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Configuring supply chain governance and digital capabilities for resilience: Evidence from the manufacturing sector

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A B S T R A C T

In an increasingly complex and turbulent global environment, achieving resilience in manufacturing supply chains has become a critical strategic priority. Drawing on a sample of 300 manufacturing firms, this study examines both the net and configurational effects of supply chain governance mechanisms and dynamic digital capabilities on supply chain resilience. Using structural equation modeling and fuzzy-set qualitative comparative analysis (fsQCA), the findings reveal that: Contractual governance, relational governance, digital sensing capability, digital resource integration, digital-driven innovation, and digital-enabled business capabilities each have a positive impact on manufacturing supply chain resilience. In the overall sample, only relational governance demonstrates a relatively strong individual effect, while none of the six governance or digital capability dimensions serve as necessary conditions for high resilience in subsample analyses. For high-tech manufacturing firms, two resilient configurations are identified: 1) basic digital enablement with strong governance synergy, and 2) advanced digital enablement with strong governance synergy. In contrast, non-high-tech firms exhibit three distinct resilient configurations: 1) digital integration–driven, 2 advanced digital enablement with relational governance dominance, and 3) dual-core digital enablement with robust governance synergy. These insights provide nuanced theoretical contributions and practical implications for configuring governance and digital strategies to build sustainable supply chain resilience in the manufacturing sector.

A R T I C L E   I N F O

Keywords:
Manufacturing supply chain;
Resilience;
Supply chain governance;
Dynamic digital capability;
Fuzzy-set qualitative comparative analysis (fsQCA);
Configuration analysis

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1. Introduction

Manufacturing supply chain resilience (MSCR) is intrinsically linked to national security and economic development. Over the past decade, manufacturing supply chains (MSCs) have been increasingly vulnerable to external shocks, including trade protectionism, technological embargoes, and global public health crises. Unanticipated disruptions—such as core component cut-offs due to sanctions—can severely impair operational performance and even threaten the survival of individual firms, triggering cascading effects across the entire supply chain network. The specialization and fragmentation of production processes have further increased systemic risks, exacerbated by the need for tighter coordination and real-time demand-supply matching.

Numerous real-world cases underscore the disruptive potential of such events. For instance, the 2023 strikes in France—sparked by public dissatisfaction with pension reforms—caused major disruptions to both maritime and inland freight flows. Similarly, the COVID-19 pandemic dramatically reshaped global supply chain structures. According to Dun & Bradstreet, up to 94 per cent of the world's top 1,000 companies experienced supply chain disruptions, with the automotive and electronics manufacturing sectors being the most affected. While some disruptions may be manageable in the short time, others pose significant threats to the long-term resilience and competitiveness of MSCs. As a result, the development of robust, long-term resilience mechanisms has garnered increasing attention from both industry practitioners and academic researchers.

Largely, previous organizations relied significantly on supply chain governance (SCG) to mitigate disruptions and build resilient supply chains. Specific SCG measures can fall into two broad categories, namely contractual governance and relational governance. The former aligned with transaction cost theory emphasizes the use of contracts to safeguard against opportunism and conflict. The latter grounded in the social exchange theory (SET) and relational exchange theory, aiming to curb opportunism by instituting relationship-based norms and developing trust – building mechanisms. Nevertheless, the inherent looseness of supply chain structures, coupled with the bounded rationality of decision-makers, amplifies the vulnerability to opportunistic risks. This, in turn, undermines the efficacy of supply chain governance, particularly within dynamically evolving environments.

According to the dynamic capabilities view (DCV) proposed by Teece *et al*., organizations often develop dynamic capabilities to mitigate the impact of unexpected risks on supply chain performance [1], particularly under highly competitive pressures and in dynamic environments, by integrating, building, and reconfiguring resources. Based on Dubey *et al*. [2] we argue that dynamic capabilities are multi-faceted, encompassing both the ability to capture new opportunities and risks and the ability to utilize available resources and technologies to address them. Crucially, firms are not necessarily strong across all types; the appropriate response to supply chain disruptions is to leverage the specific competencies in which they excel. Moreover, digital-enabled technologies as a key option in crisis scenarios play a significant role in improving supply chain resilience. To maintain competitiveness during turbulent times, organizations are required to develop their digital capabilities for enhancing supply chain resilience to remain competitive in the digital era.

Integrating the above two perspectives, MSCR features multiple concurrent causalities and encompasses different levels. This necessitates a configuration perspective to uncover the multiple equivalent configurations that build supply chain resilience. To better address issues such as “enterprises being ‘willing but unable’ when facing risks” or “possessing strong dynamic capabilities yet remaining "powerless to reverse the situation”, this study incorporates supply chain governance into the configuration analysis framework and matches it with dynamic capability. This approach aims to explore the influencing factors and their configuration mechanisms of supply chain resilience. The main problems to be solved in this paper are as follows.

- How does supply chain governance initiative and dynamic digital capabilities affect MSCR?
- Which factor configurations may constrain MSCR?
- What paths to achieving high MSCR with different technological levels?

Compared with the extant literature, this study makes three primary contributions:

- We develop and empirically validate a theoretical framework elucidating the synergistic mechanisms through which supply chain governance and dynamic capabilities jointly enhance MSCR.
- Distinguishing from net effect studies, we innovatively adopted the fsQCA approach to explore the configuration effect of multiple factors on MSCR, in response to the call from academics for mixed studies of mainstream statistical methods and qualitative comparative analysis methods.
- Considering the "causal complexity" behind supply chain resilience management, the equivalent driving mechanisms for achieving high MSCR (e.g., different routes the same destination) are revealed, which can provide an actionable scenario framework for enhancing MSCR.

The rest of this study is organized as follows. Section 2 presents the theoretical framework and the hypotheses development. Section 3 outlines the research methodology, including the questionnaire design and data-collection process. In Section 4, we conduct an empirical analysis of MSCR using SEM, while Section 5 examines the MSCR mechanism through a hybrid approach combining NCA and fsQCA. Finally, the main findings and conclusions are presented and discussed in the final two Sections.

2. Theoretical framework and research hypotheses

2.1 Supply chain resilience (SCR)

SCR refers to the ability of interconnected supply chain enterprises to maintain their own system stability and avoid chain breakage when exposed to internal and external shock risks, as well as the ability to anticipate and react to future uncertainty [3]. Subsequently, some scholars have further extrapolated this concept across the dimensions: recovery from disruptions, risk resistance, and complexity adaptation [4]. The SCR measurement metrics can be categorized into four groups, respectively: core capability indicators (e.g., supply chain flexibility, visibility agility), recovery metrics (degree/time to restore original state), financial performance, and network topology metrics [5, 6].

