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ORIGINAL RESEARCH

From Theory to Practice: Leveraging Digital Twin Technologies and Supply Chain Disruption Mitigation Strategies for Enhanced Supply Chain Resilience with Strategic Fit in Focus

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Abstract *Supply chain resilience (SCR) has been a topic of enormous interest among researchers for almost two decades. Still, there's been limited focus on the impact of digital twin (DT) technologies and supply chain disruption mitigation (SCDM) strategies on SCR. This study addresses this gap by examining how DT and SCDM strategies enhance SCR and whether strategic fit (SF) moderates these relationships. Using the dynamic capability view (DCV) as the theoretical foundation, we developed our conceptual framework and research hypotheses. Data were collected from 200 Bangladeshi manufacturing organizations through a survey-based approach, and the partial least square (PLS) technique was utilized to assess the framework and research hypotheses. The findings reveal that both DT technologies and SCDM strategies significantly boost SCR. Besides, while SF plays a critical moderating role in the relationship between DT and SCR, it does not moderate the association between SCDM strategies and SCR. This study contributes to the theoretical understanding of SCR by integrating DT and SCDM strategies within the DCV framework, offering insights into their roles in managing supply chain disruptions. Additionally, it provides practical guidance for managers on effectively leveraging DT and SCDM strategies to build resilient supply chains while emphasizing the importance of strategic alignment in optimizing digital interventions.*

Keywords Adaptability · Digital twin · Disruption mitigation · Dynamic capability view · Strategic fit · Structural equation modeling · Supply chain resilience

Introduction

In the contemporary, rapidly evolving global market, well-organized and efficient supply chains (SCs) are the heart and soul of every manufacturing organization. However, these SCs are highly dynamic, facing risks from growing globalization, technological advancements, and environmental unpredictability (Belhadi et al., 2024). Because of rapid technological advancement and significant global shifts, modern SCs have become more unpredictable and unprecedented (Agrawal et al., 2024). Management strategies change frequently with trade policies, import/export regulations, and unanticipated events caused by crises, such as natural and man-made disasters, which disturb the smooth materials and information flowing throughout the supply chain, leading to supply chain disruptions (SCD) (Dy et al., 2022). Decreased revenues, supply delays, a loss of market share, and a tainted brand image are some of the adverse effects that can result from SCDs (Li et al., 2021). Managers are now striving to maintain the smooth operation of the SC even in the face of

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SCDs. The capability of an SC to operate under unfavorable conditions and to resume regular operations in the event of disruption is widely known as supply chain resilience (SCR) (Atadoga et al., 2024). Given that SCDs present significant challenges for managers and can impede the SC's ability to function optimally, implementing supply chain disruption mitigation (SCDM) strategies becomes crucial.

Academics have proposed various SCDM strategies to improve the SCR. Examples include using time buffers for flexible transportation (Chopra & Meindl, 2001; Oppen, 2016) and mathematical models to optimize SC profit and resilience during recovery (Li & Yuan, 2024). Strategies like excess inventory, alternative configurations of SCR frameworks, vendor-managed inventory, capacity recovery, and backup suppliers are also recommended (Chowdhury et al., 2024; Hossain & Parvez, 2020; Ivanov, 2017b, 2018). Additionally, digitalization, insurance, and government support can effectively mitigate SCD impacts (Pellegrino et al., 2024). These strategies provide the flexibility needed to restore SC performance (Ivanov & Dolgui, 2019), making them essential for achieving SCR.

SCDM strategies, while valuable, struggle to adapt in real-time to dynamic changes caused by SCDs, potentially weakening supply chain resilience. To be resilient to SCDs, along with the proper SCDM strategies, the supply chain has to be visible, agile, and intelligent (Agarwal & Seth, 2024; Varma et al., 2024; Wang et al., 2022). Modern technologies are crucial in this case and have been instrumental in strengthening SR in various sectors (Tiwari et al., 2024). Visibility helps detect disruptions like delays and shortages early, agility enables quick adaptation to sudden changes, and intelligence uses predictive analytics to foresee and prevent disruptions. Digital twin (DT) technologies enhance SC visibility, agility, intelligence, and contingency planning, making them a comprehensive solution. By supporting SCDM strategies, DT technologies strengthen SC resilience against SCDs (Barykin et al., 2020; Burgos & Ivanov, 2021).

DT technologies can transmit real-time data from the physical entity and practically replicate the physical system (Huang et al., 2024). Technologies like Industrial Internet of Things (IIOT), cyber-physical system (CPS), artificial intelligence (AI), blockchain-based smart contracting (BSC), cloud computing (CC), etc. make up the DT supply chain architecture (Kamble et al., 2022; Min, 2019; Min et al., 2019). By incorporating IIOT devices, machine learning, AI, and simulation modeling, DT technologies can accurately predict demand fluctuations (Burgos & Ivanov, 2021) and assess disruption likelihood and consequences using historical data and market conditions (Badakhshan & Ball, 2024).

SC design strategies incorporate SCDM strategies, and DT technologies offer competitive advantages crucial for establishing competitive strategies. The impact of SCDM strategies and DT technologies on SCR depends on the alignment between supply chain design and competitive strategies, known as strategic fit (SF) (Kumar et al., 2023). When developing a supply chain strategy, a firm should realign its business operations to respond to the changing external environment (Nakano & Lau, 2020). A strong SF ensures that SCDM strategies align with the firm's goals and leverage the competitive advantages of DT technologies, resulting in a more cohesive and resilient supply chain.

An extensive number of researchers have investigated the influence that SCDs have on the SC's performance as a function of lead time, cost, demand, service level, and inventory levels and provided various proactive and reactive mitigation strategies (Carvalho et al., 2012; Ivanov, 2018, 2020). Some researchers also investigated how DT can manage disruptions and improve SCR (Badakhshan et al., 2023; Ivanov & Dolgui, 2021), while others highlight big data analytics to enhance resilience (Singh & Singh, 2019). However, few studies empirically investigated how SCDM strategies and DT technologies impact manufacturing organizations' ability to gain better SCR. At the same time, no studies, to the author's knowledge, have been done on the influence of SF on the relationship among SCDM strategies, DT technologies, and SCR. The following research questions are addressed in this study to fill in the gaps that have been identified in previous studies:

RQ1: What are the distinct impacts of DT technologies and SCDM strategies on SCR?

RQ2: Does SF have the potential to adjust the SCDM strategies and DT technologies to achieve better SCR?

We have set two objectives to address the above research questions:

Obj1: To identify the impact of SCDM strategies and DT technologies on SCR.

Obj2: To identify the mediating role of SF on the relationship among DT technologies, SCDM strategies, and SCR.

We proposed our conceptual model based on the dynamic capability view (DCV) to answer the research objectives. The DCV emphasizes that the organization should be able to adjust and reconfigure its existing capabilities in reaction to the rapidly changing global market conditions and disruptions (Teece, 2017), enhancing SCR. Using the partial least square structural equation modeling (PLS-SEM) technique, survey information from 200 Bangladeshi manufacturing organizations was used to validate the developed theoretical framework. The findings of this study provide some essential contributions to theoretical frameworks. First, this study shows how SCDM strategies make supply chains resilient to disruptions. Second, the study reveals how real-time data, modeling, and scenario analysis help organizations proactively manage interruptions. Finally, this study recognizes the importance of increased SF with SCDM and DT technologies for SCR. SCDM methods, DT technology, SF, and SCR literature will benefit from this acknowledgment. The findings of this study will assist policymakers in designing SCDM policies to respond to SCDs and improve supply chain flexibility promptly.

Here is how the remaining portion of this research is organized: Sect. "Theoretical Background" provides a concise overview of the theoretical foundations of this research; Sect. "Research Model and Hypothesis Formulation" discusses the development of research hypotheses and models; Sects. "Research Design" and "Data Analysis and Results" present research design and data analysis, respectively. The following section discusses this empirical study's practical and theoretical implications, limitations, and future scope. Finally, the study's concluding remarks are offered.

