification. This aggregating can eliminate product or region-specific dynamics that may impact DT performance. Therefore, the numerical results should be interpreted as representing broad FSC patterns rather than as precise predictions for any specific product category, geographic location, or technology configuration. Future research should incorporate real-world company data and product- or region-specific modelling to examine how differences in perishability, demand characteristics, and technology infrastructure influence DT performance. Furthermore, the model's applicability is constrained by its underlying assumptions, as it does not account for certain practical aspects of DT implementation, such as costs associated with employee training. Future studies should incorporate additional DT-related costs and practical implementation factors within the SD model. Third, due to the complexity of the FSC and the involvement of multiple stakeholders, collecting comprehensive and consistent data was challenging, particularly regarding real-time inventory levels, transportation delays, waste quantities, and the extent of DT adoption. These data gaps may reduce the accuracy of model inputs and limit the reliability of simulation outcomes. The current research focuses on the three stages of the upstream FSC, which impose certain limitations. Future research should aim to strengthen collaboration with FSC companies to obtain more accurate and reliable data, optimise and validate the model, and improve its precision.

Although the maturity, scope, and technological composition of DT implementations can vary, this study conceptualises DT adoption as a single configuration and compares two scenarios. Alternative adoption levels, phased deployment strategies, and hybrid configurations fall beyond the current analysis and remain

promising areas for the future research. One of the limitations of this study is that technology-specific cost structures associated with DT adoption are represented at a high level of abstraction. This reflects the conceptual and exploratory focus of the proposed system dynamics model, which aims to examine general structural mechanisms and dynamic interactions rather than detailed technology investment or optimisation decisions. As DT implementation costs vary substantially across contexts, incorporating such heterogeneity would require case-specific assumptions that fall beyond the scope of a generalised modelling framework. Future research may explore more detailed cost representations as empirical evidence on DT adoption in FSCs continues to emerge.

Additionally, this study only considered certain DT applications, focusing on key operational performance metrics, including inventory levels, unfilled orders, and lead time. Future research could expand to other supply chain operational activities, such as optimising DT applications in demand forecasting and supply chain risk control, as well as comprehensive analyses of other information technologies related to DT. Finally, this study is primarily based on SD modelling and lacks validation through company case studies. Future research should combine case studies and other empirical methods to verify the model's applicability and effectiveness. Questionnaire surveys and interviews could be conducted to evaluate companies' roles, demands, and impacts regarding DTs in the supply chain. This approach will provide a more comprehensive framework for the application and implementation of DTs in the FSC and other sectors.

Author contributions

CRedit: **Ying Huang**: Data curation, Investigation, Writing – original draft; **Abhijeet Ghadge**: Conceptualization, Methodology, Supervision, Writing – review & editing; **Nicky Yates**: Methodology, Resources, Supervision, Writing – review & editing

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributors



Dr Ying Huang obtained her PhD and MSc in Logistics and Supply Chain Management from Cranfield University, UK. She is actively engaged in advancing research in the implementation of Digital Twins within the food supply chain. Her research interests include food supply chain management and digital transformation (e.g. Big Data, the Internet of Things, Cloud Computing, and Digital Twins).



Dr Abhijeet Ghadge is an Associate Professor of Supply Chain Management at Cranfield School of Management, UK. He holds a PhD in Operations and Supply Chain Management from Loughborough University, UK, and an MTech in Industrial Engineering and Management from the Indian Institute of Technology, India. Dr Ghadge has published several peer-reviewed articles in the operations, logistics and supply chain focused journals. He follows a practice-driven approach to problems across the broad domains of supply chain risk, sustainability and Industry 4.0/5.0, and holds several years of industrial, academic and consulting experience.



Dr Nicky Yates is a Reader within the Cranfield Centre for Logistics, Procurement and Supply Chain Management and Director of Doctoral Programmes for Cranfield School of Management. An Engineer by training, she spent the first six years of her working life in the food industry for Unilever and, subsequently, Birds Eye as a Research Engineer. She has a wide general interest in many aspects of modelling the supply chain, and her teaching and research are focused in these areas, with a particular interest in the management of resilient supply chains and those which handle perishable products such as food and blood. Her research has been published in a number of internationally renowned journals, and she has carried out projects in many sectors from healthcare to construction.

Data availability statement

The authors confirm that the data used for this study are available and can be obtained from the corresponding author on reasonable request.