Currently, the research paradigm on SCR strategies has evolved from "static to dynamic" and" traditional to complex". Early studies grounded in the static resource-based theory (RBT), emphasized cooperation production, supply chain network structure design, supply chain redundancy design, contract design and governance [7], etc. To address RBT's limitations in analyzing technological shifts, changing consumer preferences, and dynamic competition, scholars have begun to apply DCV to reveal the antecedents, processes and outcomes of SCR [8]. The DCV posits that mere possession of scarce resources is insufficient for competitive advantages—these resources must be reconfigured and deployed effectively.

2.2 SCG and MSCR

Contractual governance relies on written agreements to regulate relationships among manufacturing supply chain members. These contracts include explicit terms that clearly define the responsibilities and obligations of each party [9]. When unexpected disruptions occur, clearly defined responsibilities help prevent task shirking and interpersonal conflicts. They also facilitate effective information sharing through standardized parameters such as price, quantity, logistics, and quality, thereby enhancing the efficiency of uncertainty management [10]. Moreover, comprehensive contracts address a broad spectrum of potential risks and corresponding countermeasures. This provides partners with predetermined rules and procedures, which in turn reduces decision-making uncertainty and promotes supply chain stability. Legally enforceable contracts also ensure compliance, as violations trigger timely corrective actions or penalties. This mechanism deters opportunistic behavior during crises and strengthens the supply chain's systemic resistance to risk [11].

Hypothesis H1a: Contractual governance positively affects MSCR.

Relational governance emphasizes coordinating each other's behaviors and developing long-term relationships, through the construction of social mechanisms such as trust, commitment and reciprocity [12]. As a cornerstone of social exchange, trust motivates supply chain partners to share critical information and resources, facilitating joint actions for rapid operational adaptation [13]. Consequently, institutionalizing trust mechanisms is pivotal for cultivating risk-resilient manufacturing supply chain. Relational commitment as another ingredient of SET, instills confidence in manufacturing supply chain members, put forth the essential effort and enhances MSCR by creating reciprocally beneficial exchanges [14]. According to SET, reciprocity is mutual exchanges that partners consider fair and provide long term gratification because behavior by an exchange partner will encourage reciprocal action by other partners. From a long-term view, reciprocity mechanisms can significantly enhance MSCR by facilitating resource sharing, risk sharing, and collaborative innovation, enabling partners to better cope with uncertainties [15, 16].

Hypothesis H1b: Relational governance positively affects MSCR.

2.3 Dynamic digital capability and MSCR

Digital capability is commonly defined as the abilities endowed by digital technologies that respond quickly to environmental changes. Following Teece *et al*. [17] and Sousa-Zomer *et al*. [18], a defining attribute of digital technologies amid continuous disruption is their proactive environmental scanning capability. Digital sensing capability refers to an organization's ability to collect, analyze and interpret digital information from its internal and external environments [19]. This helps with scanning the external environment for unexpected disruptions and taking preventive actions. For instance, manufacturers with strong digital sensing can predict a sudden surge in demand for a particular product and adjust production accordingly. They can also minimize the impact of disruptions on their supply chain, by proactively managing inventory, adjusting production schedules, and collaborating with suppliers. Hence, digital capabilities must possess the seizing ability.

Hypothesis H2a: Digital sensing capabilities positively affect MSCR.

Sirmon and Hitt [20] argue that resource integration refers to an organization's ability to create economic value by assembling, combining, optimizing and rationally allocating the internal and external resources. Digital resources are a key source for building dynamic digital capabilities. This dimension focuses on the ability to combine and optimize digital resources across the entire manufacturing supply chain, involving integrating data from different systems and processes to create a unified operational view [21]. When manufacturers are capable of effectively integrating digital resources, they can eliminate redundancies, enhance communication among partners, and respond swiftly to changes, resulting in improved coordination and adaptability amid disruptions. Digital resource integration capability focuses on data management, resource orchestration and process integration, whereas digital-driven innovation capability concentrates on how digital technologies can be leveraged to drive innovation [22]. In the manufacturing sector, digital-driven innovation refers to embedding digital technologies into the manufacturing process to drive improvements and create new opportunities [23]. This form of innovation goes beyond simply adopting digital tools, it entails a fundamental transformation in how manufacturing operations are conceived, executed, and managed. For instance, Internet of Things (IoT) sensors collect real-time data from devices and installations, providing valuable insights to make decisions for optimizing processes, predicting maintenance needs and addressing quality deviations. What's more, the innovative application of blockchain technology enables greater transparency and traceability in manufacturing supply chains, thereby reducing the risk of disruption.

Hypothesis H2b: Digital resource integration capacity positively affects MSCR.

Hypothesis H2c: Digitally- driven innovation capability positively affects MSCR.

In practice, numerous manufacturing firms have successfully leveraged digital technology to achieve business transformation, and digital-driven business capability has gained significant attention from organizational scholars [24]. As an important component of dynamic digital capability, digital-driven business capability refers to an organization's proficiency in utilizing digital technologies, data resources and digital mindset to drive business growth, optimization and transformation [25]. This capability manifests in various ways, including innovating business models, formulating more effective marketing strategies, expanding sales channels and customer bases, and optimizing business resourcing through various digital means [26, 27]. For instance, supported by digital technologies, firms can generate new value growth through business transformation, collaboratively address uncertainties and risks by breaking down information silos, and improve operational efficiency by creating a more agile MSCs network. It further helps to enhance MSCR through improved agility and resistance.

Hypothesis H2d: Digitally-driven business capability positively affects MSCR.

The SEM-based theoretical model is shown in Fig. 1. Moreover, it's clear that a dynamic process of developing supply chain capacity can enhance MSCR. However, some cases disclose that not all supply chains with dynamic digital capabilities are necessarily capable of actively tackling supply chain disruptions. Taking Motorola, once a leading player in the mobile phone industry, as an example, exhibited poor coordination with suppliers during the product design and manufacturing phases and was incapable of responding promptly to market demands. Eventually, it underwent multiple acquisitions and restructurings.

This implies that even if an enterprise possesses outstanding dynamic digital capabilities, without choosing effective governance initiatives, it can still lead to the enterprise's cessation of operation. Consequently, scholars have increasingly recognized that the dominant role of SCG initiatives should not be ignored and have attempted to deeply explore the internal mechanisms of MSCR from the relationship management perspective [28]. As a matter of fact, dynamic digital capabilities can provide more advanced tools and means for supply chain governance. Conversely, appropriate supply chain governance initiatives can facilitate the effective application and integration of digital resources, thereby avoiding resource waste and information silos. These two dimensions exhibit a superior synergistic effect, which has not been adequately considered in existing research [2, 29]. Therefore, this paper proposes a conceptual model of MSCR from the configurational perspective, as presented in Fig. 2.

