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Digital Technology-Enabled Configurations for Sustainable Supply Chain Resilience: A Dynamic QCA Study of Chinese Manufacturing Firms

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Abstract

Supply chain resilience (SCR) has become increasingly important for maintaining stable and sustainable manufacturing operations under growing environmental uncertainty. However, existing studies mainly focus on the net effects of individual factors, providing limited understanding of how digitalization interacts with technological, organizational, and environmental conditions in shaping resilience over time. Drawing on the Technology–Organization–Environment (TOE) framework, this study examines how configurations of digitalization, research and development (R&D) investment, return on assets, asset turnover, and industry concentration are associated with supply chain resilience in Chinese manufacturing firms. Using a balanced panel of 300 firm-year observations from 60 Chinese listed manufacturing firms during 2019–2023, this study applies dynamic qualitative comparative analysis (DQCA) to identify multiple configurations associated with high and non-high supply chain resilience. The results show that no single antecedent condition is necessary for high resilience. Five configurations are identified for high SCR and five for non-high SCR, indicating equifinality and configurational asymmetry. The high-SCR solutions include both R&D-centered and digitalization-centered pathways, whereas low digitalization appears in four of the five non-high-SCR configurations. The relative coverage of these pathways changes across 2019–2023, with one digitalization-centered configuration (G2) becoming more prominent in the later years. These findings provide longitudinal configurational evidence on how different combinations of technological, organizational, and environmental conditions are associated with resilience over time.

Keywords: supply chain resilience; digitalization; sustainable supply chain management; Technology–Organization–Environment framework; dynamic qualitative comparative analysis; manufacturing firms

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1. Introduction

Manufacturing supply chains are increasingly exposed to complex and interconnected disruptions arising from geopolitical conflicts, trade frictions, technological changes, and public health emergencies. In recent years, the rise in deglobalization has accelerated the transformation of global industrial chains from efficiency-oriented optimization toward security-oriented restructuring [1,2]. Meanwhile, China's manufacturing sector faces increasing competitive pressure from both developed and developing economies, while environmental uncertainty and operational complexity continue to intensify [3]. Under such circumstances, sustainable supply chain management requires firms not only to pursue

operational efficiency but also to maintain business continuity and adaptive capacity under persistent uncertainty. Supply chain resilience (SCR), referring to the ability of firms to absorb disruptions, recover operational functions, and adapt to environmental changes, therefore constitutes an important capability for maintaining stable and sustainable supply chain operations over the long term.

Digital technology has become an increasingly important enabler of supply chain resilience. Through digital transformation, manufacturing firms can strengthen information-processing capabilities, improve resource allocation, and enhance coordination among supply chain participants [4,5]. Technologies based on data analytics and intelligent algorithms can reduce information asymmetry, break down information silos, and facilitate the transformation of supply chains from traditional linear structures toward more flexible and interconnected networks [6]. Such digitally enabled connectivity is particularly important under uncertain environments, as it enhances visibility, coordination, and responsiveness across organizational boundaries. Nevertheless, digital transformation does not automatically translate into stronger supply chain resilience. Its effectiveness depends on whether digital capabilities are appropriately aligned with firms' technological resources, organizational conditions, operational capabilities, and external environments [7,8]. Digital technology should therefore be understood not merely as an independent technological input, but as an enabling capability whose resilience effects emerge through its interaction with other organizational and environmental conditions.

Despite growing attention to digital transformation and supply chain resilience, important research gaps remain. First, existing research has predominantly examined the net effects of individual antecedents, such as digitalization, technological investment, or organizational resources, on resilience outcomes. This linear perspective provides limited insight into how multiple conditions are jointly associated with resilient supply chains. Because firms differ substantially in their technological capabilities, resource endowments, operating efficiency, and competitive environments, similar levels of resilience may arise from different combinations of conditions. Second, although digitalization has increasingly been recognized as an important driver of supply chain transformation, less attention has been paid to its potentially heterogeneous role across different resilience configurations. Digital capabilities may complement innovation and operational capabilities in some firms, while their relevance may also vary under different resource conditions. Understanding these configurational mechanisms is particularly relevant to sustainable supply chain management because long-term resilience depends on the continuous alignment and reconfiguration of technological and organizational capabilities rather than on isolated investments. Third, existing studies largely rely on static or cross-sectional analyses, making it difficult to explain how resilience-building mechanisms evolve as firms respond to changing external environments. Consequently, how the relative relevance of resource-based and digitally enabled resilience configurations changes over time remains insufficiently understood.