ORCID

Abhijeet Ghadge  <http://orcid.org/0000-0002-0310-2761>

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Appendices

Appendix A. Key variables for the SC operations model

Key variables	Justifications for the choice	List of reference(s)
Inventory management (supplier, processor, distribution)	<ul style="list-style-type: none"> Impacts a company's ability to meet customer demand on time. Support accurate demand forecasting and production planning, enabling companies to align supply with demand and reduce lead times. Minimise disruptions caused by SC/demand variability, ensuring that material shortages do not affect production schedules. 	Heizer, Render, and Munson (2020); Christopher (2022); Gonçalves, Carvalho, and Cortez (2020).
Adjustment for low inventory level	<ul style="list-style-type: none"> Reduce risk and waste for dealing with products with short life cycles (food or seasonal items), where overstocking can result in significant losses. Serve as a buffer against demand variability and SC disruptions, allowing businesses to maintain smooth operations despite fluctuations. 	Soysal et al. (2015)
Time for inventory adjustment	<ul style="list-style-type: none"> Influenced both customer satisfaction (service level) and operational efficiency 	Heikkilä (2002)
Order processing time	<ul style="list-style-type: none"> Influenced customer satisfaction/operational efficiency/scalability Increase competitive advantage or reduce errors in order entry, packing and shipping 	Ge et al. (2004); Coyle et al. (2021).
Order fulfilment (rate)	<ul style="list-style-type: none"> Contain activities involved from the moment a customer places an order to the delivery of the product or service to the customer. Influenced customer satisfaction Key metric for operational efficiency. Reducing lead times requires streamlined processes, from inventory management to logistics. Ensure inventory levels align with demand, minimising stockouts or over-stock situations. 	Bowersox et al. (2020); Georgiadis, Vlachos, and Iakovou (2005); Kamath and Roy (2007).
Lead time	<ul style="list-style-type: none"> Lead time and fulfilment rate directly impact inventory management. Shorter lead times allow companies to keep less inventory on hand, reducing holding costs. Affects customer satisfaction, cost efficiency, inventory management, and supply chain responsiveness. 	Langroodi and Amiri (2016); Ou et al. (2010); Christopher (2022); Aljanabi and Ghafour (2021).
Production rate	<ul style="list-style-type: none"> Influence a company's ability to meet customer demand. If the production rate is too slow or insufficient capacity, the company will struggle to fulfil orders, leading to unfulfilled demand, backlogs, and dissatisfied customers. 	Heizer, Render, and Munson (2020)
Production capacity (processor)	<ul style="list-style-type: none"> Aligned production capacity ensures that resources are neither under-utilised (leading to waste) nor overburdened (leading to inefficiency and increased maintenance costs). Helps control costs by avoiding overproduction, which leads to excess inventory, and underproduction, which results in lost sales. 	Mikati (2010); Adane et al. (2019).
Manufacturing cycle time	<ul style="list-style-type: none"> By optimising cycle time, companies can improve efficiency, reduce costs, enhance customer satisfaction, and maintain greater agility in responding to market changes. 	Krajewski, Malhotra, and Ritzman (2022)
Shipment (shipping capacity/vehicle volume)	<ul style="list-style-type: none"> Optimise transportation efficiency, lower costs, reduce environmental impact, and improve customer satisfaction. These variables are essential for maintaining a robust, responsive, cost-effective logistics network. 	Chopra and Meindl (2016); Ghadge et al. (2022); Aschauer, Gronalt, and Mandl (2015).
Waste management	<ul style="list-style-type: none"> Improves efficiency, reducing costs, ensuring food safety, maintaining regulatory compliance, and enhancing sustainability. Effective management of raw material, processor, and distribution waste ensures that food products are produced, processed, and delivered to customers with minimal loss, maximise profitability and minimise environmental impact. 	Gustavsson et al. (2011); Schanes, Dobernick, and Gözet (2018); Martin-Rios et al. (2018).
Information Sharing	<ul style="list-style-type: none"> Improves demand forecasting and planning. Helps identify potential risks within SC, allowing companies to take proactive measures to mitigate them. Enhances coordination, reduces inefficiencies, and improves agility, leading to better operational performance, customer satisfaction, and cost management 	Chan (2003); Hoshimova, Mahdavisarifa, and Cagliano (2021); Cachon and Fisher (2000); Kembro, Selviaridis, and Näslund (2014).
Demand variability and demand forecast accuracy	<ul style="list-style-type: none"> Incorporate demand variability and forecast accuracy into the mental model allows companies to make better production, inventory, supply chain management, and financial planning decisions. Maintain operational stability, minimise risk and optimise overall performance. 	Chopra and Meindl (2016); Petropoulos et al. (2014); Hwarng and Xie (2008); Golroudbary and Zahraee (2015).
Unfilled demand/orders Backlogs	<ul style="list-style-type: none"> Improve decision-making regarding production planning, inventory management, customer service, and financial forecasting. Balance supply and demand and ensure long-term operational success. 	Heizer, Render, and Munson (2020); Olivares-Aguila and ElMaraghy (2021); Golroudbary and Zahraee (2015); Kochan et al. (2018).