Theoretical Background

This section analyzes the DCV theory's theoretical foundation and applicability to DT technologies, SCDM strategies, SF, and SCR. Then, the existing literature on these topics is explored. In the next section, the research model and hypothesis are developed.

Dynamic Capability View (DCV)

This study is based on the dynamic capability view (DCV), which emphasizes the need for firms to adjust and reconfigure capabilities in response to global market changes and disruptions. DCV is suitable for this study as it focuses on leveraging strategic approaches, resource management, and building competitive advantages (Teece et al., 1997). DCV focuses on developing dynamic capabilities—internal and external adjustments that allow firms to adapt to changing conditions (Eisenhardt & Martin, 2000; Teece et al., 1997). These capabilities reflect a SC's robustness and resilience (Kwak et al., 2018). From this perspective, SCDM strategies and DT technologies can be considered dynamic capabilities, enabling proactive disruption management and real-time adaptation. At the same time, SF can be viewed as a firm's resource as it represents the alignment between organizational goals (SCR) and the capabilities (DT technologies and SCDM strategies) at its disposal. Effective supply chains need proactive and reactive features to adapt to environmental and technological changes (Chowdhury & Quaddus, 2017, Ishak et al., 2023; Sharma et al., 2023). Firms can enhance their dynamic capabilities and resilience by reconfiguring and integrating technologies like AI and blockchain. The DCV theory underscores SF's role in aligning strategic objectives with dynamic capabilities, providing a comprehensive framework for understanding how DT technologies and SCDM strategies impact SCR.

Digital Twin (DT) Technologies

DT originated in aviation but has recently been adopted by the manufacturing sector (Negri et al., 2017). In supply chain management, DT involves computerized systems for continuous monitoring and visualization of the supply chain using real-time data on transportation, inventory, demand, and capacity (Ivanov & Dolgui, 2021), where the key technologies include simulation, optimization tools, and data analytics (Barykin et al., 2020). DT technologies use real-time data from RFID, track and trace frameworks, IoT sensors, and electronic databases to identify issues and provide alerts (Ivanov & Dolgui, 2021). Advances in IIoT have made large-scale data collection feasible (Lu & Xu, 2019), cyber-physical systems (CPS) bridge the real and virtual worlds (Kamble et al., 2022), and AI and ML algorithms support knowledge-based decision-making in DT supply chains (Min et al., 2019). Other integral technologies include optimization, big data analytics, supply chain risk analytics, augmented reality, and virtual reality (Ivanov & Dolgui, 2019; Ivanov et al., 2019; Medini et al., 2019). This study identifies six critical technologies for DT-enabled supply chains. From the previous literature, this study summarizes six technologies that most scholars agree are critical for creating a supply chain enabled by DT. These technologies mentioned in the previous literature are summarized in Table 1.

Supply Chain Disruption Mitigation (SCDM) Strategies

Low-frequency, high-impact events, known as supply chain disruptions (SCDs), range from minor issues like shipping delays to major events like societal calamities or pandemics (Badakhshan & Ball, 2023). SCDs cause substantial delivery delays, a drop in revenues and sales, and production halts that impact staff utilization (Ivanov & Dolgui, 2021). While SCDs are well studied (Ivanov, 2017a), research often focuses on catastrophic events. This study examines mitigation strategies for both catastrophic and operational disruptions, including transportation, supply, storage, demand, capacity, production, lead time uncertainty, reactive maintenance, and cybersecurity issues (Carvalho et al., 2012; Etemadi et al., 2021; Ivanov, 2020; Ivanov, 2017a, 2018; Lee et al., 2017; Olivares & ElMaraghy, 2021; Spiegler et al., 2012). The SCDM strategies suggested by these scholars cater to specific scenarios and

Table 1 DT technologies

DT Technologies	Sources
Machine Learning and artificial intelligence (DT1)	Cavalcante et al. (2019), Min et al. (2019)
Modeling and simulation (DT2)	Barykin et al. (2020)
Industrial Internet of Things (DT3)	Kamble et al. (2022)
Blockchain and smart contracting (DT4)	Min (2019)
Cyber-physical system (DT5)	Kamble et al. (2022)
Cloud computing (DT6)	Lu and Xu (2019), Olivotti et al. (2019)

are suited to specific case studies. The SCDM strategies addressed in this study are summarized in Table 2.

Strategic Fit (SF)

A company's business objectives are based on consumer needs (Soni & Kodali, 2011), but it must also maintain competitiveness. Most of the time, it will establish its competitive strategy solely based on the objectives of its customers. Hence, the firm must balance competitive and supply chain strategies and capabilities to maintain competitiveness and satisfy the customer. This is how the concept of SF became popular. It refers to aligning customer goals that can be accomplished through competitive strategies and SC competencies that can be developed through SC strategies (Chopra & Meindl, 2001). While incompatibility is projected to negatively affect a firm's business success, achieving coherence between SC and competitive strategies is also anticipated to have significant advantages for the firm's business performance (Chopra & Meindl, 2001). So, an organizational SC performance directly indicates its level of SF. Gunasekaran et al. (2001) divided the performance measures of SCs into six different categories: measures for planned order procedures, supply chain partnership and related measures, production level measures, delivery performance measures, customer satisfaction measures, and supply chain finance and logistics cost (Gunasekaran et al., 2001). The Supply Chain Council's SCOR model lists 13 crucial performance measures under five attributes: dependability, responsiveness, flexibility, cost, and assets (Hum & Parlar, 2014; Li et al., 2011). This study summarizes the most established and employed performance measures that indicate the level of SF in Table 3.

Supply Chain Resilience (SCR)

SCR is crucial for quickly recovering from disruptions. Scholars agree that SCR is the ability of supply chains to respond to and recover from disturbances (Kamalahmadi & Parast, 2016). Despite slight variations in definitions, the core idea remains the same: the capacity of a SC to return to normal operations after disruptions. Key pillars of SCR include robustness, resources, recovery, and review (Kelly et al., 2008). Building SCR requires developing dynamic capabilities and involves phases like anticipation, resistance, and recovery (Kamalahmadi & Parast, 2016; Pettit et al., 2013). If a firm wants to build a resilient SC, it has to analyze the capability and enabling factors needed to build SCR. Yao and Fabbe-Costes (2018) identified five capacities that enhance a firm's SCR: absorption, response, capitalization, anticipation, and adaptation (Yao & Fabbe-Costes, 2018). Jain et al. (2017) provided thirteen key enabling factors, such as adaptive capability, collaboration, trust, sustainability, etc., that contribute to the overall SCR. This study focuses on the most established and most frequently utilized capability factors, summarized in Table 4.

Table 2 SCDM strategies

SCD events	SCDM strategies	Sources
Demand disruptions	Demand stability (SCDM1)	Ivanov (2020)
Production disruptions	Production efficiency (SCDM2)	Olivares-Aguila and ElMaraghy (2021)
Supply disruption	Supply robustness (SCDM3)	Ivanov (2018), Ivanov (2017b), Ivanov (2020)
Lead time uncertainty	Lead time stability (SCDM4)	Spiegler et al. (2012)
Transportations disruption	Transportation flexibility (SCDM5)	Carvalho et al. (2012), Ivanov (2020)
Cyber security issues	Cyber security strength (SCDM6)	Etemadi et al. (2021)
Capacity disruption	Capacity flexibility (SCDM7)	Ivanov (2017b)
Reactive maintenance	Predictive maintenance (SCDM8)	Lee et al. (2017)
Storage disruption	Storage availability (SCDM9)	Ivanov (2019)

Table 3 Performance measures indicating the level of SF

Performance measures	Sources
Return on investment (SF1)	Le (2020)
Net profit vs productivity ratio (SF2)	Gunasekaran et al. (2001)
Order fulfillment cycle time (SF3)	Hum and Parlar (2014), Huan et al. (2004)
Inventory turnover (SF4)	Kleijnen and Smits (2003)
Cash to cash cycle (SF5)	Huan et al. (2004)
Service level (SF6)	Gunasekaran et al. (2001)
Order fill rate (SF7)	Huan et al. (2004), Kleijnen and Smits (2003)

Research Model and Hypothesis Formulation

This section developed our conceptual research framework based on DCV theory. Then, we created a set of hypotheses that connect DT technologies, SCDM strategies, and SCR. Our model also explains whether SF's presence significantly affects DT and SCDM's impact on SCR.