To address these gaps, this study adopts the Technology–Organization–Environment (TOE) framework to examine supply chain resilience as the outcome of interdependent technological, organizational, and environmental conditions. Specifically, digitalization and research and development (R&D) investment represent the technological dimension, return on assets and asset turnover capture organizational resource and operational conditions, and industry concentration reflects the external environmental context. Rather than estimating the isolated net effect of each factor, this study applies dynamic qualitative comparative analysis (DQCA) [9–11]. Building on the set-theoretic and configurational logic of qualitative comparative analysis while incorporating a longitudinal perspective [12,13], DQCA enables the identification of multiple configurations associated with resilience and the examination of how their explanatory relevance changes over time.

Accordingly, this study addresses three research questions: (1) Are any individual technological, organizational, or environmental conditions necessary for achieving high supply chain resilience? (2) What configurations of digitalization, technological investment, organizational resources, and environmental conditions are associated with high supply chain resilience? (3) How do these resilience-building configurations evolve over time, particularly as digital capabilities become increasingly embedded in manufacturing supply chains?

This study makes three contributions. First, it provides a configurational view of supply chain resilience by showing how digitalization and R&D operate within different combinations of organizational and environmental conditions. More importantly, the analysis considers both high and non-high SCR and shows that the two outcomes are associated with distinct configurations rather than mirror-image pathways. Second, by integrating technological, organizational, and environmental conditions within a configurational framework, this study explains how different combinations of capabilities and resources can be associated with comparable resilience outcomes, thereby extending the application of the TOE framework to complex supply chain resilience formation. Third, from a dynamic perspective, this study shows that the relative importance of resilience configurations changes over time. The results reveal the coexistence and changing prominence of R&D-centered and digitalization-centered pathways, providing a more nuanced view of how resilience configurations evolve.

2. Literature Review and Theoretical Framework

2.1. The Concept and Measurement of Supply Chain Resilience

The concept of resilience originates from ecological research and generally refers to a system's ability to absorb disturbances while maintaining its essential functions and structure [14]. It was subsequently introduced into supply chain management to explain how firms and supply chain systems respond to disruptions and restore operational continuity. Early studies primarily emphasized recovery capability, defining supply chain resilience as the ability to return to normal or improved operational states following disruptive events [15].

As supply chain environments have become increasingly complex and uncertain, the conceptualization of supply chain resilience has gradually expanded beyond post-disruption recovery. Subsequent research has incorporated resistance, preparedness, adaptation, and transformation, highlighting that resilience involves not only restoring disrupted operations but also anticipating risks and adjusting resources and processes in response to changing environments [16,17]. More recent studies therefore conceptualize supply chain resilience as a multidimensional and dynamic capability encompassing disruption resistance, recovery efficiency, operational continuity, and adaptive or transformative capacity [18,19].

This broader perspective is particularly relevant to manufacturing firms facing persistent technological, market, and supply uncertainties. From a long-term perspective, resilient supply chains are expected not merely to survive individual disruptions but also to continuously adjust their resource allocation, operational processes, and technological capabilities in response to environmental change. Accordingly, supply chain resilience contributes to sustainable supply chain operations by supporting continuity, adaptability, and renewal over time. Based on this multidimensional understanding, this study evaluates supply chain resilience through five dimensions: resistance capability, recovery capability, operational capability, supply–demand matching capability, and renewal capability.

Digital technologies can support these resilience capabilities by improving information visibility, process monitoring, flexibility, and responsiveness across supply chains [20]. A systematic review and meta-analysis also find an overall positive relationship between

digital transformation and supply chain resilience, while showing that this relationship varies with technological capabilities and contextual conditions [21].

2.2. Drivers of Supply Chain Resilience Under the TOE Framework

Supply chain resilience is unlikely to result from a single organizational attribute. Instead, it emerges from the interaction of technological capabilities, organizational resources, and external environmental conditions. The Technology–Organization–Environment (TOE) framework provides an appropriate theoretical structure for organizing these heterogeneous antecedents. It suggests that organizational outcomes related to technological adoption and application are jointly shaped by technological, organizational, and environmental contexts. At the same time, the resource-based view (RBV) emphasizes that heterogeneous internal resources and capabilities influence firms' ability to respond to uncertainty and sustain competitive and adaptive advantages. TOE provides the overarching structure for organizing technological, organizational, and environmental conditions, whereas RBV helps explain why firms facing similar external conditions may differ in how they combine and deploy internal resources. Integrating the two perspectives therefore allows this study to examine not only which conditions are relevant, but also how heterogeneous resource configurations are associated with different resilience outcomes.

