A Two-Layer Digital Twin for Implementing Simultaneous Resilience Strategies in Electronics Manufacturing

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Abstract:
While most research tends to examine resilience capabilities through the lens of a single strategy, supply chain management teams in practice often pursue integrated solutions that combine multiple strategies to achieve desired levels of resilience. Our study introduces an innovative two-layer digital supply chain twins (DSCTs) framework that connects the shop floor layer with the broader supply chain network layer. The DSCTs facilitate the simultaneous application of various resilience strategies. We then investigate the synergy of implementing six resilience strategies, which encompass operational and strategic levels, across different stages of disruption. The first four strategies are allocating available material inventory, activating backup suppliers, and deploying flexible on-demand resources such as labor and transportation. The other two strategies are strategic reserves for material substitution and repurposing. Combining six strategies into a unified decision-making framework allows us to assess the coevolution of decision processes and environmental conditions. Finally, we propose a set of structured experiments to find the best combination of strategies across various disruption profiles, considering supplier lead-time and supplier structural network characteristics. Our results include a framework for combining resilience strategies and a method to identify the best combination of such strategies—an essential component of any DSCTs solution.

Keywords: Digital twin, supply chain resilience, supply chain viability, resilience strategy, supply chain simulation.

1. INTRODUCTION

As global supply chains confront increasing challenges from natural disasters, geopolitical tensions, and technological transformation, resilience has become essential to supply chain management. According to Dolgui et al. (2018), supply chain resilience is the ability to withstand disturbances, maintain acceptable levels of operation during disruptions, and recover efficiently. Traditional risk management strategies rely on predicting specific risks and planning accordingly but often fall short of addressing unknown uncertainties. As a result, there is a notable need to shift towards innovative strategies to manage disruptions better and promote adaptability (Cohen et al., 2022).

Although existing studies have explored various dimensions of resilience, there is a lack of comprehensive frameworks to apply combined resilience strategies (Alikhani et al., 2023, 2025; Cohen et al., 2022). Ivanov (2024b) conceptualizes the supply chain as an immune system, advocating for combining strategies to adapt to changing environments. Sheffi and Rice (2005) define eight stages of a supply chain disruption: preparation, disruptive event occurs, first response, initial impact, full impact time, preparation for recovery, recovery, and long-term impact. Alikhani et al. (2025) underscore the importance of applying multiple strategies but lack guidance in deploying resilience strategies considering disruption stages. Li et al. (2023) and Kwaramba et al. (2024) propose the applications of three resilience strategies (i.e., inventory, backup capacity, and standby capability) corresponding to the disruption stages. However, other actions to maintain resilience could be proliferated.

Digital Supply Chain Twins (DSCTs) are virtual representations of physical supply chains (Guo and Mantravadi, 2024; Ivanov, 2023; Kritzinger et al., 2018; VanDerHorn and Mahadevan, 2021). In practice, defining a physical supply chain itself is challenging, as it involves the intricate interplay of material, information, and financial flows across multiple tiers (i.e., focal company, its customers, and its suppliers). DSCTs leverage low-latency data to support rapid and data-driven decision-making, enabling stakeholders to identify bottlenecks, manage production schedules, and enhance overall efficiency (Ivanov, 2023, 2024a). However, despite the potential of the technology, research on integrated DSCTs remains scarce. There is limited work on connecting shop floor activities with broader supply chain processes to facilitate vertical and horizontal decision-making.

Grounded in the interplay between resilience strategies and the role of DSCTs in strengthening supply chain resilience, we aim to answer the following research question:

How can integrated DSCTs be modeled to facilitate the implementation of multiple resilience strategies and achieve the desired level of resilience performance?

We frame our study through the lens of the complex adaptive system (CAS) approach and develop a digital-twin-based simulation combining discrete-event simulation (DES) and agent-based simulation (ABS) approaches (Choi et al., 2001; Ivanov, 2023). While DES models the supply chain, ABS captures interactions among key players (e.g., supply chain planners, managers, and suppliers). Our approach also enables the emergence of agent behaviors over time (Choi et al., 2001).

The study employs data from an electronics company comprising 19 products requiring 581 materials sourced from 69 suppliers. Both qualitative and quantitative data were collected within the framework of the ACCURATE project (Accurate, 2024). Possible combinations of resilience strategies were defined and modeled based on previous works (Alikhani et al., 2023, 2025; Cohen et al., 2022; Ivanov, 2021, 2024b; Kwaramba et al., 2024). We then propose an approach to address the research question using structured experiments (Macdonald et al., 2018).