Digital Twin (DT) and Supply Chain Resilience (SCR)

Digital twin (DT) technologies can enhance supply chain (SC) operations at both process and capability levels (Bhandal et al., 2022), acting as critical dynamic capabilities per the DCV. These technologies enable reconfigurable SC networks, allowing firms to quickly adapt to changes and disruptions (Dolgui et al., 2020). This adaptability is essential for building a resilient SC, aligning with the DCV's core principle of modifying and reconfiguring capabilities. When faced with severe SCDs, collaborative intelligent technologies like cloud manufacturing, IoT, and data analytics, which are some of the prominent technologies of DT, can assist the supply chain in remaining robust and sustainable (Dy et al., 2022). This is an example of dynamic capabilities in action, as shown in the DCV, as it utilizes sophisticated technologies to ensure the continuity and efficiency of the supply chain. A DT-based decision support framework can enhance the exploration of different proactive and reactive strategies for managing SC disruptions and developing contingency plans by leveraging the benefits of SC visibility and analysis of historical and real-time disruption data (Ivanov & Dolgui, 2021).

Badakhshan and Ball (2023) have explored the potential of using DT technologies using simulation and machine learning in SC inventory and cash management and found that by minimizing disruptions, DT technologies can improve SC performance, which is the goal of any organization. This supports the DCV perspective that dynamic capabilities like DT technologies are crucial for maintaining and enhancing SC performance by allowing firms to predict and prevent disruptions. Even though not many studies showed a direct relation between DT technologies and SCR, we can argue, based on the literature and the DCV theory, that DT technologies are crucial to improving the capabilities of a supply chain that directly contributes to the resilience of a supply chain in manufacturing organizations. This study hypothesizes the relationship as follows:

H1: DT technologies have a positive and significant impact on SCR.

Supply Chain Disruption Mitigation (SCDM) Strategies and Supply Chain Resilience (SCR)

A resilient SC can anticipate events, lessen the blow of disruptions, and fortify its capacity to bounce back swiftly. This is achieved by keeping operations running smoothly at

Table 4 Capability factors of SCR

Capability factors	Meaning	Sources
Flexibility in sourcing (SCR1)	The capability to make rapid adjustments to either the inputs or the way of receiving inputs	Pettit et al., (2013), Pettit et al., (2010)
Adaptability (SCR2)	The capability to make adjustments to operations in response to either opportunities or obstacles	Jain et al., (2017), Pettit et al., (2010)
Anticipation (SCR3)	The capability to see opportunities or circumstances that may arise in the future	Pettit et al., (2013), Pettit et al., (2010), Yao and Costes, (2018),
Recovery (SCR4)	Having the capability to revert to a regular functioning condition quickly	Brusset and Teller (2017), Eryarsoy et al. (2022), Pettit et al. (2010)
Collaboration (SCR5)	The capability to collaborate successfully with other organizations to achieve mutually beneficial outcomes	Jain et al., (2017), Pettit et al., (2010)
Visibility (SCR6)	An understanding of the present environmental conditions and the operational assets	Jain et al., (2017), Pettit et al., (2013), Pettit et al., (2010)

the desired degree of connectivity and command over function, generating competitive advantages (Pettit et al., 2013). Despite SCDM being a complex idea, and that there is a great deal of disagreement among academics as to what it means, there is a consensus that the purpose of SCDM strategies is to reduce the probability of SCDs occurring (Ho et al., 2015). Following DCV, SCDM strategies represent the dynamic capabilities of a firm to detect, evaluate, and mitigate disruptions proactively. A crucial aspect of SCDM strategies is reducing the impact of SCDs on the continuity of material and information flows throughout SC (Bode et al., 2011), which paves the way for the SC to have flexibility in sourcing and to be more adaptable. Thus, in the event of an SCD, manufacturing organizations may retain their SCR by reconfiguring and deploying resources and capabilities using SCDM strategies (Baz & Ruel, 2021). In other words, firms' dynamic capabilities are responsible for achieving their objectives, such as making SCs more resilient. This perfectly mirrors the theories presented in the DCV. Even though a few researchers have hinted at the relationship between SCDM strategies and SCR (Bode et al., 2011; Chowdhury & Quaddus, 2017), their interaction is not empirically appropriately explored. Based on the arguments above, it is possible to formulate the following hypothesis:

H2: SCDM strategies have a positive and significant impact on SCR.

Moderating Role of Strategic Fit (SF)

Since DT technologies can visualize the physical SC utilizing real-time information regarding logistics, stocks, and demand, they can be applied to monitor and supervise the supply chain and prepare for any disruption (Cavalcante et al., 2019). However, how well data are organized and distributed across the SC determines how successful DT technologies will be. This is where SF comes in, as it acts as a crucial resource in enabling the integration of data standards, protocols, and platforms across SC partners. SF plays a pivotal role in ensuring that data are shared and understood uniformly across all partners, enhancing DT technologies' effectiveness. SF enables organizations to utilize their IT infrastructures, like DT technologies, to reinforce their business framework and policies. This allows them to maximize the benefits of IT-related investments and enhance the organization's performance, competitive edge, profitability, and growth (Anuar & Kamruzzaman, 2017). So, SF acts as the resource that enhances the dynamic capabilities provided by DT technologies, contributing to the strategic goal of achieving SCR, which follows the theories presented in the DCV. Therefore, it can be argued that SF can potentially enhance the significance of DT technologies' impact on SCR.

Through simulation, Johnson et al. (2021) proved that SCDM strategies like redundancy and multi-sourcing can increase the SC's robustness and resiliency (Johnson et al., 2021). However, the effectiveness of SCDM strategies relies on close collaboration and coordination with SC partners (Baz & Ruel, 2021). A high degree of SF indicates that the company's supply chain strategy aligns with its competitive strategy and that SC partners have the exact expectations, objectives, and motivations regarding SCDM. From the DCV standpoint, SF as a resource can increase the effectiveness of the dynamic capabilities, such as SCDM strategies, and provide the groundwork for successful collaboration, one of SCR's most important capability factors.

While previous studies have hinted at a potential link between SF and a firm's efficiency (Camuffo & Wilhelm, 2016), our research is the first, to our knowledge, to delve into the influence SF can exert on the relationship between DT technologies and SCR, as well as on the connection between SCDM strategies and SCR. In light of the potential impact of SF, we propose the following research hypotheses to explore its moderating effect on these relationships:

H3: SF positively moderates the relationship between DT technologies and SCR.

H4: SF positively moderates the relationship between SCDM strategies and SCR.

Control Variables

In addition to the study's main constructs, two important control variables are added to account for the key variations across manufacturing organizations. Firstly, firm size (FS) is considered one of the important indicators of variance. One straightforward way to tell if a firm has built a culture that encourages growth is by looking at the size of the firm (Shah & Ward, 2007). By the suggestions put forth by Tortorella et al. (2019), firms are divided into two categories: those with over 500 employees and those with fewer than 500. Larger firms may have more resources and capabilities to achieve better strategic fit. Secondly, firms in different fields or industries may have to deal with varying amounts of competition and have supply chains that work at different speeds (Devaraj et al., 2007). An essential aspect that might lead to increased adoption of DT technologies is a firm's technological intensity (TI), which is correlated with the kind of industrial sector the firm belongs to (Tortorella & Fettermann, 2018). Hence, we consider TI to be the second control variable. Following the Brazilian National Confederation of Industry, we classified TI into two groups: high and medium–high intensity and low and medium–low intensity, based on the concentration of the technological positioning of the firm (Tortorella et al., 2021).