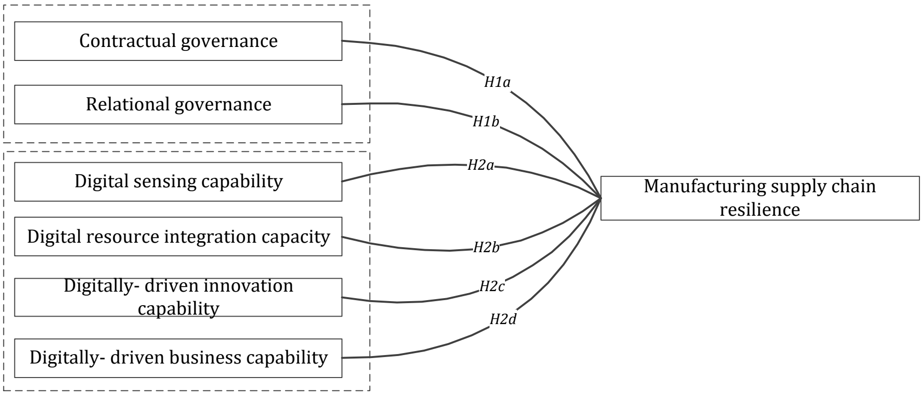

Fig. 1 The SEM-based theoretical model

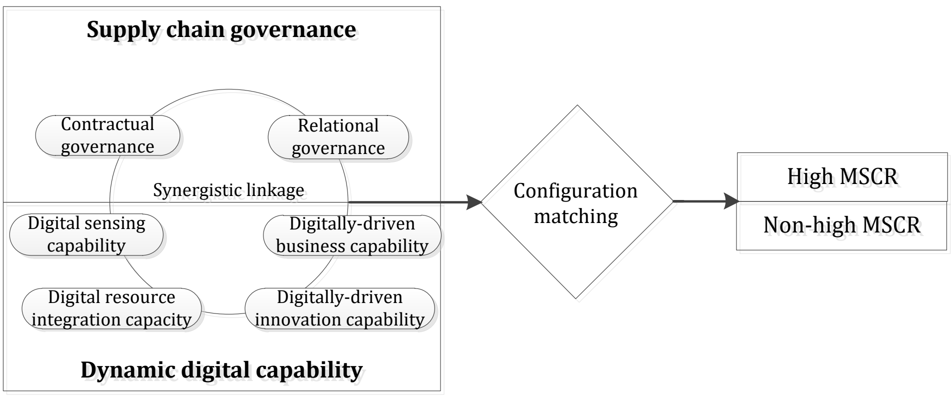

Fig. 2 Conceptual model based on a configurational perspective

3. Research methodology

3.1 Method of hybrid NCA and fsQCA

As a case-oriented method, Qualitative Comparative Analysis (QCA) is designed to capture the causal complexity and interdependence among multiple conditions in configurational research. Among its variants, fsQCA has emerged as a mainstream analytical paradigm, as it accommodates continuous variables and partial membership, thereby enhancing both analytical practicality and generalizability. However, fsQCA primarily identifies configurations of antecedent conditions associated with an outcome, offering qualitative insight rather than quantitative assessment of the degree to which specific conditions are necessary. Especially in fuzzy-set contexts, necessity is not a binary concept ("yes" or "no") but rather a matter of degree. To address this limitation, Necessary Condition Analysis (NCA) can be integrated with fsQCA. NCA quantitatively assesses the extent to which a condition is necessary for a particular outcome, thereby complementing fsQCA and enriching the explanatory power of social science theories. This hybrid approach significantly enhances both descriptive precision and theoretical robustness.

This study begins by using SEM to explore the effects of dynamic digital capabilities and SCG initiatives on MSCR. Following this, the NCA method is employed to identify whether certain dimensions of digital capabilities or SCG initiatives constitute necessary conditions for high MSCR, and if so, to what degree. Concurrently, the QCA approach is applied to verify the robustness of these necessary condition findings. Finally, fsQCA is utilized to delve into the complex causal mechanisms through which dynamic digital capabilities and SCG initiatives shape high levels of MSCR. A heterogeneity analysis is also conducted across industries with differing levels of technological sophistication. As a configurational method, fsQCA conducts cross-case comparative analysis from a holistic perspective. It aims to uncover which combinations of conditions lead to the presence—or absence—of the outcome. This approach is well-suited for examining the multifactorial and complex formation mechanism of MSCR.

3.2 Questionnaire design

We employ the questionnaire survey data from manufacturing firms to study the impact of the configuration mechanism between dynamic digital capabilities and SCG initiatives on MSCR. To ensure the sample reliability and validity, this questionnaire mainly draws on the mature content that has been published in domestic and foreign literature (as shown in Table 1). Primary data collection utilized a five-point Likert scale, where values ranging from 1 ("strongly disagree") to 5 ("strongly agree"), capturing progressive agreement levels across all variables.

Table 1 Measurement items of each variable

Constructs	Measurement items	References
Contractual governance (CG)	CG1: Sign an agreement with supply chain partners. CG2: The agreement improves product quality. CG3: The agreement ensures that both sides understand the product. CG4: The agreement improves communication efficiency with partners.	[30, 31]
Relational governance (RG)	RG1: Have close cooperative relationship with supply chain partners. RG2: Share the long-term and short-term plans with partners. RG3: Trust the commitments made by partners.	[31]
Digital sensing capability (DSC)	DSC1: Accurately predict industry technology trends leveraging digital technology. DSC2: Fully track the changes and trends of customer needs leveraging digital technology. DSC3: Identify opportunities brought by competitive changes leveraging digital technology. DSC4: Identify opportunities brought by supply and demand changes (e.g., changes in supplier quotations, emerging supply markets, and changes in consumer preferences) leveraging digital technology.	[2]
Digital resource integration capability (DRIC)	DRIC1: Be able to effectively achieve the transfer and combination of digital resources. DRIC2: Be able to effectively allocate and utilize data resources. DRIC3: Be able to obtain abundant data resources from the supply chain network.	[22, 32]
Digitally-driven innovation capability (DIC)	DIC1: Have a high tolerance for losses stemming from innovation. DIC2: Use digital means to introduce more new products and services. DIC3: Use digital means to continuously improve the manufacturing process. DIC4: Use digital means to transform production mode at a faster speed.	[33]