To reduce the experiment's complexity, we propose to categorize supplier nodes into groups that share similar attributes based on network metrics. Within each category, we select one material to represent the group, thereby reducing the number of replications needed. In each experiment, we remove several representative materials and measure the total cost of resilience. The experiment is replicated multiple times to collect resilience performance across various combinations of strategies. Ultimately, we collect data and identify the most effective combination of resilience strategies.

Our study contributes in several ways. First, we propose an architecture for digital-twin-based simulation that effectively captures the emergence of supply chains and the interaction between decisions and the evolving supply chain environment. Our methodology illustrates supply chains as complex systems on an industrial scale by leveraging digital-twin technologies (Choi et al., 2001; Ivanov, 2023). Second, we describe how to determine the best combination of supply chain resilience strategies. By employing a structured experimental design to collect resilience cost data and using statistical analysis, we propose how a company could identify the optimal combination of resilience strategies.

The rest of our paper is organized as follows. In Part 2, we discuss the background of our work, focusing on key technological advancements in DSCTs and how different resilience strategies work together. We describe our methods and experimental design in Part 3 and present the initial results in Part 4. Finally, we conclude our study in Part 5.

2. BACKGROUND

2.1 Combining supply chain resilience strategies

Resilience refers to the capability of a supply chain to survive and recover from disruptions while achieving the designed performance (Dolgui et al., 2018). Supply chains are, in fact, CAS that continuously evolve to adapt to external changes (Choi et al., 2001). Instead of limiting the perspective to a closed system, Ivanov (2024c) propose viewing resilience from an open system perspective. Resilience aims to recover (bounce back) to the designed state and adapt (bounce forward) to achieve new states. The open system perspective introduces the notion of viability. Ivanov and Dolgui (2020) define viability as the ability of a supply chain to maintain itself and survive in a changing environment by redesigning structures and replanning performance with long-term impacts.

Companies can deploy strategies such as intertwining, scalability, substitution, and repurposing (Ivanov, 2021, 2024b) to foster resilience. Intertwining leverages cross-sector or even competitor networks, while scalability refers to the effective use of structural redundancies. Substitution focuses on finding alternative solutions for materials or products (product-oriented strategies), whereas repurposing involves utilizing fungible resources and reconfiguring processes (process-oriented strategies). While most strategies emphasize preparedness, there is limited research on reaction-based strategies, known as improvisation tactics. These include expediting shipments, reallocating resources, working overtime, and adapting planning parameters (Dohmen et al., 2023; Richey et al., 2022).

An alternative approach to enhancing resilience is identifying the challenges to resilience. Cohen et al. (2022) outline eight supply chain attributes and propose three archetypes of supply chain resilience: process complexity, partnership complexity, and product complexity. However, organizations often face multiple complexities simultaneously. For instance, a printed circuit board (PCB) assembler may encounter thousands of product variations requiring stringent assembly and testing processes, frequently utilizing shared resources.

Adding more mud to the waters, Kwaramba et al. (2024) describe how companies often utilize resilience resources sequentially, aligning their deployment with the duration of disruptions. Initially, growth and maintenance resources address immediate needs, followed by on-demand flexibility for medium-term continuity and strategic reserves to mitigate long-term consequences (Kwaramba et al., 2024). In contrast, Ivanov (2024b) adopts an immune system metaphor, suggesting resilience resources can be deployed simultaneously to respond effectively to disturbances. Like immune system functions, resilience strategies are categorized into three types: innate, passive adaptive, and active adaptive strategies (Ivanov, 2024b). Innate strategies rely on existing measures such as structural redundancy, process flexibility, and multiple sourcing to safeguard supply chain performance. Passive adaptive strategies involve leveraging pre-existing resources and backup plans, such as business continuity plans, to address known uncertainties. In contrast, active adaptive strategies focus on dynamic responses, such as expediting shipments, reallocating resources, and implementing recovery policies.