In this instance, Fig. 1 illustrates the theoretical model that serves as the foundation for this study.

Research Design

This study used a two-staged mixed method where these two stages were sequential (Schilke, 2014). In the first stage, a series of exploratory qualitative interviews were conducted. These interviews aimed to understand the strategies currently involved in mitigating the SCDs in the interviewee's industry, the current state and usage of DT technologies, and learn about their practices to achieve SCR. Another purpose of these interviews was to pre-test the survey questionnaire. The second stage involved the use of this survey questionnaire. A cross-sectional survey was carried out in the second stage. The hypotheses, independent and dependent constructs, and survey data were all examined. The following flow diagram in Fig. 2 shows all the processes carried out in the research design and data analysis sections.

Interview and Survey Questionnaire Design

In January 2023, fifteen senior managers from Bangladeshi manufacturing organizations and five academics participated in semi-structured interviews. These managers were involved in policymaking. Appendix 1 displays the participant profiles from the interviewing sessions. Each interview lasted 45–50 min on average. There were two phases of this interview. In the first phase, participants discussed emerging technologies to mitigate SCDs and improve SCR, with a consensus on the benefits of integrating DT technologies for real-time monitoring. Some of the participants also mentioned hyper-automation and big data analytics. The participants were also asked about their views on whether SCDM strategies may enhance SC resilience in manufacturing organizations. Even though the participants suggested different strategies, they all agreed that managers have to implement SCDM strategies catered to specific SCDs to make SCs more resilient to the SCDs. Finally, they were asked whether a higher degree of SF can improve the effectiveness of DT technologies and SCDM strategies to achieve SCR more easily. Most participants, including many academics, agreed that achieving a high degree of SF would make it easier for DT technologies and SCDM strategies to enhance SC resilience. In the second interview phase, participants validated the proposed hypotheses by discussing the importance of SF in strengthening the impact of DT technologies and SCDM strategies on SCR. While some were uncertain about SF's impact on SCR, most agreed that adopting SCDM strategies and DT technologies in the presence of SF increases the likelihood of achieving SCR.

In the second stage, an extensive literature review was conducted, focusing on the four main themes of this study: DT technologies, SCDM strategies, SF, and SCR. This review served as the foundation for developing the survey questionnaire. The goal was to identify the most significant supply chain disruptions and assess whether DT technologies and SCDM strategies could address them. Based on the literature, the questionnaire was divided into four

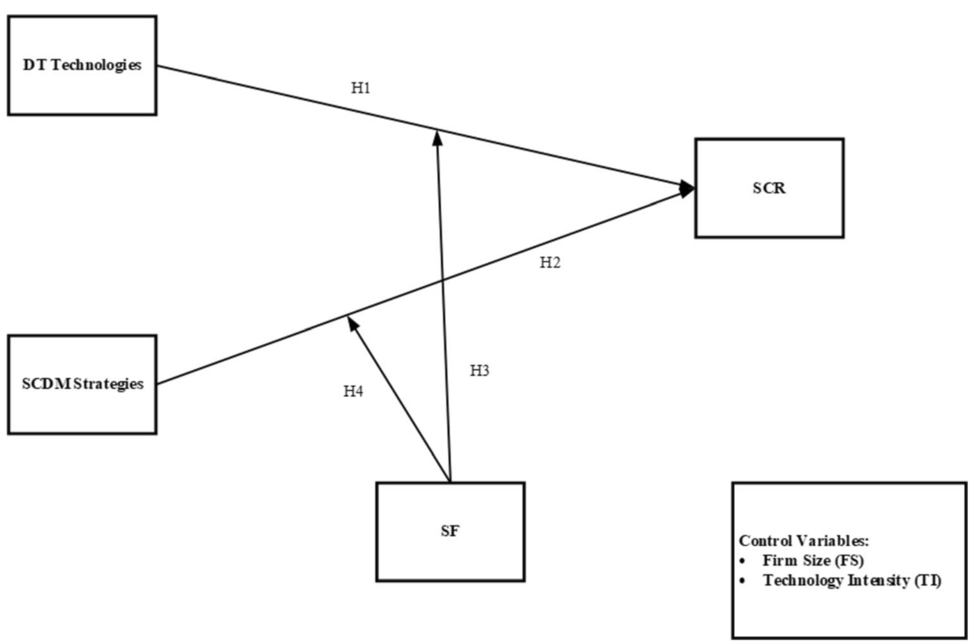

Fig. 1 Proposed theoretical model

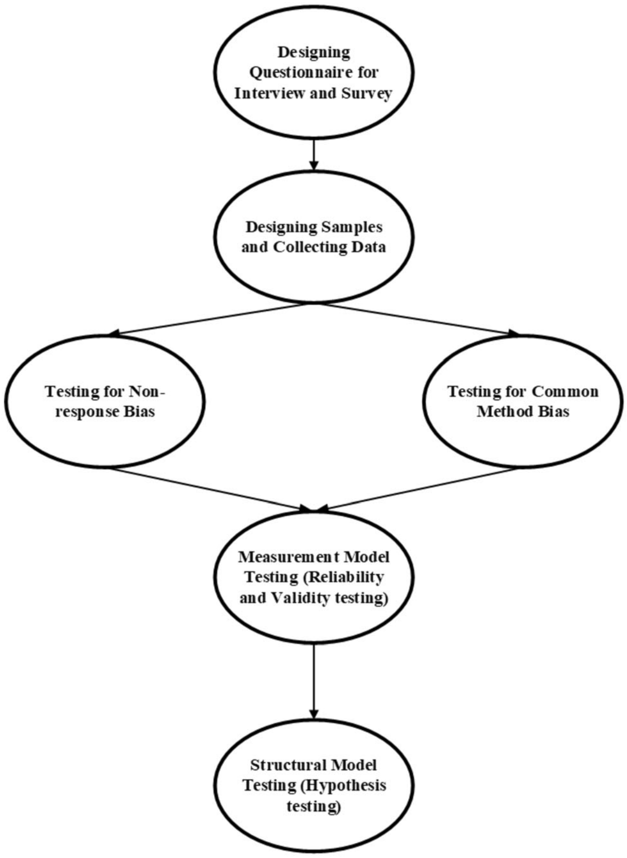

Fig. 2 Sequential steps in research design and data analysis

parts. The first section focused on implementing DT technologies, aiming to determine the extent to which manufacturing organizations have integrated these technologies into their operations. The second section addressed the execution of SCDM strategies, seeking insights into how firms manage predicted and unforeseen disruptions in the supply chain. The third section contained questions about the current state of organizational SF, aiming to capture the respondents' perspectives on this issue. The last section of the questionnaire includes inquiries about the condition of current SCR in their respective organizations. The primary purpose of this section is to understand to what degree the current state of their supply chains is resilient to SCDs. Participants shared their viewpoints using a five-point Likert scale, ranging from strong agreement (5) to strong disagreement (1).

Sampling Design and Data Collection

The experimental context of this research involves various manufacturing organizations from different industries engaged in other strategies to mitigate SCDs through the application of DT technologies and various SCDM strategies in Bangladesh. In this study, manufacturing organizations serve as the unit of analysis, and a single respondent was intended to complete the survey questionnaire. The emphasis on the firm as the unit of analysis for SCD and SCR analysis grew somewhat from 2001 to 2010 (60.00%) to 2010–2018 (67.68%) (Carter et al., 2020).

With the help of Dun and Bradstreet, one of the most widely accessible and utilized commercial databases in the world (Powell et al., 2011), contact information of 350 manufacturing organizations was obtained. Then, the details and specifics of each organization were examined through a series of internet searches. Among 350 companies, 270 were found to utilize modern technologies like simulation, artificial intelligence, blockchain, etc. So, these companies had a high potential to realize the full benefits of DT technologies. These companies have already taken action to mitigate their SCD through technologies.