Table 1 (Continuation)

Digitally-driven business capability (DBC)	DBC1: Enabled by digital technology, we can promptly execute countermeasures once major competitors target our customers with promotional activities. DBC2: Digital technology empowers us to execute timely and effectively marketing strategies. DBC3: Leveraging digital technology, we can proficiently acquire and assimilate fundamental and pivotal business technologies. DBC4: Digital technology facilitates the continuous development of initiatives aimed at reducing production costs. DBC5: Digital technology allows for the efficient organization of production processes. DBC6: Digital technology enables the efficient allocation of resources across production and other departments.	[25]
Manufacturing supply chain resilience (MSCR)	MSCR1: Preparedness for potential disruption impacts across the supply chain. MSCR2: Rapid respond to supply chain disruption events MSCR3: Maintain basic business operations in the event of disruption. MSCR4: Preserve the desired level of control over structure and function in the event of disruption. MSCR5: Recover speed to its original state after being disrupted. MSCR6: Adaptive transformation to an improved post-disruption state.	[34]

3.3 Sample selection and data collection

To empirically test the proposed hypotheses, data were collected from manufacturing firms in China. The survey participants included top and middle managers, and confidentiality of their responses was strictly maintained. The qu items were adapted from validated measurement scales in prior research, with item wording carefully adjusted to align with our research context. A pilot test was conducted with 20 enterprises to finalize the questionnaire, which was refined for a large-scale distribution. These procedures ensured reliability and validity. Data collection employed both field research and online distribution methods, yielding a total of 300 valid responses, including 102 from field surveys. Sample characteristics are summarized in Table 2, while Table 3 presents the descriptive statistical for all variables.

The classification of industry technology level follows the OECD's high-tech industry classification standard, aligned with China's Industrial Classification of National Economy (GB/T 4754-2017). According to this criterion, manufacturing sectors with relatively high R&D intensity are categorized as high-tech manufacturing industries. These encompass six major categories: aerospace vehicle and equipment manufacturing, electronic and communication equipment manufacturing, computer and office equipment manufacturing, pharmaceutical manufacturing, medical equipment and instrument manufacturing, and information chemical manufacturing. The remaining industries are classified as non-high-tech manufacturing industries.

Table 2 Descriptive statistics of the sample

	Sample characterization	Norm	Sample size	Percentage (%)
Firm information	Firm size (no. of employees)	≤ 50	7	2.3
		51-200	63	21.0
		201-500	114	38.0
		501-1000	74	24.7
		> 1000	42	14.0
	Firm age	1-3	10	3.3
		4-6	33	11.0
		7-9	62	20.7
		≥ 10	195	65.0
	Industry technology level	High-technology	104	34.7
		Non-high-technology	196	65.3
Respondent information	Educational attainment	Below bachelor's degree	18	6
		Bachelor's degree	235	78.3
		Master's degree or above	47	15.7
	Current position	Top manager	20	6.7
		Middle manager	280	93.3

Table 3 Descriptive statistical analysis of variables

Statistical indicators	Antecedent condition						Outcome variable
	Supply chain governance		Dynamic digital capability				Manufacturing supply chain resilience
	CG	RG	DSC	DRIC	DIC	DBC	/
Average value	4.242	4.231	3.970	4.148	3.961	4.176	3.968
Median value	4.500	4.667	4.250	4.667	4.200	4.500	4.333
Standard deviation	0.770	0.874	0.944	0.921	0.806	0.890	0.927
Minimum value	1.250	1.333	1.250	1.333	1.400	1.500	1.500
Maximum value	5.000	5.000	5.000	5.000	5.000	4.833	5.000

4. Empirical analysis of MSCR mechanism based on SEM

4.1 Reliability and validity

The reliability of the scale data is typically assessed using two indicators: internal consistency coefficient (Cronbach's α coefficient) and composite reliability (CR value). In this study, SPSS 26.0 software was used for analysis. The results presented in Table 4 show that the Cronbach's α and CR value for all variables exceed 0.8, indicating that the scale used in this study has good reliability.

Validity analysis includes four aspects: content validity, structural validity, convergent validity, and discriminant validity. Content validity has been addressed previously. Structural validity, convergent validity, and discriminant validity were examined using confirmatory factor analysis (CFA) with Amos 26.0 software for testing. Prior to CFA, KMO and Bartlett's sphericity test were firstly carried out by using SPSS 26.0 software. The results of the KMO and Bartlett's sphericity test indicate that the data sample is suitable for factor analysis (the KMO value is $0.917 > 0.6$; the Bartlett's sphericity test is significant with $p = 0.000 < 0.05$). CFA results demonstrated a good model fit: $x^2/df = 1.128 < 3, RMSEA = 0.038 < 0.05, GFI = 0.914, NFI = 0.922, CFI = 0.990, IFI = 0.990, TLI = 0.989$, all of which are greater than 0.9, indicating that the model overall fit was good, and the scale had excellent structural validity. The factor loadings of each question item were all greater than 0.6, and the combined reliability CR was greater than 0.8, indicating that the aggregation validity of the scale basically met the standard. The square root of AVE for each variable was greater than the correlation coefficient of that variable with the rest of the variables, indicating that the scale used in this study had good discriminant validity.

Table 4 Reliability and validity analysis

	CG	RG	DSC	DRIC	DIC	DBC	MSCR
CG	0.579						
RG	0.371***	0.644					
DSC	0.379***	0.352***	0.673				
DRIC	0.292***	0.394***	0.371***	0.69			
DIC	0.321***	0.368***	0.382***	0.34***	0.555		
DBC	0.295***	0.353***	0.297***	0.346***	0.336***	0.676	
MSCR	0.462***	0.566***	0.485***	0.508***	0.513***	0.533***	0.641
Cronbach's Alpha	0.845	0.844	0.891	0.867	0.861	0.926	0.914
CR	0.846	0.845	0.892	0.869	0.862	0.926	0.914
The square root of AVE	0.761	0.802	0.820	0.831	0.745	0.822	0.801

4.2 Common method bias test

The data samples used in this study are mainly micro-level data obtained through research. However, a single data source has the potential to cause common method bias and thus affect the research results. In view of this, we apply one-way validation factor analysis to test the data for common method bias using MSCR as a latent factor. As can be seen in Table 5, compared to the original fitted model, the model after the one-way validated factor analysis was poorly fitted and did not meet the reference standard; therefore, this study does not suffer from a serious common method bias problem.