From a technological perspective, digitalization represents a central enabling capability. Digital transformation can improve information transparency, facilitate information sharing, and increase decision-making efficiency by reducing information asymmetry across organizational and supply chain boundaries [22]. Digital technologies also enable real-time information processing, resource optimization, and rapid operational adjustment, thereby enhancing firms' visibility, flexibility, and responsiveness when disruptions occur [23,24]. Importantly, however, digitalization should not be viewed as a universally sufficient condition for resilience. The value generated from digital technology depends on how it is combined with complementary technological and organizational capabilities. Digital capability may complement innovation and operational resources in some firms, while under resource-constrained conditions its relevance may depend more strongly on information-processing and coordination capabilities. R&D investment constitutes another important technological condition. R&D activities facilitate technological accumulation, innovation, and problem-solving capabilities, enabling firms to respond more effectively to unexpected supply- and technology-related disruptions [25]. Unlike digitalization, which primarily enhances connectivity, information processing, and coordination, R&D investment strengthens firms' capacity to generate and apply new technological knowledge. The two technological conditions may therefore play different but potentially complementary roles in resilience formation. Their effects may also depend on firms' organizational resources and environmental contexts rather than operating independently. Configurational studies have examined how combinations of capabilities contribute to supply chain resilience. Jiang et al. [26] identify multiple configurations involving supply chain integration and big data analytics capabilities. Ahmed et al. [27] highlight the role of digital agility, while Gomes and Silva [28] examine the interplay between digitalization and supply chain agility, adaptability, and alignment. These findings support examining how technological capabilities interact with organizational and environmental conditions in shaping resilience.

From an organizational perspective, return on assets (ROA) and asset turnover (AT) reflect firms' internal resource utilization efficiency and operational capability. From an RBV perspective, internal resources and capabilities provide firms with the foundation for absorbing shocks, maintaining operational continuity, and adapting to environmental change [29,30]. ROA reflects firms' ability to generate returns from available resources and indicates the effectiveness of internal resource allocation. Stronger financial performance

may provide firms with greater capacity to mobilize resources, support recovery activities, and invest in resilience-enhancing capabilities following disruptions [31]. Asset turnover, by contrast, reflects the efficiency with which firms use their asset base to support production and supply chain operations. High asset turnover may indicate efficient resource utilization and strong operational responsiveness. However, resilience does not necessarily require maximum efficiency. A relatively lower level of asset turnover may also reflect the presence of operational slack or redundant resources, which can provide buffering capacity during unexpected disruptions [32]. Consequently, the relationship between resource efficiency and resilience may be configurational rather than uniformly positive: both efficient utilization and resource buffering can contribute to resilience when combined with appropriate technological and environmental conditions.

From an environmental perspective, industry concentration, measured by the Herfindahl–Hirschman Index (HHI), reflects the competitive structure and resource conditions faced by firms. Industry environments influence resilience development by shaping competitive pressure, resource accessibility, and strategic choices. A lower level of industry concentration (low HHI) increases competitive pressure, encouraging firms to enhance flexibility, innovation, and responsiveness. Conversely, a higher level of concentration (high HHI) may provide firms with relatively stable market positions and greater opportunities to accumulate financial slack and strategic resources, thereby strengthening their buffering capacity and resilience investment ability [33,34]. Therefore, industry structure represents an important external condition that influences how firms configure resources and capabilities to achieve supply chain resilience.

2.3. Research Gaps

Despite extensive research on supply chain resilience, three gaps remain. First, most studies focus on the independent effects of individual antecedents and rely on linear additive assumptions, which provide limited understanding of how technological, organizational, and environmental conditions work together to shape resilience. Although recent studies have identified configurations associated with supply chain resilience [26,28], further research is needed to examine a broader range of antecedent conditions within an integrated framework. Second, although digitalization has received increasing attention in supply chain research, its role may vary across different combinations of organizational resources and environmental conditions rather than producing the same effect in all firms. Third, existing studies often adopt static or cross-sectional approaches, making it difficult to capture how resilience-building configurations change over time. These gaps call for a longitudinal configurational analysis that examines the interplay of technological, organizational, and environmental conditions and tracks the evolution of resilience-related configurations.