Combining resilience strategies does not always yield positive outcomes regarding resilience performance (Kumar and Park, 2019). Few studies have focused on investigating the synergy of different resilience strategies. For instance, Alikhani et al. (2023) examine using six resilience tactics in a high-level retail network, including fortification, cybersecurity, direct shipping, safety stock, multiple set covering (reassignment), and supply chain mapping. The authors replace cybersecurity with collaboration in a subsequent study by Alikhani et al. (2025). While both studies provide insights into determining the suitable set of resilience strategies, there is limited information regarding the timing and execution of resilience strategies. It is important to note that some mitigation strategies are only deployed when previously implemented actions fail to adequately address the consequences of disruptions (Kwaramba et al., 2024). Additionally, the cost of executing specific actions can depend on the stage of disruption and specific constraints. For example, expedited shipping is feasible only when inventory is available in upstream echelons, and expedited shipping is only necessary when the focal plant has demand. Neglecting the timing for implementing resilience strategies in the model may overlook real-world complexities. Therefore, we aim to bridge the mentioned research gaps by detailing how resilience strategies are deployed, considering the timing of six strategies in our model.

2.2 Digital supply chain twin

Digital twins represent virtual replicas of physical systems that dynamically mirror real-time behavior, enabling continuous synchronization and bidirectional interactions between the physical and digital domains (Guo and Mantravadi, 2024; Ivanov, 2023, 2024a; Kritzinger et al., 2018; VanDerHorn and Mahadevan, 2021). Unlike digital shadows, which passively collect and display data, digital twins actively simulate, predict, and optimize system performance, providing advanced decision-making support (Ivanov, 2023, 2024a; Kritzinger et al., 2018). DSCTs expand the digital twins concept in supply chains by integrating operational, logistical, and strategic dimensions into a unified solution. The integration of smart agents further enhances DSCTs capabilities.

DSCTs are powerful decision-support tools, combining real-time data, predictive analytics, and simulation to stress-test supply chain resilience, viability, and performance (Ivanov, 2023; Stadtfeld et al., 2024). By incorporating modeling approaches such as agent-based and discrete-event simulations, DSCTs enable stakeholders to evaluate scenarios like reallocating resources or optimizing inventory under dynamic conditions (Guo and Mantravadi, 2024; Ivanov, 2023, 2024a). The decision-making process supported by DSCTs benefits from low data latency and ensures rapid and informed responses to emerging challenges. For instance, DSCTs facilitate the identification of bottlenecks or disruptions and recommend actionable measures, such as adjusting production schedules or reallocating available resources (Ivanov, 2023, 2024a).

Moreover, DSCTs allow researchers to investigate the supply chain as a CAS through the seamless connection between simulation and optimization models (see Figure 1). DES simulation represents the supply chain system, while purposeful agents with optimization models encapsulate how decisions are made. The most important thing is that

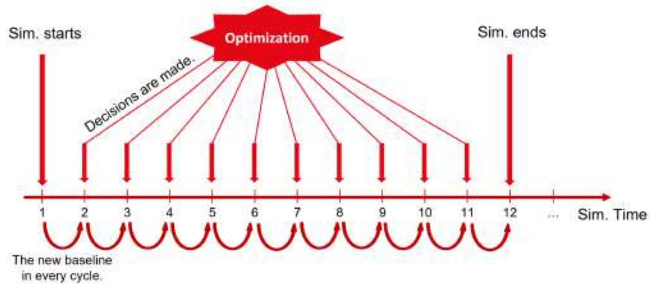

Fig. 1. Illustration of the interaction between simulation and optimization in DSCTs.

after decisions are made, the supply chain system and its environment are also updated (Choi et al., 2001; Ivanov, 2023). Therefore, we can leverage technology to investigate the coevolution of the supply chain and the choice of resilience strategies, which is also a contribution of our study. The synergy of various resilience strategies highlights the transformative potential of DSCTs in fostering adaptability and viability.

Our approach offers greater flexibility compared to the more structured nature of the sequential modeling approach. While sequential decision analysis addresses effectively structured decisions, our DSCT-based approach using ABS can support less structured problems. The flexibility enables us to explore interactions between human decision-makers and decision support systems, a significant value of DSCTs (Ivanov, 2023). By leveraging CAS, DSCTs effectively capture the dynamic nature of supply chains and their ever-changing constraints. Additionally, DSCTs could be highly customized, allowing businesses to tailor key performance indicators—such as lost sales—to fit firm-specific needs.