The target participants were mainly top-level managers and some junior managers in these organizations who understand the application of DT technologies in the supply chain. Because of the vast distances among these organizations, only electronic platforms (e-mails) were used to obtain the essential information. During February 2023, these 270 organizations were issued e-mail invites. After three waves of reminders, 200 usable replies were eventually collected by the end of June 2023. The data were collected using a random sample approach. The response rate was 74.07%, as indicated by the data. The obtained response rate is adequate for examining this research framework, which has been previously validated by a multitude of studies that mainly focused on survey-based analysis (Dubey et al., 2014; Gupta et al., 2019). The respondents did not receive any gifts or donations due to financial limitations. Table 5 shows the demographic features of the people who responded to the survey. According to the table, general managers accounted for 7.69 percent of all responses (11), senior managers accounted for 61.54 percent (88), managers accounted for 16.08 percent (23), and the remaining 14.69% were junior managers (21).

Non-response Bias Test

Non-response bias in survey-based research occurs when non-respondents differ significantly from respondents. It is present in all surveys; however, in some instances, it occurs at a negligible level and may be disregarded. However, the amount of bias is defined by the dissimilarity between respondents and non-respondents and the proportion of the population who did not respond to the survey (Lavrakas, 2008). The non-response bias in the gathered dataset was analyzed using two distinct methodologies. First, a comparative analysis was conducted between early and late responses to identify potential bias (Armstrong & Overton, 1977). The samples were divided into equal-sized groups

Table 5 Sampling profile

Criteria	Respondents categories	Respondents (In percentage)
Position in the company	General manager	7.69
	Senior manager	61.54
	Manager	16.08
	Junior manager	14.69
Experience (Years)	Above 20	68.43
	10–19	16.88
	Below 10	14.69
Firm Size (FS)	Large (more than 500 employees)	34.85
	Small and medium (less than 500 employees)	65.15
Technology intensity (TI)	High and medium–high intensity,	58.15
	Low and medium–low intensity	41.85

based on the day of the week the responses were received, and a t-test was performed to compare these groups. The analysis showed no significant differences between the groups at a 95% confidence level. Next, 25 non-respondents were contacted and asked to complete one question from each section of the survey to check for discrepancies using a t-test (Iqbal et al., 2021a). Again, no statistically significant differences were found between respondents and non-respondents at the 95% confidence level. Leven's variance test of homogeneity was also utilized in this study. However, the obtained values were not statistically significant. Therefore, the non-response bias present in this research is not a significant cause for worry.

Common Method Bias

Since a single-respondent survey was used to gather the data for this study, there's a possibility that this may have contributed to common method bias (CMB) (Podsakoff & Organ, 1986; Podsakoff et al., 2003). This study implemented several procedural solutions to mitigate the negative consequences of data collection from a single source (MacKenzie & Podsakoff, 2012).

Qualitative interviews were conducted, as mentioned earlier, to determine the difficulty in understanding questions. Since item ambiguity can contribute to CMB (Podsakoff et al., 2003) and hamper accurate information gathering (Krosnick, 1991), the wording was made straightforward and concise. Additionally, to avoid CMB caused by twofold questions, which often confuse respondents (Krosnick, 1991), such questions were completely excluded from the study. Instead, the questions focused on assessing the current situation, allowing respondents to provide immediate and accurate answers.

The standard single-factor Harman's test was applied in conjunction with procedural remedies. According to the results of this test, nearly 27% of the total variance was explained by a single factor, which is below the recommended threshold of 50% (Kock, 2022), indicating no significant CMB issues. However, the single-factor Harman's test is not regarded by some academics as an effective way to evaluate the common method variance (CMV), while being notably advantageous when applied to information supplied by a single participant (Hulland et al., 2018; Podsakoff et al., 2003). So, CMB was investigated using the correlation marker approach (Lindell & Whitney, 2001).

This method involves using unrelated variables to identify correlations due to CMB (Williams et al., 2010). The significance of these correlations was further evaluated using Lindell and Whitney's (2001) formulas. Comparing adjusted and unadjusted correlations revealed minimal differences, suggesting that the potential effects of CMV are not substantial. Consequently, CMB is not a significant concern in this study.

Measures

For our proposed conceptual model, a multi-item variable assessment was used to improve accuracy, enhance the diversity of survey respondents, and minimize potential inaccuracies in measurement (Churchill Jr, 1979). A comprehensive set of twenty-eight items was considered for operationalizing the latent constructs: six items were allocated to DT, nine items were assigned to SCDM strategies, seven items were designated for SF, and six items were allocated to SCR. Each item was checked for authenticity by fifteen specialists from various fields of industry and the academy before being incorporated into the final document. Sorting and pre-testing of items were carried out thoroughly following the methodology outlined by Anderson and Gerbing, with five industry and academic experts with extensive knowledge and experience in this field (Anderson & Gerbing, 1988). In this study, all of the experts' opinions were taken into account. The questions were improved by using the proper language and phrasing, thanks to the advice of the experts. This research addresses several latent constructs, and the list of all the measuring items related to those constructs is presented in Appendix 2.

Data Analysis and Results

The relationship among several latent variables can be verified statistically using a variety of methods, like SEM, factor analysis, the analytic network approach, and regression analysis (Mai & Liao, 2021; Talapatra et al., 2019). The majority of academics chose SEM analysis because it was more sophisticated and advanced than the others (Hair et al., 2010). Factor analysis and path analysis are combined in SEM, a multivariate approach that elevates the technique's level of sophistication (Iqbal et al., 2021b). The Partial Least Squares (PLS) approach is predominantly linked to the study of variance (Hair et al., 2019). Along with the study of variance, there is also another commonly accessible methodology for SEM analysis, known as covariance-based SEM. This study used the PLS-SEM algorithm to analyze the data using WarpPLS, a statistical program. The following factors led to the selection of this algorithm (Dubey et al., 2018; Gupta et al., 2019; Talapatra et al., 2019):

1. The algorithm possesses the capability to process a large number of variables simultaneously.
2. It is an effective method for examining and verifying the relationship between the parts of a complex model.
3. It can manage incomplete and non-normalized data with ease.
4. It can be used in circumstances where predictability is important.

This approach has been employed in numerous research, such as researching the viability of implementing lean manufacturing principles in the context of Industry 4.0 (Saha et al., 2023), determining the influence of big data analytics on agility and flexibility for the supply chain that focuses on humanitarian aspects (Dubey et al., 2022), looking at the connection between information alignment and collaboration and the agility of supply chain operations (Dubey et al., 2021). Traditional PLS-SEM, according to Kock (2019b), overlooks measurement errors, which commonly leads to specific recognized sources of bias and reduces the path coefficients compared to the genuine values that correspond to such coefficients. Due to the traditional PLS-SEM approaches being composite based rather than factor based, Warp PLS 8.0 is used in this study to overcome these issues.

Measurement Model Reliability and Validity

To validate our model, this study used a process consisting of two steps recommended in numerous previous studies (Kock, 2019b). The constructs of this study are reflective. At first, calculations of scale composite reliability (SCR) and average variance extracted (AVE) for each construct, as well as factor loadings for each measuring item, were carried out to evaluate the validity and reliability of the measurement model (Fornell & Larcker, 1981). Table 6 displays all of the confirmatory factor analysis (CFA) findings. Measuring items should be chosen only for the PLS-SEM analysis if their factor loading values are at least 0.5 or more than 0.5; otherwise, they should be discarded (Hair et al., 2017). Only one item (SCDM8) is not included in the study as its factor loading value was less than 0.5 (0.12). Compared to their respective threshold values of 0.7 and 0.5, the SCR and AVE values given in Table 6 are higher than those (Tan & Ooi, 2018). So, on both the indicator and construct levels, convergent validity is adequate (Fornell & Larcker, 1981). Additionally, Cronbach's alpha of each of these constructs was also determined to check the accuracy and consistency of the model further. The alpha values in Table 6 all exceed the critical value of 0.6, demonstrating the measurement model's strong internal consistency and reliability (Molina et al., 2007).