Appendix B. Summary of the key SC performance indicators and DT's relevant technologies variables

SC performance indicator	Description	Influence of DT's relevant technologies	References
Raw material costs	Included all purchased raw material costs	<ul style="list-style-type: none"> DT: reduce production time and operation costs. 	Ben-Daya, Hassini, and Bahrour (2019); Dutta et al. (2020); Maheshwari et al. (2023a); Chan et al. (2023); Beamon (1999); Beamon (1998); Singh et al. (2023); Hobbs (1996); Wang et al. (2016); Lai, Ngai, and Cheng (2002). Novais, Maqueira, and Ortiz-Bas (2019); Singh et al. (2023a); Read et al. (2020).
production costs	The cost combination of raw materials and labour when producing products	<ul style="list-style-type: none"> IoT: Reduce costs by achieving visibility on more parts and raw materials and increasing revenue-combined product and after-sales service. 	
Inventory costs (holding)	Include the work-in-process and finished goods inventories	<ul style="list-style-type: none"> BDA/Al: optimise inventory operations, optimise financial performance, and minimise operational costs. 	
Delivery /shipping/distribution costs	Include the transportation and handling costs, safety stock costs, and duty	<ul style="list-style-type: none"> BC: reduce costs. 	
Profit/revenue	The positive income from investment or business activities is calculated after subtracting all the costs	<ul style="list-style-type: none"> DT: influences SC performance, visibility, and efficient inventory strategies. 	
Inventory	The merchandise, raw materials, and finished and unfinished goods that have not been sold	<ul style="list-style-type: none"> CC: reduce inventory level and associated costs. 	
Waste (Food waste)	Food waste inflates costs in various ways, including the disposal of unsellable products, loss of revenue from potential sales, overproduction, excess inventory, and inefficient resource use.	<ul style="list-style-type: none"> DT: improve efficiency, reduce food waste, and improve customer satisfaction. 	
Fill rate	The percentage of orders shipped	<ul style="list-style-type: none"> IoT: reduce food waste, increase food safety, and optimise operational efficiencies. 	
Total cycle time	In production and supply chain management, total cycle time includes all process stages, such as order receipt, material procurement, production, inspection, and delivery of the finished product to the customer.	<ul style="list-style-type: none"> DT: simulate the order quantity and delivery time and reduce response time. IoT: inventory tracking-time savings and real-time visibility, more traceability-reduce lead time BDA/Al: Data-driven insights help manage inventory more effectively, ensuring the right products are available to improve the fill rate. DT: Low lead time/real-time monitoring, real-time processing, reduced lead time, and inventory maintenance. IoT: inventory tracking, time savings and real-time visibility; BC-saving time. BDA/Al: Companies can proactively adjust operations by predicting potential disruptions or inefficiencies, reducing lead time. BC: creates a dynamic and real-time SC that better utilises its resources. 	Ben-Daya, Hassini, and Bahrour (2019); Choi, Wallace, and Wang (2018). Maheshwari et al. (2023b); Beamon (1999); Heizer, Render, and Munson (2020); Queiroz, Telles, and Bonilla (2019); Hofmann (2017); Maheshwari et al. (2023a); Gunasekaran, Patel, and Tirtiroglu (2001)

(continued).

Table A2. Continued.