Table 5 Common method bias test

Indicator	One-way validated factor analysis model	Original fitted model	Reference standard
x^2/df	7.285	1.128	<3
GFI	0.510	0.914	>0.9
RMSEA	0.145	0.038	<0.08
CFI	0.504	0.990	>0.9
NFI	0.469	0.922	>0.9
IFI	0.506	0.990	>0.9
RMR	0.130	0.038	<0.05

4.3 Hypothesis testing

We used Amos 26.0 to conduct the structural equation model test. Consequently, we got the path analysis diagram shown in Fig. 3, and the specific results are shown in Table 6. As can be seen from Table 6, CG($\beta = 0.134, p = 0.015$), RG($\beta = 0.247, p = 0.000$), DSC($\beta = 0.165, p = 0.002$), DRIC($\beta = 0.143, p = 0.010$), DIC($\beta = 0.185, p = 0.001$), DBC($\beta = 0.242, p = 0.000$) all have a significant positive impact on MSCR. Thus, hypotheses H1a~H2d are all supported.

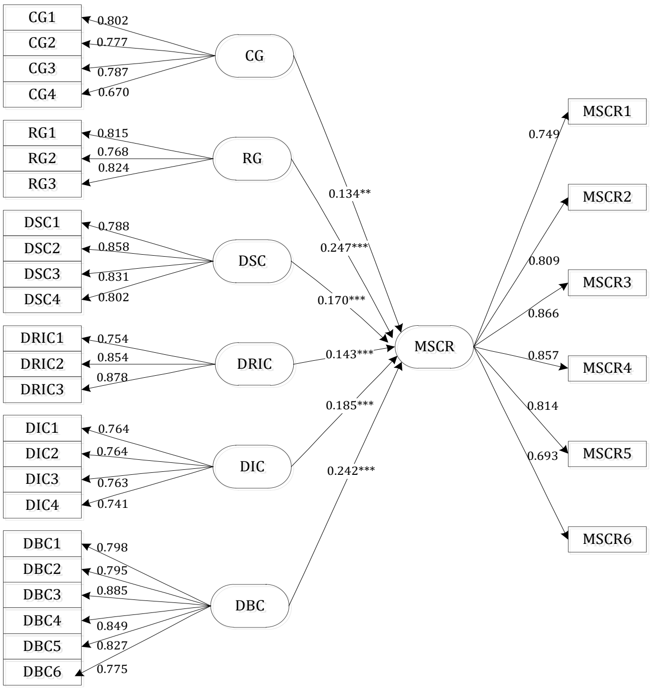

Fig. 3 SEM path diagram

Table 6 Hypothesis testing results

Hypothetical path	Hypothesis	Unstandardized coefficient	Standardized coefficient	S.E.	C.R.	P
CG → MSCR	H1a	0.186	0.134	0.077	2.423	**
RG → MSCR	H1b	0.248	0.247	0.059	4.179	***
DSC → MSCR	H2a	0.165	0.170	0.054	3.089	***
DRIC → MSCR	H2b	0.129	0.143	0.050	2.600	***
DIC → MSCR	H2c	0.201	0.185	0.061	3.302	***
DBC → MSCR	H2d	0.253	0.242	0.056	4.548	***

Notes：** indicates P-value < 0.05；*** indicates P-value < 0.01.

5. MSCR mechanism analysis based on hybrid NCA and fsQCA methods

5.1 Necessary condition analysis

The NCA method adopted in this article can not only identify whether a specific condition is a necessary condition for a certain result but also quantify the effect size of that necessary. The effect size, also termed the bottleneck level, represents the lowest level of a necessary condition required to achieve a particular result, ranging between 0 and 1. Generally, two methods, ceiling regression (CR) and ceiling envelopment (CE), can be used for estimation. A condition is deemed necessary if its effect size (d) is ≥ 0.1 and the permutation-based Monte Carlo simulation test yields a significant result. Table 7 presents the NCA results. Overall, none of the antecedent conditions within dynamic digital capabilities meet both criteria. In terms of SCG, in the total sample, only RG has an effect size greater than 0.1 and a significant result, which is a necessary condition for MSCR with a medium-level effect. For this reason, we conducted a further sub-sample analysis and obtained $d_{CR} = 0.093, d_{CE} = 0.04$ in the high-tech manufacturing sample, and $d_{CR} = 0.038, d_{CE} = 0.046$ in the non-high-tech manufacturing sample. The effect sizes are all less than 0.1, so that CR is not a necessary condition for high MSCR.

Table 8 presents the bottleneck level analysis for antecedent conditions. The results show that there is a bottleneck of dynamic digital capabilities for MSCR level, and to achieve 70 % level (member membership score > 0.7) of MSCR requires 35.1 % level of DBC, 23.5 % level of DIC, and 9.3 % level of RG. No bottleneck effects were found for DRIC, DSC, and CG at this level. However, to reach a high MSCR level of 90 % (membership score > 0.9), higher thresholds are needed: 9.3 % for DRIC, 39.9 % for DBC, 50 % for DSC, 41.2 % for DIC, 9.3 % for RG, and 66.7 % for CG.

In addition, we conducted an analysis of the necessity of individual conditions based on the fsQCA method and further examined the necessary conditions for high MSCR and non-high MSCR in the high-tech and non-high-tech manufacturing industries, and the results are shown in Table 9. The consistencies of the antecedent conditions in the four dimensions of digital dynamic capabilities and the two dimensions of supply chain governance are all less than 0.9, indicating that none of the above eight antecedent conditions are necessary conditions for high MSCR and non-high MSCR.

Table 7 Results of NCA analysis

Antecedent	Estimation method	Ceiling zone	Precision (%)	Effect size	P-value
CG	CR	1.284	96.2	0.098	0.057
	CE	1.708	100	0.130	0.021
RG	CR	1.295	99.0	0.101	0.042
	CE	1.388	100	0.108	0.049
DSC	CR	1.162	99.0	0.095	0.002
	CE	1.535	100	0. 125	0.002
DRIC	CR	1.006	99.0	0.078	0.110
	CE	1.272	100	0.099	0.095
DIC	CR	1.580	98.1	0.133	0.060
	CE	1.932	100	0.162	0.004
DBC	CR	1.539	98.1	0.132	0.095
	CE	2.083	100	0.179	0.000

Notes: (1) The data are the calibrated fuzzy-set membership values. (2) Range of effect size (d): 0 < d < 0.1 is regarded as “small effect”, and 0.1 ≤ d < 0.3 is regarded as “medium effect”. (3) Permutation test (test. rep = 10,000), when p is within the range of less than 0.05, it is significant.