Secondly, a discriminant validity test was implemented to address the discriminant issues of our structural model. To determine whether or not the measures have divergent validity, the criteria developed by Fornell and Larcker (1981) and the HTMT (heterotrait-monotrait ratio of correlations) method were used (Henseler et al., 2015). The inner-correlation matrix was produced in accordance with the suggestions made by Fornell and Larcker (1981), and the square root of the AVE values was included in the primary diagonal components of Table 7. All of the latent variables have discriminant validity because the square root values of the AVE for each one are higher than the correlation coefficients for those variables in the same column. (Fornell & Larcker, 1981).

After that, the HTMT criterion was also used to examine the constructs for discriminant validity. According to Henseler et al. (2015), the HTMT ratio, a novel metric, may provide a more accurate discriminant validity assessment. To illustrate different aspects of the model, the authors compared the average correlations of measurements within and outside the same latent variable to those across latent variables. Table 8 shows that all reflective constructs have appropriate discriminant validity, as values

Table 6 Measures of constructs and factor loadings

Construct	Item	Factor loading	Variance	Error	SCR	AVE	Cronbach's alpha
DT technologies	DT1	0.500	0.250	0.750	0.918	0.659	0.889
	DT2	0.890	0.792	0.208			
	DT3	0.923	0.852	0.148			
	DT4	0.810	0.656	0.344			
	DT5	0.856	0.733	0.267			
	DT6	0.818	0.669	0.331			
SCDM strategies	SCDM1	0.883	0.780	0.220	0.968	0.793	0.961
	SCDM2	0.918	0.843	0.157			
	SCDM3	0.923	0.852	0.148			
	SCDM4	0.932	0.869	0.131			
	SCDM5	0.678	0.460	0.540			
	SCDM6	0.852	0.726	0.274			
	SCDM7	0.951	0.904	0.096			
	SCDM8	0.120 (not included)	0.014	0.986			
	SCDM9	0.951	0.904	0.096			
SF	SF1	0.911	0.830	0.170	0.958	0.765	0.948
	SF2	0.911	0.830	0.170			
	SF3	0.950	0.903	0.098			
	SF4	0.876	0.767	0.233			
	SF5	0.790	0.624	0.376			
	SF6	0.754	0.569	0.431			
	SF7	0.911	0.830	0.170			
	SCR1	0.842	0.709	0.291	0.963	0.815	0.954
	SCR2	0.933	0.870	0.130			
SCR	SCR3	0.894	0.799	0.201			
	SCR4	0.897	0.805	0.195			
	SCR5	0.929	0.863	0.137			
	SCR6	0.917	0.841	0.159			

less than 0.85 show proper discriminant validity (Henseler et al., 2015).

It is vitally crucial to investigate endogeneity issues before delving into this study's research hypotheses. The nonlinear bivariate causality direction ratio (NLBCDR) was checked to see if there were any endogeneity issues for the model (Kock & Lynn, 2012). The causality assessment indices are shown in Table 9. It has been determined via the study that the value of NLBCDR is 1.00, which is more than the permitted value of 0.7. According to this study, 100 percent of the occurrences associated with the path agree with the assumptions the model established. Furthermore, there is no statistical evidence to show that the conceptual constructs might be related in any direction (Kock, 2019a). So, these results show that our suggested model has no causality problems. Table 10 presents supplementary data on the model fit and quality indices, supporting the aforementioned conclusion.

Table 7 Discriminant validity

	DT technologies	SCDM strategies	SF	SCR
DT technologies	0.812	–	–	–
SCDM strategies	0.375	0.890	–	–
SF	0.398	0.293	0.875	–
SCR	0.549	0.603	0.227	0.903

Table 8 HTMT values

	DT technologies	SCDM strategies	SF	SCR
DT technologies	–	–	–	–
SCDM strategies	0.413	–	–	–
SF	0.467	0.317	–	–
SCR	0.594	0.633	0.282	–

Hypothesis Testing

The research's proposed hypotheses were validated using PLS-SEM (WarpPLS 8.0). Table 11 shows the path coefficient (β) and the p values obtained from the PLS-SEM analysis, which contains the study's findings.

Statistically significant evidence favors hypothesis H1, which states that DT technologies will help the firm achieve SCR ($\beta = 0.37$, $p < 0.01$). Based on this result, it seems that a company has the potential to become more competitive in the global market and build a resilient supply chain if it can implement DT technologies.

The second hypothesis, H2, is also statistically significant, implying that SCDM strategies significantly impact a firm's ability to create and improve SCR ($\beta = 0.47$, $p < 0.01$). Based on this finding, the importance of SCDM strategies in building a resilient and robust supply chain can be easily understood.

After that, the moderating impact of SF on the model was examined. SF substantially moderated the path connecting DT technologies and SCR ($\beta = 0.23$, $p < 0.01$). This discovery suggests that SF in manufacturing organizations can mediate the interaction between DT technologies and SCR. So, when implemented in the presence of a high degree of SF in a firm, DT technologies can significantly boost the firm's ability to achieve SCR. However, the moderating impact of SF on the path connecting SCDM strategies and SCR was insignificant ($\beta = 0.10$, $p = 0.07$). This finding indicates that the presence of SF in a manufacturing organization may not impact the relationship between SCDM strategies and SCR.

However, the control variables FS ($\beta = 0.01$; $p > 0.1$) and TI ($\beta = 0.05$; $p > 0.1$) did not show evidence of support. These findings directly indicate that a manufacturing organization's SCR is not significantly impacted by its size or the intensity of the technology.

Table 9 Causality assessment indices

Parameters	Values
Simpson's paradox ratio (SPR)	1.00
R-squared contribution ratio (RSCR)	1.00
Statistical suppression ratio (SSR)	1.00
Nonlinear bivariate causality direction ratio (NLBCDR)	1.00

The coefficient of determination (R^2) of the endogenous constructs was also analyzed in this study because it can showcase how much explanatory power our model has. According to the calculated value of R^2, DT technologies, SCDM strategies, and SF are important determinants for obtaining SCR. The value of R^2 also shows that DT technologies and SCDM strategies under the moderating effect of SF explain 34.7% of the overall variance ($R^2 = 0.347$). It is clear from this finding that the structural model can explain a significant percentage of the phenomena (Dubey et al., 2023).

Constructs' effect sizes are also examined. After determining the effect size, it was seen that the effect size of DT technologies on SCR is 0.209, and the effect size of SCDM strategies on SCR is 0.317. For both of these cases, the effect size is medium because, according to Cohen, $f^2 \geq 0.02$, $f^2 \geq 0.15$, and $f^2 \geq 0.35$ represent small, medium, and large effect sizes, respectively (Cohen, 1988). Additionally, researchers using the PLS-SEM method have shown a great deal of interest in the predictability values (Q^2) of the explanatory variables (Chin, 1998). It was found that the Q^2 value of the endogenous construct is 0.577 for SCR, which is greater than zero. This result shows that DT technologies and SCDM strategies are significant predictors of SCR. This also indicates how accurate this model's predictions are. Table 12 presents the values of R^2, Q^2, and f^2.