SC performance indicator	Description	Influence of DT's relevant technologies	References
Lead time	The total time required to produce a particular item or service, once the product begins its manufacture until the time it is completely processed, is made up of processing time, handling time, and transportation time. The time taken from placing an order to delivery is linked to customer satisfaction. The degree to which customers are satisfied with the products or services provided.		
Customer response time			
Customer satisfaction		<ul style="list-style-type: none"> • DT: ensure the service level. • IoT: capturing products data while in use and increasing customer satisfaction • BC: help track the status of an item during a process. • DT: found a notable 6% reduction in backlog, further streamlining operations and enhancing efficiency. 	Wang et al. (2016); Maheshwari et al. (2023b); Lai, Ngai, and Cheng (2002). Beamon (1998); Gunasekaran and Kobu (2007). Badakhshan and Ball (2023); Heizer, Render, and Munson (2020); Ben-Daya, Hassini, and Bahroun (2019); Burgos and Ivanov (2021); Sarkar and Chung (2020); Kouhizadeh, Saberi, and Sarkis (2021); Gunasekaran and Kobu (2007).
unfilled demand/lost sales	The sales are supposed to gain but are lost due to situations such as stock out.		
Backlog	Refers to unfulfilled customer orders that are waiting to be processed or shipped.		
Order filled rate	The impact on customer satisfaction, revenue, and operational efficiency, as higher fulfillment rates reduce the risk of lost sales due to stockouts or delays.		
Raw material Inventory	The stock of basic materials or components that a company holds and uses in the production process to create finished goods.		
WIP inventory	It consists of items that are in the process of being manufactured but are not yet completed.	<ul style="list-style-type: none"> • DT: determining suitable inventory replenishment policies ensures that inventory is at the right place at the right time and provides a productive SC with a high customer service level. • CC: reduce inventory level and associated costs. • DT: stress the importance of SC digital twins, end-to-end visibility, and inventory management. 	Badakhshan and Ball (2023); Heizer, Render, and Munson (2020). Ben-Daya, Hassini, and Bahroun (2019); Burgos and Ivanov (2021); Sarkar and Chung (2020). Kouhizadeh, Saberi, and Sarkis (2021).
Processing/production inventory	It refers to the stock of goods that are being produced.	<ul style="list-style-type: none"> • IoT: improve inventory accuracy by tracking products. 	
Distribution inventory	It consists of finished products stored and ready to be distributed to customers. It includes the stock held at warehouses or distribution centres.	<ul style="list-style-type: none"> • BC: helps companies optimise inventory by reducing lead time and enhancing stakeholder trust. 	