3. METHOD AND EXPERIMENT DESIGN

3.1 Digital-twin based simulation

Our DSCT solution integrates several key components to simulate and optimize supply chain processes (see Figure 2). Input data comprises supply chain operations, shop floor activities, data integration, and transformation. The simulation module, which is the core of the DSCTs, processes input data to replicate the behavior of the supply chain under different scenarios. A vital feature of the DSCTs is the interaction between the simulation module and the decision-making support modules. While the simulation module generates output, the decision-making support modules leverage that output to inform decisions, such as inventory management or resource allocation. The user interface module allows users to access the simulation results, making complex results more transparent and explainable. The solution enables dynamic, near-real-time analysis and decision-making, improving supply chain resilience and efficiency.

From the perspective of CAS, we view DSCTs as an advanced technology that integrates high-granularity simulation with decision-making processes. CAS approach enables the coevolution of decisions (strategies) and the en-

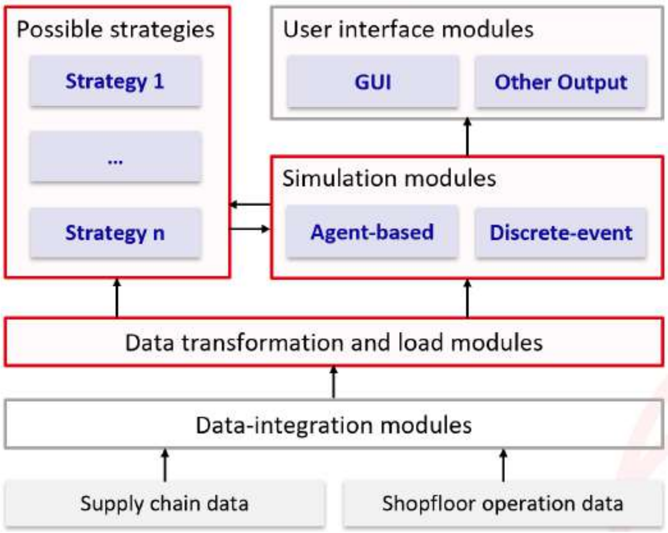

Fig. 2. High-level architecture of our DSCTs solution (Accurate, 2024).

vironment (modeled supply chain), illustrating how strategies evolve and adapt in response to changing conditions. The feedback loops between agents and their environment provide insights into the dynamic behaviors of supply chains, which traditional models fail to capture Choi et al. (2001). By simulating the complex interactions, DSCTs offer an understanding of how strategic decisions and environmental factors co-evolve. The technology allows us to collect data on resilience performance and find the optimal combination of resilience strategies.

3.2 Integrated resilience strategies

To develop the pool of resilience strategies, we employ three agents representing three typical decision-makers in the supply chain: supply chain planner, supply chain manager, and senior manager.

Agent 1 captures how a supply chain planner utilizes growth and maintenance resources to mitigate material shortages. Our study considers two primary resilience resources: available inventory (A_1) and backup suppliers (A_2). The resilience strategy for Agent 1 aims to maximize the total supply of products (Q_t^p) while ensuring that the supply constraints are met. The objective function is as follows:

$$
\begin{aligned}
\max \sum_{p\in P} & Q_t^p \cdot \pi^p && \textit{(Strategy } A_1\textit{)} \\
\text{s.t.} \sum_{p\in P} & Q_t^p \cdot r^{p,m} \le I_t^m\,, && \forall m \in M \\
& Q_t^p \le \mathcal{O}_t^p\,, && \forall p \in P \\
& Q_t^p \in \mathbb{N}_0\,, && \forall p \in P
\end{aligned}
$$

where Q_t^p represents the quantity of product p at time t, and π^p is the profit associated with product p. The constraints ensure that the quantities produced (Q_t^p) do not exceed the available material inventory (I_t^m) and that orders (Q_t^p) cannot exceed the operational capacity ($\mathcal{O}_t^p$).

$$
\gamma_t^{m,s} = \begin{cases} \gamma^{m,s} + \dfrac{\sum_{s\in S^-} \gamma^{m,s}}{|S^+|} & \text{if } s \in S^+ \\ 0, & \text{if } s \in S^- \end{cases} \qquad \textit{(Strategy } A_2\textit{)}
$$

where $\gamma_t^{m,s}$ represents the percentage of the total volume of m sourced from supplier s at time t. S^- is the set of disrupted qualified suppliers for material m, while S^+ is the set of available suppliers for material m.