Discussion

Based on the theoretical foundation provided by the DCV, this research focused on investigating the effect of SCDM strategies and DT technologies on SCR, along with the moderating effect of SF on the effectiveness of SCDM strategies and DT technologies for achieving SCR in manufacturing organizations in Bangladesh, which was previously unexplored in the literature. Based on the findings presented in the section under "Data Analysis and Results," it has been determined that the first hypothesis has a coefficient of 0.37 ($p < 0.01$), which indicates that it is statistically significant. This significant finding shows the importance of DT technologies in strengthening SCR and helping organizations stay competitive in the global market. DT technologies play a crucial role in enabling proactive monitoring, management, and disruption anticipation by offering real-time visibility and control over the supply chain. This result aligns with previous research, which has consistently highlighted the benefits of DT technologies in improving SCR (Ivanov & Dolgui, 2021;

Table 10 Model fit and quality indices

Parameters	Values	Acceptable range	References
Average path coefficient (APC)	0.293, $p < 0.001$	$p < 0.05$	Dubey et al. (2022)
Average R-squared (ARS)	0.347, $p < 0.001$	$p < 0.05$	Dubey et al. (2022)
Average block VIF (AVIF)	3.930	$0 < \text{AVIF} < = 5$	Kock (2019b)
Tenenhaus GoF (GoF)	0.540	large $> = 0.36$	Tenenhaus et al. (2005)

Table 11 Hypothesis testing results

Hypothesis	PLS Path	Path coefficient (β value)	p value	Result
H1	DT → SCR	0.37	$p < 0.01$	Accepted
H2	SCDM → SCR	0.47	$p < 0.01$	Accepted
Interaction effect				
H3	SF * DT → SCR	0.23	$p < 0.01$	Accepted
H4	SF * SCDM → SCR	0.10	$p = 0.07$	Not accepted
Control variables				
FS	FS → SCR	0.01	$p = 0.46$	Not significant
TI	TI → SCR	0.05	$p = 0.27$	Not Significant

Johnson et al., 2021). However, this study provided empirical evidence to emphasize the need for DT technologies within a developing economy like Bangladesh, where adopting such advanced technologies can be difficult.

Regarding the second hypothesis, it is found that this hypothesis is also statistically significant, with a coefficient of 0.47 ($p < 0.01$). This result strongly supports the idea that manufacturing companies need to have effective SCDM strategies to achieve SCR. It suggests that companies can improve their ability to adapt, be flexible, and recover from disruptions in the supply chain by carefully putting strategies in place to lessen the effects of problems in transportation, lead time, capacity, and supply. The alignment of these SCDM strategies with the firm's bigger operational goals, like SCR, reinforces the supply chain against disruptions and ensures sustained competitiveness in the global market. This finding is not only consistent with previous research, which has similarly highlighted the importance of SCDM strategies in fostering SCR (Baz & Ruel, 2021), but also extends the existing literature by pointing out that SCDM strategies are indispensable in emerging economies like Bangladesh, where SCs are often subjected various disruptions.

Table 12 Co-efficient of variation (R^2), predictability (Q^2), and effect size (f^2)

			f^2 in relation to	
Construct	R^2	Q^2	DT	SCDM
SCR	0.347	0.577	0.209	0.317

This study also explores whether the impact of SCDM strategies and DT technologies on SCR is amplified in the presence of SF, regarded as this study's third and fourth hypotheses. The statistical examination of the PLS algorithm indicates that the third hypothesis is similarly statistically significant, with a coefficient of 0.23 ($p < 0.01$), indicating that it is also worth considering. This result implies that DT technologies' effect on SCR is significantly boosted when applied in the presence of SF. So, organizations that can guarantee a strong fit between their competitive strategies and their overall supply chain objectives are better suited to achieve SCR. However, the fourth and the last hypotheses were not statistically significant, as the result for this hypothesis was obtained as $p = 0.07$ with a coefficient of 0.10. This indicates that the presence of SF in a firm may not impact the relationship between SCDM strategies and SCR. Despite literature suggesting that the effectiveness of SCDM strategies can be influenced by the level of collaboration and SF within the firm (Baz & Ruel, 2021), there might be some underlying reason for the non-significance of the fourth hypothesis. Some respondents gave plausible explanations for this result. One possibility is that SF's effect on SCDM strategies and SCR is inconsistent across settings or samples, especially in Bangladesh. Some organizations with high SF fail to adopt effective supply chain and SCDM strategies due to market volatility, supplier reliability, or rapid consumer demand changes. Other organizations with limited SF can get strategic competitive advantage by using adaptive or inventive tactics customized to their situation. Therefore, SF's impact on SCDM strategies and SCR may not be significant or consistent across settings. SF's role is multifaceted and implies that SCDM strategies' effects on SCR can vary depending on external and internal circumstances. This nuanced understanding stands out as one of the most significant outcomes of this study, highlighting the need for a context-specific approach when examining the moderating effects of SF.

Theoretical Implications

The theoretical implications of this study are significant, offering valuable contributions to the existing literature on supply chain management, particularly in the areas of DT technologies, SCDM strategies, SF, and SCR. While previous studies have explored the roles of DT technologies and SCDM strategies in managing SCDs (Badakhshan & Ball, 2023; Burgos & Ivanov, 2021; Cavalcante et al., 2019; Ivanov & Dolgui, 2019), their impact on improving SCR and the moderating effect of SF on the effectiveness of these technologies and strategies in enhancing SCR has been largely overlooked. This study addresses this gap, offering several important theoretical insights. First, this investigation enhances the SC literature by empirically establishing associations among DT technologies, SCDM strategies, and SCR. For example, the study shows that the employment of DT technologies enhances supply chain visibility and supports the supply chain's ability to anticipate and respond to disruptions, which is critical for achieving resilience. Similarly, the findings demonstrate that effective SCDM strategies are key to building a resilient supply chain, particularly in environments characterized by frequent SCDs, such as those faced by manufacturing organizations in Bangladesh. Second, this study also widens the scope of SC literature by examining the synergistic impact of SF on the relationship among DT technologies, SCDM strategies, and SCR, which has not been empirically tested before. By introducing SF as a moderating variable, this study emphasizes how aligning a firm's strategic goals with its operational capabilities can enhance or hinder the effectiveness of DT technologies and SCDM strategies in achieving SCR. Third, this research utilized the DCV to connect the DT technologies, SCDM strategies, SF, and SCR, which makes a unique contribution to the existing literature. The resource-based view (RBV) has been used to examine a firm's ability to use its resources to gain a competitive advantage (Grant, 1991). However, it falls short in addressing global markets' dynamic and rapidly changing nature. In contrast, the DCV offers a more appropriate theoretical perspective, underscoring the significance of a company's capacity to adjust, integrate, and reconfigure internal and external capabilities to address changing environments (Helfat & Peteraf, 2003). By analyzing the moderating impact of SF, this study extends the DCV literature as it demonstrates how SF can act as a critical organizational resource to manage dynamic capabilities like DT technologies and SCDM strategies to make the SCs more resilient. Finally, this study presents a collection of validated measurement items for DT technologies, SCDM strategies, SF, and SCR. The procedure of empirical validation was used to evaluate the validity of these measures. These empirically validated measures can be implemented in various business sectors, particularly those facing comparable challenges and disruptions, with only minor modifications.

Practical Implications

This study sheds light on how SF can improve the effectiveness of SCDM strategies and DT technologies in a manufacturing organization, which can help the firm achieve SCR. This research presents substantial insights for managers, executives, and policymakers in manufacturing organizations implementing modern technologies in their supply chains. First, the study demonstrates how DT technologies improve real-time monitoring, predictive analytics, and scenario simulations, enabling proactive disruption detection and quick reaction. For instance, managers can leverage predictive analytics enabled by DT to see the upcoming supply chain bottlenecks and take measures to fix them before they escalate into major disruptions. This proactive method lowers risks and ensures that operations run more smoothly, even when the market is volatile. Second, this study focuses on how different SCDM strategies improve SC adaptability and flexibility. Businesses may strengthen their SCs and make them more resilient to disruptions by implementing strategies like supplier diversification, inventory optimization, flexible transportation options, etc. Third, this study emphasizes the interplay among SCDM strategies, DT technologies, SF, and SCR, which can help the managers understand SF's influence over SCDM strategies and DT technologies to improve SC performance and build a more resilient SC. Managers will realize that resilient supply chains can better respond to changing market needs and bounce back fast from disruptions when a company's strategic goals align with its technological capabilities. Finally, the latent constructs' identified measurement items can assist managers in examining their relative value to their firms. Armed with these insights, managers can confidently handle the deployment of DT technologies, enabling more resilient and strategically aligned supply chain ecosystems.

Understanding and using SF will help them create more robust, flexible, competitive supply chains that survive in a fast-paced worldwide marketplace.