2.4. Theoretical Framework and Research Model

This study develops a configurational framework based on the Technology–Organization–Environment (TOE) perspective and the resource-based view (RBV) to examine how technological, organizational, and environmental conditions are jointly associated with supply chain resilience in manufacturing firms. Digitalization level and R&D investment represent the technological dimension, return on assets and asset turnover represent the organizational dimension, and industry concentration represents the environmental dimension.

These conditions are treated as interdependent rather than independent antecedents. Their effects may differ depending on how they are combined, which is consistent with the principle of equifinality in configurational analysis [10]. In particular, digitalization is

considered an important enabling condition, but its contribution to resilience may depend on the presence or absence of other technological and organizational resources.

The resulting research model is presented in Figure 1. Dynamic Qualitative Comparative Analysis (DQCA) is then used to identify alternative configurations associated with high and non-high supply chain resilience and to examine how the relative importance of these configurations changes over time.

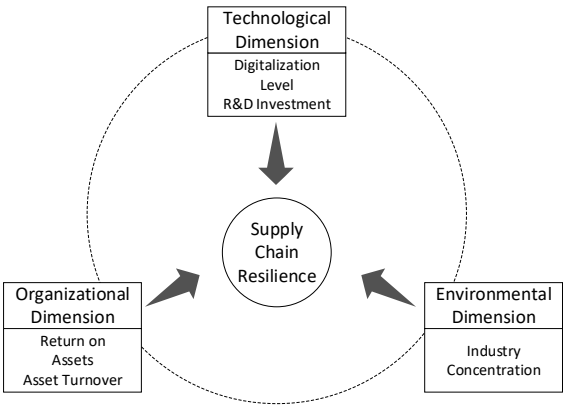


Figure 1. Configurational Research Model of Supply Chain Resilience.

3. Methodology

3.1. Research Design

This study adopts a configurational research design based on the Technology–Organization–Environment (TOE) framework to examine how combinations of different conditions are associated with supply chain resilience in manufacturing firms. The TOE framework is used to identify technological, organizational, and environmental conditions, while the configurational approach is used to examine how these conditions are jointly associated with different resilience outcomes.

Given the complex nature of supply chain resilience, this study employs Dynamic Qualitative Comparative Analysis (DQCA) to examine both configurational relationships and their changes over time [9–13]. DQCA accommodates configurational asymmetry, equifinality, and conjunctural relationships, making it possible to identify multiple configurations associated with high and non-high supply chain resilience. The method is therefore suitable for examining how manufacturing firms combine different resources and capabilities to maintain resilience under uncertain environments.

ChatGPT (OpenAI, GPT-5.5) was used as an auxiliary tool in the development and refinement of R scripts for the dynamic qualitative comparative analysis (DQCA). Specifically, it assisted with drafting selected portions of the code, modifying existing scripts, and addressing coding issues. The authors reviewed and verified the AI-assisted code and remained responsible for conducting the analyses, checking the results, and interpreting the findings.

3.2. Data and Sample

The empirical analysis is based on a balanced panel of 60 Chinese listed manufacturing firms covering the period from 2019 to 2023. This period spans pre-pandemic conditions, pandemic-related disruptions, and the early post-pandemic recovery, providing substantial variation in supply chain conditions for examining temporal changes in resilience configurations. The manufacturing sector is selected because its complex and interconnected supply chain structures make firms particularly exposed to external disruptions and require continuous adjustment of technological, operational, and organizational capabilities.

The sample was constructed through a two-stage purposive sampling procedure. In the first stage, candidate firms were primarily identified with reference to two national pilot and demonstration lists released by the Ministry of Industry and Information Technology of China (MIIT) in 2023: the Pilot Demonstration List for Industrial Internet and the Demonstration List for the Integration of Next-Generation Information Technology and Manufacturing. These lists provide an appropriate initial sampling frame because they contain manufacturing firms actively engaged in digital transformation and industrial digitalization. The two official lists contain 236 and 184 demonstration projects, respectively. After name matching and eligibility screening, 22 listed manufacturing firms in the final sample were direct matches to the two MIIT lists.