For **Agent 2**, we model actions that a supply chain manager may implement to increase short-term capacity (A_3) or expedite material deliveries (A_4). Short-term capacity can be increased by paying overtime costs to increase labor. The objective function of Strategy 3 is to minimize the gap between demand and operational capacity.

$$
\begin{aligned}
\min \sum_{p\in P} & (D_t^p - \mathcal{O}^p + o_t^p) * \pi^p + C_t^p && \textit{(Strategy } A_3\textit{)} \\
\text{s.t. } & \mathcal{O}_t^p \le D_t^p\,, && \forall p \in P \\
& o_t^p \in \mathbb{R}^+\,, && \forall p \in P
\end{aligned}
$$

where D_t^p is the demand for the product p at time t, and C_t^p represents the cost incurred in fulfilling corresponding demand. The decision variable o_t^p represents the additional short-term capacity gain.

In strategy 4, the supply chain manager pays more money (C^m) to expedite the material shipping and increase available material for production.

$$
\begin{aligned}
\max \sum_{m\in M^-} & I_t^m + I_{t^-}^m && \textit{(Strategy } A_4\textit{)} \\
\text{s.t. } \sum_{m\in M^-} & C_t^m \le W^T
\end{aligned}
$$

where $I_{t^-}^m$ is the quantity of material m in transit, and W^T represents the maximum budget for expediting.

Agent 3 models how the management team deploys strategic reserves to address disruptions. This strategy involves increasing operational capacity ($\mathcal{O}_t^p$) and inventory (I_t^m) to mitigate disruptions (see Equation A_5 and A_6).

$$
\mathcal{O}_t^p = \mathcal{O}^p + \mathcal{O}^{p*} \qquad \textit{(Strategy } A_5\textit{)}
$$

$$
I_t^m = I_t^m + I_t^{m*} \qquad \textit{(Strategy } A_6\textit{)}
$$

where $\mathcal{O}^{p*}$ and I^{m*} represent the additional operational capacity and inventory that are added to address the disruption. The overall cost of implementing six resilience strategies is measured by the following key performance indicator:

$$
C = LS + C^p + C^h + C^T + C^{\mathcal{A}5} + C^{\mathcal{A}6}
$$

where LS refers to lost sales, and the terms C^p, C^h, C^T, $C^{\mathcal{A}5}$, and $C^{\mathcal{A}6}$ correspond to the costs associated with each strategy.

3.3 Structured experiment design

To evaluate the effectiveness of different resilience strategy deployment approaches, we design a structured experimental setup based on structured experiments (Macdonald