Limitations and Future Scope

While research on the association between DT technologies, SCDM strategies, SF, and SCR is encouraging, some limitations should be acknowledged. Firstly, our sample size is limited to 200 participants from Bangladeshi manufacturing organizations. Despite this sample size being adequate for PLS-SEM analysis, a bigger sample size may provide more depth to this study. Secondly, the continuously changing nature of technology and business contexts may impact the longevity of the SCDM strategies and insights, imposing constant changes to remain relevant. So, further research on developing agile strategies and collaborative ecosystems is encouraged. Thirdly, the study employed cross-sectional data for analysis. This dataset is quite accessible and expeditious, yet it cannot offer insights into temporal variations or trends. To avoid such restrictions, it is recommended that future studies be conducted using longitudinal data. Besides, the nature of the majority of the measures included in the study is subjective. Even though the authenticity and biases of the data have been verified, there is still the chance of concerns with validity and biases arising in the case of subjective measurements (Dubey et al., 2023). Researchers are encouraged to employ objective measurements in future studies to avoid such problems. Finally, the data sample consisted exclusively of respondents from three distinct categories of Bangladeshi manufacturing organizations (Textiles, Mechanical, and Electronics), limiting the research's applicability to other industries and nations. One way to expand the quantitative and qualitative richness of the sample would be to include respondents from a wider variety of sectors or countries in the data-gathering activities.

Conclusion

In conclusion, this study significantly contributes to understanding how DT technologies and SCDM strategies can revolutionize supply chain management practices, addressing key gaps in the existing literature. Focusing on SCR, this research underlines the vital importance of resilience as a cornerstone of success and profitability in an increasingly globalized and volatile business environment. The findings of this study reveal the practical benefits of integrating DT technologies and SCDM strategies into supply chain operations. These technologies provide real-time monitoring, predictive analytics, and rapid response capabilities, enabling firms to anticipate and mitigate disruptions more effectively. As a result, organizations can build supply chains that are robust, resilient, adaptable, and flexible, essential in navigating the complexities of today's markets. Moreover, this research sheds light on the previously unexplored moderating role of strategic fit (SF) in enhancing the effectiveness of DT technologies and SCDM strategies. The study demonstrates that SF plays a critical role in aligning these capabilities with a firm's strategic objectives, thereby increasing the supply chain's responsiveness to disruptions and its overall resilience. By incorporating the Dynamic Capabilities View (DCV), this study offers a nuanced perspective on the adaptability required for successful disruption management. For managers and executives in manufacturing organizations, the insights gained from this study provide a clear roadmap for adopting DT technologies and SCDM strategies, highlighting their potential to transform SCR. Future supply chain practitioners can use the presented guidelines as a road map to traverse the constantly shifting landscape, paving the way for supply chain ecosystems that are more robust, responsive, future-proof, and resilient. Ultimately, this research advances theoretical understanding and equips industry leaders with the knowledge needed to build more robust, responsive, and resilient supply chains, ensuring long-term competitive advantage in a dynamic global market.

Appendix 1. Sample for Interviews

Participant	Gender	Organization Type	Experience (years)	Position
1	M	University	> 16	Professor
2	M	University	> 17	Professor
3	F	University	> 15	Professor
4	F	University	> 15	Professor
5	M	University	> 18	Professor
6	M	Mechanical	> 10	Operations Manager
7	F	Textiles and Apparel	> 10	Senior Manager (Manufacturing)
8	M	Electronics	> 14	Supply Chain Manager
9	M	Mechanical	> 9	Production Manager
10	F	Electronics	> 14	General Manager
11	M	Textiles and Apparel	> 12	Supply Chain Manager
12	M	Electronics	> 16	Chief Operations Officer
13	M	Mechanical	> 8	Senior Manager (Manufacturing)
14	F	Electronics	> 15	Country Manager
15	M	Textiles and Apparel	> 13	Production Manager

Appendix 2. Measurement Scales

Construct	Items	Statement	Adapted from
DT	DT1	Our organization has created AI-powered engines to optimize production, quality control, and forecasting processes	Kamble et al. (2022), Bhandal et al. (2022), Liu et al. (2021)
	DT2	We use virtual prototyping and 'what-if' analysis to test new products, designs, and production scenarios	
	DT3	We capture real-time data from our machines and equipment and remotely monitor and control them using sensors	
	DT4	We use blockchain technology and smart contracting to secure the security and traceability of our supply chain and automate payment and delivery processes	
	DT5	Our machines and equipment are linked together to form a single system with a high degree of automation	
	DT6	We use cloud-based collaboration solutions to streamline our workflow and communication	

Appendix continued

Construct	Items	Statement	Adapted from
SCDM strategies	SCDM	We have a number of suppliers and backup plans to guarantee a steady supply of materials	Carvalho et al. (2012), Ivanov (2017a), Ivanov (2017b), Spiegler et al. (2012), Ivanov (2018), Olivares-Aguila and ElMaraghy (2021), Ivanov (2020), Min (2019), C. Lee et al. (2017)
	SCDM2	We examine previous sales information and market trends to predict demand accurately and reduce volatility	
	SCDM3	Our extensive network of transportation choices and real-time tracking systems allow us to respond to shifting logistical requirements, optimize transportation routes, and minimize delays	
	SCDM4	We use automation and cutting-edge technologies to simplify processes and boost production	
	SCDM5	Our manufacturing facilities are built to expand and adapt capacity in response to changes in demand	
	SCDM6	We have implemented systems and procedures to guarantee regular and dependable lead times	
	SCDM7	We use real-time inventory tracking to ensure that products are available for timely order fulfillment	
	SCDM8	We use condition monitoring tools to anticipate potential maintenance problems	
	SCDM9	We periodically conduct security audits and employ authentication and encryption protocols	
SF	SF1	We regularly review and modify our investment methods to maximize our return on investments	Gunasekaran et al. (2001), Kleijnen and Smits (2003), Hum and Parlar (2014), Huan et al. (2004)
	SF2	We aim to increase the productivity while preserving a healthy level of net profit	
	SF3	We focus on reducing order fulfillment cycle time to enhance customer satisfaction	
	SF4	We use inventory management techniques to increase inventory turnover and reduce obsolescence	
	SF5	We streamline our procedures and work with suppliers and customers to reduce the cash-to-cash cycle time	
	SF6	We constantly strive to improve our service level through process improvement and customer feedback	

Appendix continued

Construct	Items	Statement	Adapted from
	SF7	We evaluate order fill rate data to find areas for improvement in order processing and fulfillment	
SCR	SCR1	We use different suppliers or sources depending on their availability, cost, quality, and reliability to reduce the risk of SCDs and optimize our procurement	Pettit et al., (2013), Pettit et al., (2010), Jain et al., (2017), Yao and Costes, (2018), Eryarsoy et al., (2022), Brusset and Teller, (2017)
	SCR2	We adjust our design, processes, and operations to meet structural shifts, disruptions, and changing customer behavior to improve our resilience, agility, and competitiveness	
	SCR3	We forecast and prepare for future demand, supply, and price fluctuations to optimize our inventory levels, production capacity, and logistics operations and avoid stock outs, excess inventory, or missed sales opportunities	
	SCR4	We restore our normal operations and performance after a SCD by implementing contingency plans, backup systems, and recovery procedures	
	SCR5	We work with our suppliers, customers, and partners to share information, resources, and risks to improve our supply chain efficiency, effectiveness, and innovation	
	SCR6	We monitor and track our supply chain activities, performance, and status using data, analytics, and technology to enhance our decision-making, responsiveness, and transparency	

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Key Questions for Further Reflection

1. How do digital twin technologies directly influence supply chain resilience (SCR)?
2. What role do supply chain disruption mitigation strategies play in enhancing supply chain resilience?
3. Does strategic fit moderate the relationship between digital twin technologies and supply chain resilience?
4. Does strategic fit moderate the relationship between supply chain disruption mitigation strategies and supply chain resilience?
5. How can the integration of digital twin technologies and SCDM strategies, guided by strategic fit, create more resilient supply chains in manufacturing organizations?

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