In the second stage, additional A-share listed manufacturing firms were purposively selected across different manufacturing subsectors. This supplementary sampling was used to broaden cross-industry coverage, increase variation in digitalization and organizational conditions, and avoid concentrating the sample exclusively on digitally advanced pilot firms. The same eligibility criteria were applied to all sampled firms: firms designated as ST or *ST and firms lacking complete data for the variables used in the analysis during 2019–2023 were not included. The resulting sample consists of 60 firms with complete observations over five consecutive years, yielding 300 firm-year observations. Data were collected from the China Stock Market & Accounting Research (CSMAR) database, the Wind database, and firms' annual reports.

The dataset therefore contains 60 firms as longitudinal panel units and 300 firm-year observations. For the pooled configurational analysis, each firm-year constitutes an analytical observation in truth-table construction. Repeated annual observations of the same firm are retained as part of the longitudinal panel structure rather than treated as separate cross-sectional firms. The panel structure is subsequently evaluated through the between-group and within-group consistency-adjusted measures in the DQCA procedure, while the year-specific analysis contains 60 firm observations in each year.

3.3. Variable Measurement

3.3.1. Outcome Variables: Measurement of the Supply Chain Resilience Indicator System

Supply chain resilience (SCR) is measured using a multidimensional indicator system comprising five dimensions: resistance capability, recovery capability, operational capability, supply–demand matching capability, and renewal capability. Following Su et al. [35], these dimensions reflect firms' abilities to withstand external disturbances, restore performance after disruptions, maintain operational continuity, respond to changes in supply and demand, and renew technological capabilities. The five dimensions are subsequently aggregated using the entropy-weighting method to construct the composite SCR index. Entropy weighting is used to account for differences in the information content of the five dimensions and to avoid imposing arbitrary equal weights on the composite SCR index. The resulting entropy weights are 0.0213 for resistance capability, 0.0164 for recovery capability, 0.6518 for operational capability, 0.0298 for supply–demand matching capability, and 0.2806 for renewal capability.

Resistance capability is measured by the natural logarithm of the ratio of accounts receivable to operating revenue. A lower value indicates lower dependence on credit sales and less occupation of working capital by downstream customers, thereby reflecting greater stability in supply chain relationships. Recovery capability is measured using a regression-residual approach. Firm performance is measured as earnings before interest and taxes divided by the number of employees, and the residual between observed and predicted performance is used to capture the firm's ability to recover from external disturbances. A larger residual indicates stronger recovery capability.

Operational capability is jointly measured using accounts-receivable turnover and accounts-payable turnover, which reflect the efficiency of working-capital circulation across customer and supplier relationships. Supply–demand matching capability is measured by the natural logarithm of the absolute year-on-year change in net inventory. A larger inventory adjustment indicates a greater deviation between supply and demand and therefore weaker matching capability. Renewal capability is measured by the natural logarithm of the number of granted invention patents plus one, reflecting firms' technological renewal and adaptive innovation capabilities. The detailed measurement system is reported in Table 1.

Table 1. Comprehensive Evaluation Index System for Supply Chain Resilience.

Primary Dimension	Secondary Indicator	Indicator Direction	Measurement Method
Resistance Capability	Dependence on Accounts Receivable	Negative Indicator	Natural logarithm of the ratio of accounts receivable to operating revenue
Recovery Capability	Performance Recovery	Positive Indicator	Residual between observed and predicted firm performance
Operational Capability	Accounts-Receivable Turnover	Positive Indicator	Operating revenue/[(Beginning net accounts receivable + Ending net accounts receivable)/2]
	Accounts-Payable Turnover	Positive Indicator	Operating cost/[(Beginning accounts payable + Ending accounts payable)/2]
Supply–demand Matching Capability	Inventory Fluctuation Magnitude	Negative Indicator	Natural logarithm of the absolute change in net inventory year-on-year
Renewal Capability	Output of Invention Patents	Positive Indicator	Natural logarithm of (number of granted invention patents + 1)

3.3.2. Antecedent Variables

Following the Technology–Organization–Environment (TOE) framework, this study includes five antecedent conditions: digitalization level (DIG), R&D investment (RD), return on assets (ROA), asset turnover (AT), and industry concentration (HHI). DIG and RD represent the technological dimension, ROA and AT represent the organizational dimension, and HHI represents the environmental dimension.