Table 8 Bottleneck level analysis results (%)

MSCR	CG	RG	DSC	DRIC	DIC	DBC
0	NN	NN	NN	NN	NN	NN
10	NN	NN	NN	NN	NN	NN
20	NN	NN	NN	NN	NN	NN
30	NN	NN	NN	NN	NN	NN
40	NN	NN	NN	NN	NN	NN
50	NN	NN	NN	NN	NN	NN
60	NN	NN	NN	NN	NN	NN
70	NN	9.3	NN	NN	23.5	35.1
80	NN	9.3	14.3	9.3	35.3	35.1
90	66.7	9.3	50.0	9.3	41.2	39.9
100	93.3	91.0	92.9	91.0	82.4	95.2

Notes: The analytical method is CR, and NN means "not necessary".

Table 9 Necessary condition test for QCA methodology in high-tech and non-high-tech industries

Antecedent condition		Outcome Variable	
		High MSCR	Non-high MSCR
Supply Chain Governance	CG	0.816 (0.841)	0.599 (0.595)
	~CG	0.417 (0.389)	0.688 (0.672)
	RG	0.714 (0.729)	0.512 (0.553)
	~RG	0.528 (0.562)	0.785 (0.784)
Dynamic digital Capability	DSC	0.778 (0.814)	0.521 (0.583)
	~DSC	0.466 (0.470)	0.780 (0.746)
	DRIC	0.802 (0.711)	0.631 (0.563)
	~DRIC	0.472 (0.623)	0.706 (0.824)
	DIC	0.751 (0.800)	0.478 (0.571)
	~DIC	0.449 (0.450)	0.767 (0.719)
	DBC	0.684 (0.866)	0.535 (0.623)
	~DBC	0.625 (0.463)	0.846 (0.759)

Note: The values in parentheses are the analysis results for non-high-tech manufacturing industries.

5.2 Configuration analysis

Using fsQCA 3.0 software, we analyzed and extracted distinct configurational pathways leading to high MSCR, illustrating the principle of equifinality, where different paths lead to the same destination". A total of 104 valid samples were collected from the high-tech industry. Accordingly, the case frequency threshold was set to 3, the original consistency threshold to 0.8, and the PRI consistency standard to above 0.6. For the non-high-tech industry, the case frequency threshold was set to 4, the original consistency threshold to 0.8, and the PRI consistency standard to above. Core conditions in each grouping were identified by comparing the nested relationship between the intermediate and simple solution via counterfactual analysis: if a grouping appears in both the intermediate solution and the simple solution, it is a core condition, and if it appears only in the intermediate solution, it is an auxiliary condition.

(1) Configurational analysis for high-tech manufacturing industries

Table 10 presents the results following the standard QCA configuration format. We identified two distinct configurations (M1a, M1b, and M2) that consistently generate high MSCR. Notably, each configuration demonstrates a consistency scores exceeding 0.9, signifying their status as sufficient conditions for achieving high MSCR. The overall solution coverage is 0.615, surpassing the 0.5 threshold, which highlights the strong explanatory power of these configurations. To succinctly capture the core attributes and highlight the uniqueness of each configuration, we performed a qualitative analysis of representative cases and took the intensity of SCG and the elementary or advanced dynamic digital capability as the "anchors" for naming the configurations.

Table 10 Sufficiency analysis of condition configuration - High-tech industries

Antecedent condition	High MSCR		
	M1a	M1b	M2
CG	●	●	●
RG	●	●	●
DSC	●	●	⊗
DRIC	●	●	●
DIC		•	⊗
DBC	⊗		●
Consistency	0.937	0.975	0.907
Raw coverage	0.402	0.468	0.237
Unique coverage	0.021	0.105	0.028
Solution consistency	0.953		
Solution coverage	0.615		

Notes: ⊗ and ● respectively indicate that the level of antecedent conditions is not high and relatively high; The large circle represents the core condition, and the small circle represents the auxiliary condition; a blank space indicates that the condition is not important for the generation of results.

a) Configuration M1 *(Elementary digital application—Strong governance synergy type).* Configuration M1 demonstrates that core conditions—CG, RG, DSC and DRIC—jointly drive high MSCR with DBC or DIC serving as auxiliary conditions. In this configuration, the attributes of the high-tech industry highlight the critical role of strong governance. It suggests that focal firms in the manufacturing supply chain should foster both CG and RG to leverage complementary governance advantages. Essentially, digital sensing is the initial detection of digital value, while integration is the optimal combination of value carriers (digital resources). Together, these two capabilities establish a foundational level for extracting digital value, paving the way for more advanced capabilities, such as DIC and DBC.

Configuration M1 comprises two distinct paths:

- Path M1a: The antecedent construct is represented as "CG*RG*DSC*DRIC*~DBC".
- Path M1b: The antecedent construct is represented as "CG*RG*DSC*DRIC*DIC".

Configuration M1a exhibits a consistency score of 0.937, with an original coverage of 0.402 and a unique coverage of 0.021. This configuration accounts for approximately 40.2 % of the cases, primarily in highly regulated sectors such as shipbuilding, aviation, aerospace, and equipment manufacturing. In these sectors, a robust governance structure empowers supply chain partners to navigate complex regulatory and market environments, ensuring compliance and transparency throughout the digital transformation process. In this context, DSC plays a vital role. It enables enterprises to swiftly capture shifts in market demand while providing proactive data support for addressing potential risk events. Additionally, DRIC serves as a collaborative tool for enhancing SCR. By facilitating digital resource integration, it fosters synergistic effects that improve the overall elasticity and stability of the manufacturing supply chain.

Configuration M1b features a consistency of 0.975, an original coverage of 0.468, and a unique coverage of 0.105, explaining the largest number of cases at 46.8 %. These cases are mainly concentrated in industries such as electronic and communication equipment manufacturing, computer and office equipment manufacturing, pharmaceutical manufacturing, and medical instrument and device manufacturing. A notable difference between M1a and M1b is that, M1b incorporates DIC as a auxiliary condition, while M1a includes DBC. This difference can be attributed to significant variations in market environment, product characteristics, and innovation demands between these two industry types. The industries covered by configuration M1b are characterized by rapid technological iteration, intense market competition, and a strong orientation toward mass-market consumer products. In this setting, firms must proactively drive innovation and application of digital technologies to sustain their competitive edge. In contrast, sectors such as shipbuilding and aerospace typically produce highly customized products with stable user demands and longer R&D cycles. Consequently, these industries place less direct reliance on DIC and prioritize developing foundational digital capabilities to ensure product reliability and compliance.

b) Configuration M2 *(Dual-core digital-driven—Strong governance synergy type).* The antecedent construct is "CG*RG*DRIC*DBC*~DSC*~DIC". This configuration indicates that CG, RG, DRIC and DBC are core conditions, while DSC and DIC are absent auxiliary conditions in achieving high MSCR. This configuration yields a consistency of 0.907, with raw coverage of 0.237 and unique coverage of 0.028, explaining approximately 23.7 % of the observed cases. These cases are predominantly situated in the information chemical manufacturing industry, which features long, complex supply chains and high sensitivity to fossil fuel price fluctuations. This configuration highlights the importance of digital optimization and execution across production and operational processes. Specifically, the combined strength of DRIC and DBC facilitates agile resource allocation and rapid response under external shocks, such as war, geopolitical conflict, or abrupt price volatility. These digital capabilities enable supply chain nodes to maintain visibility, redistribute constrained resources, and reconfigure operations in real time. When such capabilities are embedded in a governance structure with CG and RG, firms are better positioned to absorb shocks, contain their propagation, and swiftly restore operational continuity. Therefore, the synergy between strong governance redundancy and dual-core digital capability serves as a critical resilience mechanism against severe external disruptions.