Appendix C. Mapping data sources to SD variables and feedback loops

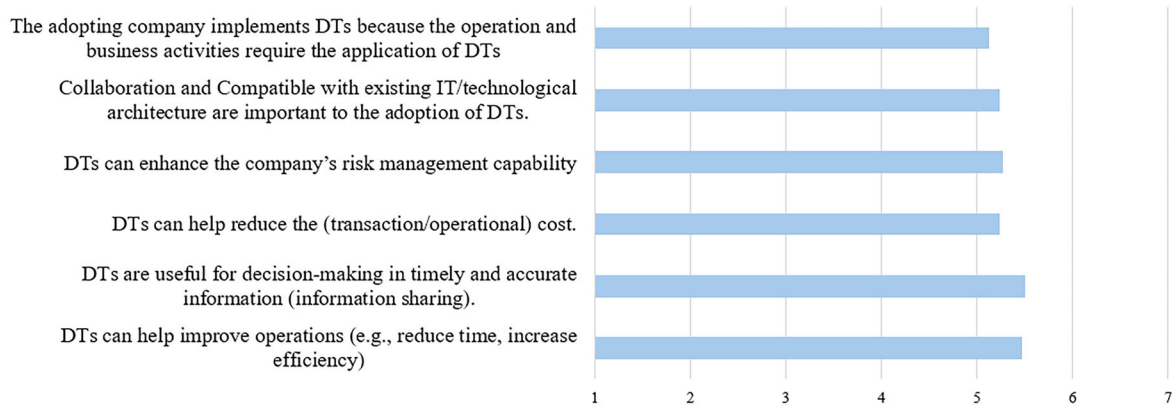
Data Sources	Insights	Inputs in the mental model and CLD	Model variables/parameter	Feedback loops
Questionnaire Survey	Identify the key FSC stages	To confirm the modelling boundary for the development of the causal loop diagram and stock flow diagram, because nearly 64.51% of questionnaire respondents were from the upstream of FSC, such as food sourcing, manufacturing, and distribution, which applied this to support the determination of the model boundaries.	<ul style="list-style-type: none"> Structural boundaries of the stock–flow model Inclusion of raw material inventory, WIP, and distribution inventory stocks Order generation and propagation logic 	<p>All loops, because boundary selection determines which flows participate in the following:</p> <ul style="list-style-type: none"> Forecasting–Production Loop Visibility and Synchronisation Loop Inventory Adjustment Loop Order Fulfilment Stabilisation Loop <p>Efficiency Improvement Loop – faster processing → faster WIP clearance → lower delays → improved scheduling → reinforces production performance</p>
	Identify key impacts of DT for the FSC	DTs reduce operation time and increase efficiency;	<ul style="list-style-type: none"> Processing time parameter reduced by DT Order processing delay constant reduced Production rate responsiveness increased Information delay constant Signal smoothing delay reduced under DT Forecast accuracy parameter improved 	<p>Demand Forecasting Reinforcing Loop – better forecast → better production → lower deviation → improved forecast And</p> <p>Information Delay Reduction Loop – shorter delays reduce oscillations</p> <p>Inventory Adjustment Loop – closer alignment between actual and desired inventory</p>
		DTs are useful for information sharing among SC operations and decision-making;	<ul style="list-style-type: none"> Inventory adjustment rate parameter modified. Desired inventory coverage reduced (cost-reduction effect) Visibility (IoT) Forecast accuracy factor (AI/BDA) Order traceability variable (Blockchain) Data-processing rate variable (Cloud computing) Raw material inflow rate WIP transformation rate Distribution order fulfilment logic 	<p>Visibility and Synchronisation Loop – higher visibility → improved decisions → reduced error → increased visibility</p> <p>Order Fulfilment Balancing Loop – demand triggers production → shipment → demand is satisfied → loop closes</p>
Previous Literature	Detailed SC operation activities in the SC's three key stages (sourcing, manufacturing and distribution).	Identified from the literature includes inventory management (supplier, processor, and distribution because inventory impacts a company's ability to meet customer demand on time and minimise disruptions caused by SC/demand variability, ensuring that material shortages do not affect production schedules) (Christopher 2022; Heikkilä 2002; Heizer, Render, and Munson 2020), adjustment for low inventory level (serve as a buffer against demand variability and SC disruptions, allowing businesses to maintain smooth operations despite fluctuations) (Soysal et al. 2015), order processing time (influenced customer satisfaction/operational efficiency/scalability) (Coyle et al. 2021; Ge et al. 2004), order fulfilment (key metric for operational efficiency, and ensures inventory levels align with demand), information sharing, waste management, and demand variability and forecast accuracy (Bowersox et al. 2020; Georgiadis, Vlachos, and Iakovou 2005; Kamath and Roy 2007).		

(continued).

Table A3. Continued.