Digitalization level (DIG) is constructed from three complementary firm-level indicators: digital technology-related intangible assets, digital patent output, and digitalization-related disclosure in annual reports. The first component is measured as the proportion of digital technology-related intangible assets in total intangible assets. The second component is measured as the annual number of independently granted digital-economy patents. In the underlying patent dataset, this measure includes independently granted digital-economy invention patents and utility-model patents, while jointly granted patents are excluded. The digital patent data were obtained from the CSMAR database.

The third component captures firms' digitalization-related disclosure in annual reports. Following Wu et al. [23], the text-based measure is constructed from 76 digitalization-related keywords classified into five categories: artificial intelligence, big data, cloud computing, blockchain, and digital technology applications. The total annual keyword frequency is

transformed as ln (Frequency + 1). The complete keyword classification is reported in Supplementary Table S1.

The three indicators are subsequently normalized using min–max standardization over the pooled firm-year sample. Because they represent distinct but complementary dimensions of firm digitalization and there is no strong theoretical basis for assigning greater ex ante importance to any single component, equal weights are assigned to the three normalized indicators. The composite DIG index is therefore calculated as the arithmetic mean of the three standardized component scores [23,36]. The three components capture different manifestations of firm digitalization—digital asset embodiment, technological innovation output, and strategic disclosure—and are therefore treated as complementary rather than redundant indicators.

R&D investment (RD) is measured as R&D expenditure as a percentage of operating revenue, capturing firms' innovation intensity and technological accumulation capability.

Return on assets (ROA) is calculated as net profit divided by average total assets, reflecting firms' profitability and resource utilization efficiency.

Asset turnover (AT) is measured as operating revenue divided by average total assets, reflecting firms' operational efficiency and asset utilization capability.

Industry concentration (HHI) is measured using the Herfindahl–Hirschman Index, calculated as the sum of squared market shares based on firms' operating revenue. Industry market shares are calculated using the full population of firms within each industry rather than only the 60 sampled firms.

The operational definitions of all variables are summarized in Table 2.

Table 2. Variable Descriptions.

Analytical Role	Variable Dimension	Variable Name	Code	Measurement Method
Outcome Variable		Supply Chain Resilience	SCR	Entropy Weight Method
Antecedent variables	Technological	Digitalization Level	DIG	Equal-weighted mean of min–max normalized digital intangible-asset ratio, independently granted digital-economy patents, and annual-report digitalization text indicator
		R&D Investment	RD	R&D expenditure as a percentage of operating revenue
	Organizational	Return on Assets	ROA	Net profit/Average total assets
		Asset Turnover	AT	Operating revenue/Average total assets
	Environmental	Industry Concentration	HHI	Sum of squared industry market shares based on operating revenue (full industry population)

3.3.3. Variable Calibration

Before the QCA analysis, all continuous variables are calibrated into fuzzy-set membership scores ranging from 0 to 1. Following the direct calibration method, the 95th, 50th, and 5th percentiles of each variable are used as the thresholds for full membership, the crossover point, and full non-membership, respectively [9–11]. Distribution-based anchors are adopted because the continuous firm-level variables used in this study do not have universally established substantive thresholds that are applicable across different manufacturing subsectors. The 95th and 5th percentiles represent observations near the upper and lower ends of the sample distribution while reducing the influence of extreme values,

whereas the median provides a transparent crossover point between relatively high and relatively low set membership.

Importantly, calibration is performed on the pooled 2019–2023 sample of 300 firm-year observations rather than separately for each year. The resulting calibration anchors are therefore held constant across the five-year period. This approach ensures that set membership retains a consistent meaning over time and allows the year-specific configurational results to be compared on a common calibration basis.

To avoid cases falling exactly at the maximum-ambiguity crossover point of 0.5, calibrated scores equal to 0.5 are adjusted by 0.001. The calibration anchors and descriptive statistics are reported in Table 3.

Table 3. Calibration anchors and descriptive statistics for result variables and condition variables.