(2) Configurational analysis for non-high-tech manufacturing industries

As shown in Table 11, there are three types of configurations (L1a, L1b, L2, and L3) that contribute to high MSCR. All of their consistencies exceed 0.9, indicating that these configurations are sufficient conditions for achieving high MSCR. Additionally, the solution coverage is 0.697, which is significantly above the threshold of 0.5, demonstrating strong explanatory power. Combined with theory and industry cases analysis, we took DRIC, RG and the elementary or advanced dynamic digital capability as the "anchors" for configuration naming that takes into account both integrity and uniqueness.

Table 11 Sufficiency analysis of condition configuration – non-high-tech industries

Antecedent condition	High MSCR			
	L1a	L1b	L2	L3
CG	•	•	•	
RG		•	●	●
DSC		•		⊗
DRIC	●	●		●
DIC	•		●	⊗
DBC	•		●	●
Consistency	0.959	0.950	0.937	0.910
Raw coverage	0.534	0.511	0.520	0.180
Unique coverage	0.070	0.056	0.056	0.018
Solution consistency	0.917			
Solution coverage	0.697			

a) Configuration L1 *(Digital resource integration dominant type*). This configuration highlights the core role of digital resource integration capability in enhancing MSCR, as it effectively breaks down information silos, facilitates collaboration among stakeholders, and optimizes resources. This, in turn, enhances the decision-making flexibility and market responsiveness of the supply chain, thereby improving the resilience of member enterprises in dynamic market environments.

Configuration L1 comprises two distinct paths:

- Path L1a: The antecedent construct is represented as "CG*DRIC*DBC*DIC".
- Path L1b: The antecedent construct is represented as "CG*RG*DSC*DRIC".

Configuration L1a identifies DRIC as the core condition, with DBC, DIC, and CG serving as auxiliary conditions contributing to high MSCR. The consistency of this configuration is 0.959, with a raw coverage of 0.534 and unique coverage of 0.07. This configuration accounts for approximately 53.4 % of the cases, primarily within the agricultural and food processing sectors. These industries operate in a highly demand-driven market, where seasonal variations and fluctuations in consumer preferences directly influence production and inventory decisions. Moreover, growing societal concerns over food safety highlight the pivotal role of DRIC in enabling real-time monitoring and traceability across the supply chain. DBC and DIC function as auxiliary conditions that support enterprises in optimizing processes and driving innovation. However, in such a responsive market, their effectiveness relies on the foundational support provided by DRIC. Additionally, CG ensures collaboration and compliance among supply chain partners, further enhancing MSCR.

Configuration L1b also identifies DRIC as the core condition, but includes DSC, RG and CG serving as auxiliary conditions. This configuration has a consistency of 0.95, with a raw coverage of 0.511 and unique coverage of 0.056. It accounts for approximately 51.1 % of the cases, primarily within the chemical fiber, rubber and plastic manufacturing, non-ferrous metal smelting, and metal manufacturing sectors. These industries share common characteristics, including complex production processes, high dependence on raw materials, and frequent fluctuations in market demand. Therefore, in practical operational management, on one hand, the focus is on leveraging DRIC and DSC to optimize process flows and enhance market responsiveness, aiming to achieve cost reduction, efficiency improvement, and risk mitigation. On the other hand, the collaborative advancement of CG and RG provides a more comprehensive management framework, enhancing the cooperation efficiency and adaptability of supply chain members.

b) Configuration L2 *(Advanced digital-driven—Relationship-oriented governance synergy type).* The antecedent construct is represented as "CG*RG*DIC*DBC", where CG serves as an auxiliary condition, while the others are considered core conditions. The consistency of this configuration is 0.937, with a raw coverage of 0.52 and unique coverage of 0.056. This configuration accounts for approximately 52 % of the cases, primarily within general and specialized equipment, automotive manufacturing, and electrical machinery and equipment manufacturing sectors. In such an industrial environment with complex products and a highly dependent supply chain, DIC and DBC can effectively work in coordination, drive business process reengineering, and facilitate innovation and optimization in product design, production, and services. This is of vital importance for maintaining a competitive advantage and achieving a high MSCR. Additionally, compared with CG, RG can accelerate knowledge flow and promote collaborative innovation, while CG is more of a support for this relationship. This distinction is particularly significant for understanding the condition configuration in which they jointly achieve high resilience with DIC.

c) Configuration L3 *(Dual-core digital-driven—Relationship-prioritized governance synergy type)*, has its antecedent construct represented as "CG*~DSC*DRIC*~DIC*DBC". The consistency of this configuration is 0.91, with a raw coverage of 0.18 and unique coverage of 0.018. Approximately 18 % of the cases can be explained by this configuration, primarily those in the papermaking, paper products and printing industries, as well as in the manufacturing sectors of cultural, educational, sports and entertainment products. In the digital era, these industries regard the assetization of digital resources as both a foundation and a strategic direction for development. At the same time, real-world cases of digital transformation further underscore the necessity of leveraging digital technologies to optimize operations, enhance customer experience, and improve marketing strategies. Thus, it is evident that DRIC and DBC emerge as the dual-core digital drivers for achieving high MSCR. This configuration also suggests that an RG model should be prioritized to enhance the adaptability and flexibility of manufacturing supply chain by building long-term trust and reciprocity among partners, rather than a CG model that focuses only on short-term compliance.