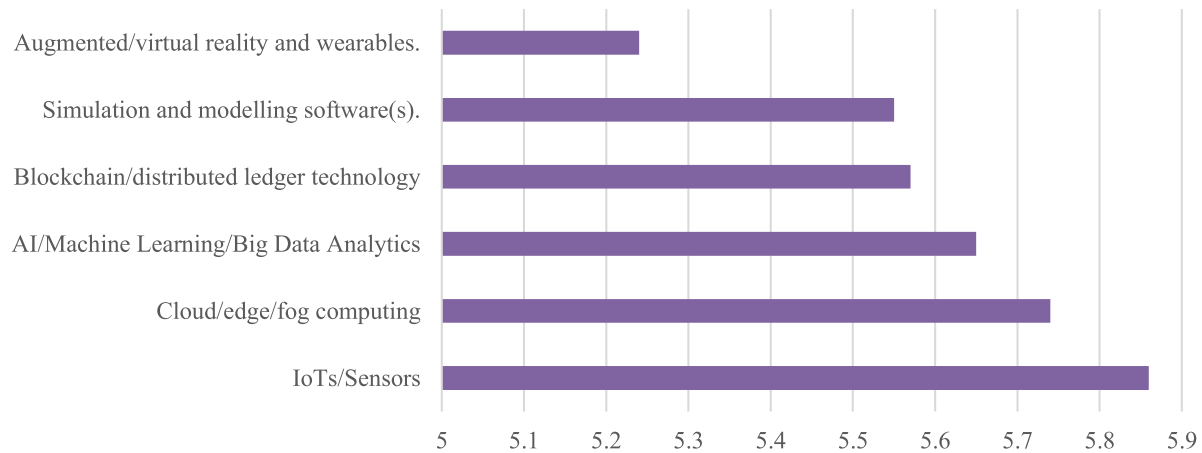
Data Sources	Insights	Inputs in the mental model and CLD	Model variables/parameter	Feedback loops
Industrial reports	Based on information technology (such as DT integrative technologies), which influenced SC through information sharing (management information for demand forecasting and monitoring efficiency), inventory management, and order processing	DT improves forecast accuracy, reduces processing time, and improves synchronisation (Badakhshan and Ball 2023; Ben-Daya, Hassini, and Bahrour 2019; Burgos and Ivanov 2021).	<ul style="list-style-type: none"> Forecast error variable Processing time reduction coefficient Inventory variance parameter 	Improved forecasting and processing accelerate system responsiveness
	Performance indicators influenced by DT (waste, delay, inventory, fulfilment)	DT reduces production time and operation costs (Badakhshan and Ball 2023; Burgos and Ivanov 2021), IoT reduces cost by achieving visibility on more parts and raw materials (Ben-Daya, Hassini, and Bahrour 2024; Weißhuhn and Hoberg 2021). BDA/AI optimises inventory operations and minimises operations costs (Tao and Zhang 2017), which influenced cost parts such as inventory holding cost, delivery cost, total SC cost, profit/revenue, inventory, waste (DT improves efficiency, reduces food waste, and improves customer satisfaction/IoT reduces food waste), customer satisfaction (which can be influenced by DT, IoT, and BC), demand forecasting accuracy, supplier performance, unfilled demand, customer response time, and order fulfilment lead time (which can be influenced by DT, IoT, BDA/AI and BC).	<ul style="list-style-type: none"> Waste outflow rate equations at three stages Lead-time calculation structures Unfulfilled order stock 	Waste Reduction Loop – waste reduces effective inventory → affects production and fulfilment
	Food waste relevant statistical data	Approximately 9% of food is wasted as raw products during post-harvest and storage, 25% is wasted as processed foods at the manufacturing stage, and 10–17% of food is wasted as processed foods at the distribution stage (FAO 2011). DT reported a 50% decrease in processing order time (McKinsey & Company 2024) Providing a range of the DT development/maintenance/integration costs (Visarterch 2024)	<p>Direct parameter input for baseline waste generation</p> <p>Parameter for DT scenario</p> <p>Support for the cost estimation</p>	
	Processing time and DT			
	DT development cost/maintenance cost			

Appendix D. Summary of responses capturing the benefits of Digital Twins in FSCs



Notes: 7=strongly agree, 6=agree, 5=somewhat agree, 4=neither agree nor disagree, 3=Somewhat disagree, 2=disagree, 1=strongly disagree

Appendix E. Results of different technologies for developing and operating DT (7 Likert scale for mean values)



Appendix F. Input parameters used for SD models

Parameters	Conventional FSC	DT-enabled FSC	Source and justification
Order from customer	RANDOM NORMAL (6000, 16,000, 11,000, 2000, 1)		Industrial cases/reports and academic literature on DT indicated a 50% reduction/decrease in processing order time due to holistic information on stock availability (Maheshwari et al. 2024; McKinsey 2024). Insights from Sterman (2000), page 721 According to FAO (2011), approximately 9% of food is wasted as raw products. DT could reduce waste by 20% to 50% (Attaran and Celik 2023; McKinsey & Company 2024; Sengupta and Dreyer 2023). A similar approach is followed for Blockchain applications by Vu, Ghadge, and Bourlakis (2025).
Order processing time	2	1	
Manufacturing time / Process time	2	2	
Spoilage rate (SR1)	9%	6%	
SR2	18%	12%	We adopted this from Kochan (2018)
SR3	16%	10%	
Inventory Adjustment	2	1	

Appendix G. Inputs and parameters used in estimating operation cost for the models

Variable	Value/Formulas	Justifications/comments
Inventory holding cost	Unitcost * 0.4%	The inventory holding cost is estimated to be 20% of the unit cost annually, equating to 0.4% weekly, based on 50 working weeks (assumed) per year. The unit cost is estimated at \$0.50 per unit. Unit cost = \$10
Manufacturing cost	Unitcost * 50%	The percentage is adapted from Er Kara et al. (2021) and Vu, Ghadge, and Bourlakis (2025)
Transportation cost	Unitcost * 0.5%	The percentage is adapted from Er Kara et al. (2021) and Vu, Ghadge, and Bourlakis (2025)
Order processing cost	Unitcost * 0.2%	Order processing costs typically range from 5% to 15% of the total SC costs, according to Sachan, Sahay, and Sharma (2005)
DT development cost	\$ 120K one-time cost	As explained in a prior discussion
DT maintenance cost	\$ 4K/50-80 per week	As explained in a prior discussion
Cost calculation rate	For the conventional case	' = Inventoryholdingcost+Manufacturingcost+Transportationcost+Orderprocessingcost'
Cost calculation rate	For DT-enabled FSC case	' = Inventoryholdingcost+Manufacturingcost+Transportationcost+Orderprocessingcost+Digitaltwindevelopmentcost+Digitaltwinmaintanancecost'