Variable Name	Fuzzy-Set Calibration			Descriptive Statistics			
	Full Member	Crossover Point	Full Nonmember	Mean	Median	Minimum	Maximum
SCR	0.259	0.149	0.032	0.502	0.5	0.033	0.978
DIG	0.438	0.213	0.014	0.503	0.499	0.041	0.991
RD	14.241	4.67	0.613	0.477	0.497	0.037	1
ROA	0.198	0.048	0.038	0.484	0.499	0	0.992
AT	1.307	0.724	0.339	0.48	0.499	0.013	1
HHI	0.12	0.037	0.017	0.517	0.5	0.029	0.992

Note: Calibration anchors are derived from the pooled 2019–2023 sample (N = 300 firm-year observations) and are applied consistently across all five years. Calibration anchors are reported in the original measurement units; RD is expressed in percentage points, whereas ROA and AT are expressed as ratios. Descriptive statistics refer to calibrated fuzzy-set scores.

4. Results

4.1. Necessity Analysis

A necessity analysis is conducted to examine whether any individual condition or its negation is necessary for the presence or absence of supply chain resilience (SCR). Following the conventional QCA criterion, a condition is considered necessary if its consistency score exceeds 0.90 [9,11].

As shown in Table 4, the consistency scores of all antecedent conditions (DIG, RD, ROA, AT, HHI) and their negations (~DIG, ~RD, ~ROA, ~AT, ~HHI) are below the 0.90 threshold for both high and non-high SCR. This indicates that no single condition qualifies as a necessary condition for supply chain resilience.

Table 4. Results of the Necessity Analysis of Conditional Variables.

Variable	High SCR				Non-High SCR			
	Consistency	Coverage	Between-Group Consistency-Adjusted Distance	Within-Group Consistency-Adjusted Distance	Consistency	Coverage	Between-Group Consistency-Adjusted Distance	Within-Group Consistency-Adjusted Distance
DIG	0.729	0.726	0.019	0.002	0.603	0.598	0.02	0.002
~DIG	0.596	0.602	0.02	0.002	0.724	0.726	0.019	0.001
RD	0.653	0.686	0.015	0.002	0.62	0.648	0.02	0.002
~RD	0.665	0.638	0.018	0.001	0.7	0.667	0.014	0.001
ROA	0.644	0.667	0.029	0.004	0.688	0.708	0.033	0.002
~ROA	0.718	0.699	0.031	0.001	0.676	0.653	0.027	0.001
AT	0.645	0.674	0.03	0.003	0.589	0.611	0.008	0.002
~AT	0.627	0.606	0.007	0.002	0.685	0.657	0.027	0.003
HHI	0.673	0.653	0.028	0.007	0.663	0.639	0.014	0.003
~HHI	0.629	0.653	0.014	0.003	0.64	0.66	0.03	0.011

This result suggests that supply chain resilience cannot be explained by a single dominant factor. It is therefore necessary to further examine how different combinations of conditions are associated with high and non-high SCR.

4.2. Sufficiency Analysis

The sufficiency analysis is conducted in R using the QCA package. To strengthen the directional consistency of the identified configurations, the truth table is constructed using three simultaneous decision criteria: a case-frequency threshold of 1, a raw consistency threshold of 0.85, and a proportional reduction in inconsistency (PRI) threshold of 0.50. Only truth-table rows satisfying both the consistency and PRI criteria are coded as sufficient for the corresponding outcome and retained for logical minimization. The PRI criterion is used to reduce simultaneous subset relations in which the same configuration is substantially associated with both the outcome and its negation.

To distinguish core from peripheral conditions, the parsimonious and intermediate solutions are compared following Fiss [10]. Conditions appearing in both solutions are classified as core conditions, whereas conditions appearing only in the intermediate solution are classified as peripheral conditions. For high SCR, positive directional expectations are specified for DIG, RD, ROA, and AT, while HHI is left directionally unspecified. For non-high SCR, directional expectations are specified for the absence of DIG and RD, while ROA, AT, and HHI are left unspecified. In the present analysis, all 32 logically possible configurations generated by the five antecedent conditions are empirically represented. Accordingly, the complex, parsimonious, and intermediate solutions are identical for both high and non-high SCR. No peripheral conditions are therefore identified, and all conditions reported in Table 5 are core conditions.

Table 5. Results of Configurational Analysis for High and Non-High Supply Chain Resilience.