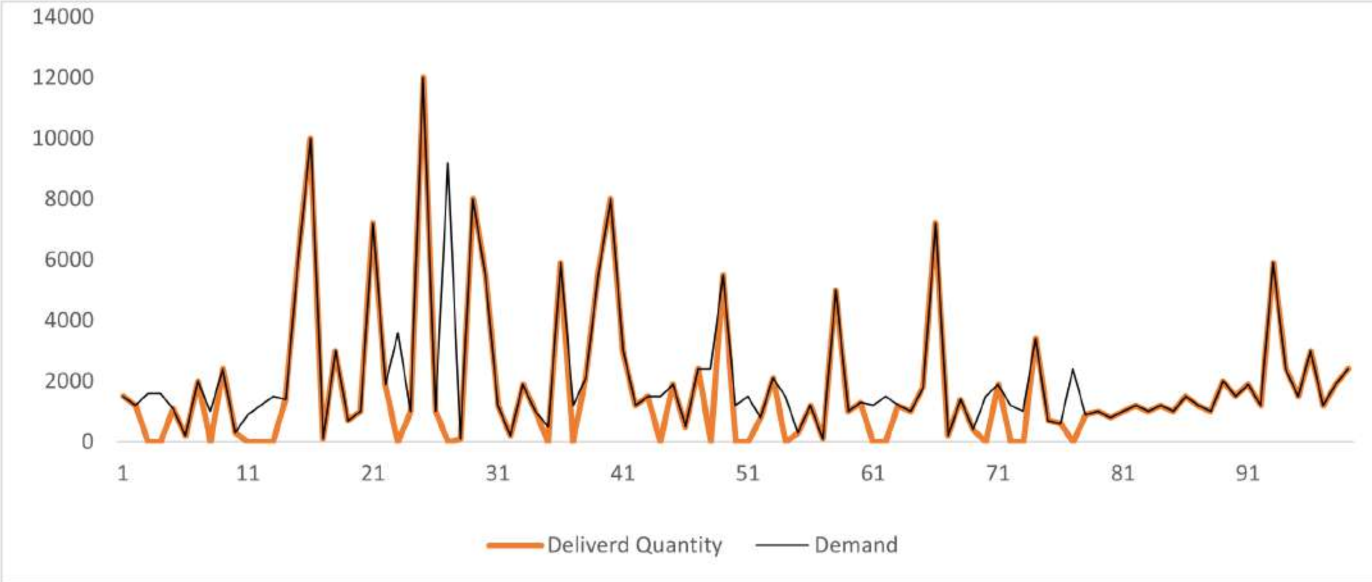

Fig. 3. Results of the baseline model.

et al., 2018). The disruption profile includes three key parameters: disruption nodes, disruption start time, and disruption duration. For disruption nodes, we systematically remove individual supplier nodes from the supply chain network—the choice for the node to be removed or the target node is made using network analysis. Potential network metrics include degree-, betweenness-, and eigenvector-centrality (Brintrup et al., 2016). The disruption start time is varied across three discrete weeks, and the disruption duration spans three levels: low-, medium-, and high-severity (Alikhani et al., 2025).

In each experiment, we also need to define the disruption stages (Sheffi and Rice, 2005) and the timing to apply six resilience strategies. In essence, we follow seminal works of Kwaramba et al. (2024) and Li et al. (2023). First, Agent 1's strategies are implemented immediately after the disruption, followed by Agent 2's strategies if Agent 1's actions do not sufficiently mitigate the disruption. Finally, Agent 3's strategies are applied if the previous strategies are still insufficient. The approach allows us to compare the cost-effectiveness of combined strategies deployment under varying disruption scenarios.

4. RESULTS

The current result of our project is to model the two-layer supply chain system and integrate six resilience strategies. The baseline model provides a foundational understanding of supply chain performance under normal operating conditions. Figure 3 compares the delivered volume and demand over time. Initially, the supply chain exhibits fluctuations in meeting demand due to typical lead-time variations and customer demand signals. As the system stabilizes, the fill rate is marching toward 94%, demonstrating the supply network's ability to sustain performance.

Additionally, we observe significant variance in demand patterns over time, which may stem from the order batching effect—a common phenomenon in supply chains when customers apply periodic ordering policies. This effect can increase volatility in production scheduling, inventory levels, and transportation planning.

The baseline assessment, our current result, serves as a benchmark against which disruption scenarios and resilience strategies are evaluated. It allows us to measure deviations in key performance indicators such as lost sales. To continue our project, we will collect experiment results and performance analysis and provide insights on the combination of resilience strategies.

5. CONCLUSION

Our research introduces a two-layer DSCTs solution to strengthen supply chain resilience by integrating the shop floor layer with the supply network level. The proposed approach supports the simultaneous application of multiple resilience strategies, offering an adaptive mechanism to navigate disruptions. We expect to provide a framework that guides supply chain management teams on how and when to deploy combined resilience strategies to achieve the desired level of resilience.

As a next step, we plan to conduct structured experiments to continue investigating the research question. To measure key resilience performance metrics, we simulate various disruption scenarios with varying target nodes, disruption start times, and durations. Insights gained from these experiments will refine the DSCTs framework and guide the development of best practices for deploying resilience strategies.

This study has three major limitations. First, we consider six resilience strategies across three decision-making levels. We acknowledge that supply chain practitioners may implement additional strategies beyond those examined in this study. Second, while integrating the shop floor and supply chain levels into a DSCT solution, we simplify many supply chain processes and focus primarily on bottleneck operations. Lastly, the timing of resilience strategy implementation requires further investigation. We plan to apply a uniform timeline across all experiments to ensure a consistent comparison between approaches. However, a more detailed sensitivity analysis is needed to assess the impact of implementation timing.

Future research can expand the scope of our study by exploring the applicability of DSCTs across different industries and broadening the range of resilience strategies. Investigating additional decision-making levels, implementation timelines, and industry-specific constraints could provide deeper insights into enhancing supply chain resilience. Moreover, integrating more sophisticated supply chain processes and real-time data analytics could further advance the implementation of resilience measures.

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