Appendix H. Validation tests for SD models

1. Structural validity test: including boundary adequacy assessment, was used to confirm that the model captures the essential components and interactions of FSC operations and performance under DT influence. This assessment was informed by and extensive review of relevant literature, industrial reports, and questionnaire survey. The inclusion of model variables and causal relationships was evaluated to ensure their relevance for representing the real system. All variables were derived from a structured triangulation of survey insights, literature and industry reports. The causal connections in the CLD and stock-flow structure were manually checked to ensure each relationship reflects known FSC and DT dynamics.
2. Consistency test: This test verifies that the mathematical structure, equations, and units are logically correct. All equations were checked for dimensional consistency, ensuring that flows, delays, and stock units were aligned. Inventory, processing, fulfilment, and waste dynamics were cross-checked against established models in the SC and IT/DT literature.
3. Sensitivity test: Numerical sensitivity occurs when a change in assumption or input variables changes the numerical values of the results. No exponential growth, sudden collapses, or periodic oscillations indicate that the model is relatively stable and ready for assessment.
as follows: By changing the order processing time and distributing (setting = RANDOM_UNIFORM (0.1,2) under the modelling) to check the changes in output variables, including distribution inventory level and SFP for shipping, as well as the relevant sensitivity graph from Vensim below.

Figure A1 illustrates the sensitivity graph of the distribution inventory level; the fluctuation range of this input variable is between 4000 and 28,500 (50–95% range). The fluctuation range is relatively moderate and falls within the acceptance range. In addition, the inventory will not suddenly return to zero, nor will it grow exponentially, which shows that its control logic is feasible. The confidence intervals for distribution inventory illustrate that 50% (yellow), 75% (green) and 95% (blue) areas are relatively stable, with no sudden expansion or contraction.

Figure A2 shows the 'SFP for shipping' passed sensitivity analysis, in which variable fluctuations are moderate, and the SC system is stable; the confidence interval is reasonable, the response is moderate, and there is no excessive sensitivity. The model logic is consistent with actual logistics. Specifically, the 50% (yellow), 75% (green), 95% (blue), and 100% (grey) confidence intervals change relatively smoothly. The confidence interval does not expand or contract suddenly and sharply, indicating that the model's output shows a certain degree of predictability as the input changes and does not appear overly sensitive. (The distribution of the confidence interval is relatively even, indicating that the model is more robust; furthermore, the 75–95% confidence interval (green + blue) is between 5000–20,000, not overextended).