5.3 Test of robustness

QCA is a set-theoretic approach that is considered robust when slight adjustments to the operation, with subset relationships between the results produced, do not change the substantive explanation of the research findings. We evaluated the robustness of the antecedent configuration that achieves high MSCR by increasing the case frequency threshold and consistency. First, the case frequency thresholds for high-tech manufacturing and non-high-tech manufacturing were adjusted upward by 1, resulting in new configurations that are fundamentally subsets of the original configurations, with no significant changes in core conditions. Second, by increasing the consistency from 0.80 to 0.90, the resulting configurations remained consistent with the original configurations, with no changes in consistency or coverage. The robustness test indicates that the results are robust.

6. Discussion

6.1 Interpretation of findings

This study empirically confirms that supply chain governance and dynamic digital capabilities serve as dual drivers of high MSCR. SEM results show both positively contribute to resilience outcomes, while NCA indicates that no single factor—whether contractual governance, relational trust, or digital innovation— is indispensable, highlighting the causal complexity involved. FsQCA further identifies five distinct high-resilience configurations across high-tech and non-high-tech sectors. These results reveal that resilience does not stem from isolated excellence, but emerges from context-specific combinations of governance and capability elements. High-tech firms tend to benefit from strong governance paired with either foundational or advanced digital enablement, whereas non-high-tech firms rely more on digital resource integration and relational governance. Overall, the findings underscore that high MSCR is shaped by configuration fit and strategic alignment, not from uniform solutions. Firms must tailor strategies to their technological and organizational contexts, embracing configuration logic in place of one-size-fits-all models.

6.2 Theoretical implications

Several theoretical implications are noteworthy. First, in contrast to prior empirical summaries and conceptual models, our study verifies the positive influence mechanism of SCG and dynamic digital capability on enhancing MSCR through SEM. It highlights the critical importance of an organization's dynamic digital capabilities in addressing supply chain risks [2], and also emphasizes the strategic value of effective SCG in securing competitive advantage in volatile environments. These findings enrich our understanding of the logical linkages among the multiple dimensions of SCG, dynamic digital capability, and MSCR.

Second, prior research on SCR has predominantly emphasized the net effects of individual factors, often overlooking how multiple resources and capabilities may interact in a configurational manner to drive resilience. Beyond the conventional SCG initiatives, developing dynamic digital capabilities has emerged as a critical option for building SCR in uncertain and turbulent environments. However, existing studies have seldom investigated the synergistic configuration of SCG and digital capabilities within a complex systems framework. By addressing this gap, the present study offers new theoretical insights that enrich and refine the conceptual foundations of SCR, particularly under conditions shaped by digital transformation.

Finally, this research presents the "causal complexity" of constructing MSCR by identifying multiple, equally effective configurations that lead to high resilience. This finding aligns with Fiss's configuration theory, which posits that similar outcomes can emerge from divergent causal paths [34]. It underscores the industry-specific and context-dependent nature of resilience-building strategies. Firms should adopt a configuration mindset to identify and leverage their core capability combinations to address specific market environments and challenges.

6.3 Managerial implications

This research presents three key managerial implications. First, adapting governance models to industry characteristics is essential. Enterprises are advised to select appropriate governance models based on their technological attributes. The industry heterogeneity analysis reveals no universally applicable conditional configuration, indicating that high-tech and non-high-tech manufacturing sectors follow distinct paths toward achieving high MSCR. Specifically, high-tech industries ought to accentuate the synergy between CG and RG to ensure that all stakeholders remain coordinated amidst technological shifts and market fluctuations. Conversely, non-high-tech manufacturing industries should leverage governance methods suited to their resource profiles and capability structures. Actively fostering trust, commitment, and reciprocity through informal governance can further facilitate the efficient flow of knowledge and resources, thereby enhancing the stability and synergy of the supply chain.

Second, firms should prioritize the development of digital capabilities based on strategic needs. In high-tech sectors, investment should focus on DSC and digital DRIC. DSC enables agile detection of technological trends and shifting market demands, while DRIC enhances the coordination of internal and external data to support supply chain synergy. For non-high-tech manufacturing industry, the strategic priority lies in customer value creation. Here, the emphasis should be placed on developing DBC and DRC. By introducing IoT, big data analysis, and other digital technologies to optimize product design, production processes, and service models, firms can foster business model innovation and improve the responsiveness and flexibility of the supply chain.

Third, managers should adopt a configuration-oriented mindset in decision-making. Rather than relying on single-factor approaches, firms should consider how different combinations of SCG and digital capabilities contribute to MSCR. This study reveals that, equivalent configurations may feature either different core conditions or identical core conditions with varying auxiliary conditions. The existence of such multiple-condition configuration reflects the complexity of MSCR management. Accordingly, firms should avoid blindly replicating successful strategies from other contexts. Instead, they should assess their own technological orientation, resource base, and market conditions to develop adaptive, context-specific capability-governance portfolios.

6.4 Limitations and future research

While this study provides valuable theoretical and practical insights, several limitations should be acknowledged. First, the cross-sectional design limits causal inference, limiting the ability to capture temporal dynamics in resilience development. Future research could adopt longitudinal designs or temporal QCA to explore how configurations evolve over time. Second, resource endowment, particularly the constraints faced by small enterprises, represents a critical contextual factor influencing the feasibility of resilience configurations. Due to the limited representation of small firms in the current sample, conducting a dedicated fsQCA for this subgroup was not feasible. Future research should consider expanding the sample size of small firms and incorporate firm size as a moderating variable to further clarify how resource constraints shape configuration selection and performance. Third, cultural and institutional contexts may influence the effectiveness of relational governance mechanisms such as trust and reciprocity, suggesting the need for cross-cultural comparative studies. Finally, the study focuses on governance and digital capabilities, leaving other potential factors—such as policy support or organizational learning—for future exploration. Addressing these areas may enhance the robustness and generalizability of configuration-based resilience research.

7. Conclusion

This study rigorously examines the dual influence of SCG and dynamic digital capabilities on MSCR by integrating SEM, NCA, and fsQCA. Empirical results confirm that both governance mechanisms and digital capabilities significantly enhance MSCR, however, it also reveals inherent causal complexity: no single factor can ensure resilience alone. Five distinct, context-specific configurations across high-tech and non-high-tech sectors were identified, indicating that resilience emerges from tailored combinations of governance and capability elements rather than uniform solutions. These findings deepen theoretical understanding by framing MSCR as a configurational outcome shaped by the interplay of multiple factors under varying contextual conditions. Managerially, they highlight the imperative for firms to align governance models and digital capability development with their specific industry characteristics and strategic priorities, enabling the creation of context-sensitive strategies to withstand supply chain disruptions. Ultimately, this research moves the resilience discourse forward by demonstrating that strategic alignment and configuration fit—not generic prescriptions—are fundamental to sustaining competitive advantage amid escalating supply chain uncertainties.

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