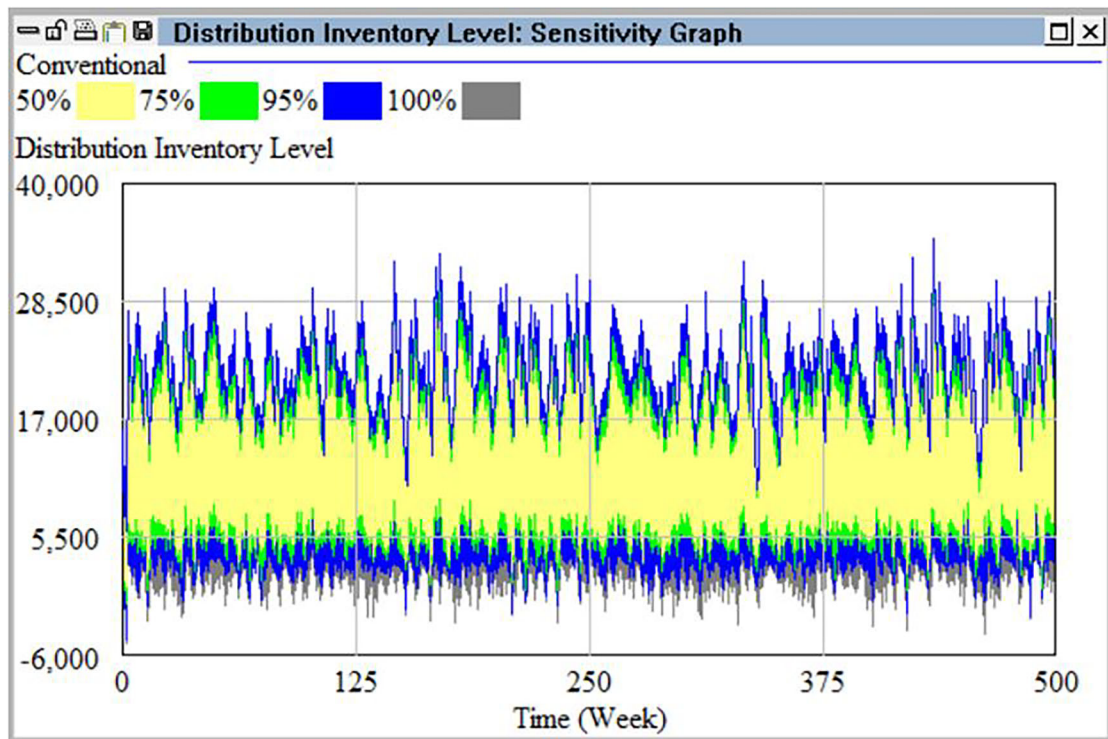


Figure A1. The sensitivity graph for the distribution inventory level.

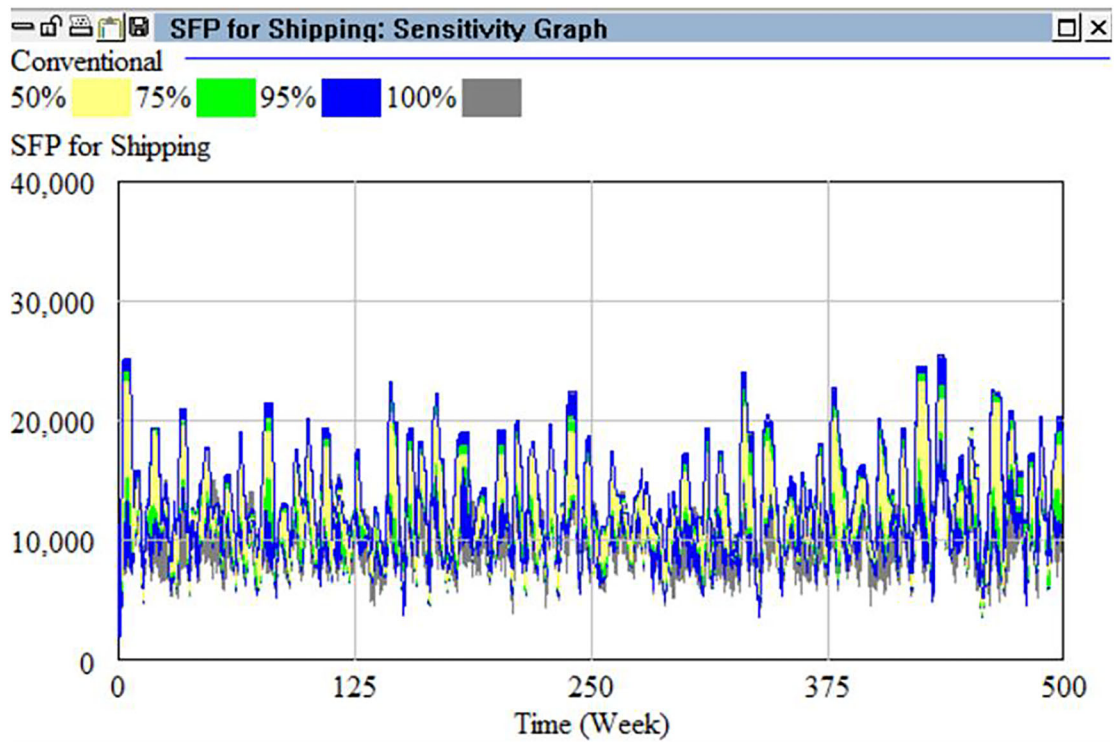


Figure A2. The sensitivity graph for 'SFP for shipping'.



DSPACE

<https://dspace.org/>

Impact of digital twin adoption on food supply chain performance: a system dynamics approach

Huang, Ying; Ghadge, Abhijeet; Yates, Nicky

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