Variable	Configurations for High SCR					Configurations for Non-High SCR				
	G1	**G2**	**G3**	**G4**	**G5**	**F1**	**F2**	**F3**	**F4**	**F5**
DIG		●	●			⊗	⊗	⊗	⊗	
RD	●			●	●	⊗	⊗			⊗
ROA		⊗		⊗	●		●	⊗	●	●
AT			●	●	⊗		⊗	⊗	●	⊗
HHI	●	⊗	⊗			⊗		⊗	⊗	⊗
Consistency	0.792	0.862	0.865	0.865	0.812	0.829	0.837	0.860	0.847	0.850
PRI	0.545	0.656	0.649	0.652	0.510	0.554	0.530	0.576	0.531	0.557
Raw coverage	0.482	0.433	0.360	0.367	0.404	0.410	0.346	0.350	0.319	0.321
Unique coverage	0.045	0.038	0.024	0.002	0.028	0.014	0.066	0.049	0.018	0.041
Between consistency adjusted distance	0.112	0.028	0.038	0.071	0.127	0.073	0.043	0.043	0.077	0.049
Within consistency adjusted distance	0.271	0.225	0.209	0.219	0.243	0.274	0.286	0.245	0.247	0.257
Overall PRI			0.541					0.571		
Overall consistency			0.758					0.800		
Overall coverage			0.676					0.592		

Note: A solid circle (●) indicates the presence of a core condition, whereas a circle with a cross (⊗) indicates the absence of a core condition. Blank cells indicate that the corresponding condition is not part of the configuration. Core conditions are identified as conditions appearing in both the parsimonious and intermediate solutions, whereas peripheral conditions appear only in the intermediate solution. In this analysis, the parsimonious and intermediate solutions are identical for both high and non-high SCR; therefore, no peripheral conditions are identified.

As shown in Table 5, five configurations are identified for high SCR. The overall solution consistency is 0.758, the overall PRI is 0.541, and the overall solution coverage is 0.676. The consistency values of the individual configurations range from 0.792 to 0.865, while their PRI values range from 0.510 to 0.656. These results indicate that the retained high-SCR configurations exhibit clearer directional consistency after incorporating the PRI criterion. The 0.85 cutoff applies to truth-table rows prior to logical minimization; consistency values of minimized solution terms may therefore fall below this threshold. Given the overall solution consistency of 0.758, these configurations are interpreted as empirically relevant configurational associations rather than unequivocal sufficient relations.

Five configurations are also identified for non-high SCR. The overall solution consistency is 0.800, the overall PRI is 0.571, and the overall solution coverage is 0.592. The configurations associated with high and non-high SCR differ substantially, further illustrating the configurational asymmetry of the two outcomes.

4.2.1. High Supply Chain Resilience Configurations

The revised sufficiency analysis identifies five configurations associated with high SCR. These configurations can be broadly grouped into two families according to their dominant technological characteristics: R&D-centered configurations (G1, G4, and G5) and digitalization-centered configurations (G2 and G3). This classification is descriptive rather than mutually exclusive and is intended to highlight the principal technological condition contained in each pathway. Representative firms are used only to illustrate the empirical characteristics of the configurations and are selected from firm-year observations that exhibit relatively strong membership in both the corresponding configuration and the outcome.

G1 (RD * HHI) combines high R&D investment with high industry concentration. This configuration indicates that high SCR is associated with sustained innovation investment under a relatively concentrated competitive environment. With a raw coverage of 0.482, G1 has the highest empirical coverage among the high-SCR configurations. Dongfang Electric is a representative case of this configuration, exhibiting this combination repeatedly during the observation period.

G4 (RD * ~ROA * AT) combines high R&D investment and high asset turnover with relatively low profitability. This configuration shows that high SCR can coexist with strong innovation input and efficient asset utilization even when profitability is comparatively constrained. Great Wall Motor is a representative case of G4. In contrast, G5 (RD * ROA * ~AT) combines high R&D investment and high profitability with relatively low asset turnover. Mindray is a representative case of G5. The contrast between G4 and G5 indicates that R&D investment is associated with high SCR under different organizational-resource combinations rather than requiring a single financial or operational profile.

The second family is characterized by digitalization. G2 (DIG * ~ROA * ~HHI) combines high digitalization with relatively low profitability and low industry concentration. FiberHome is a representative case of this configuration, demonstrating that a high-digitalization configuration can be associated with high SCR even under comparatively constrained profitability. G3 (DIG * AT * ~HHI) combines high digitalization, high asset turnover, and low industry concentration. Unisplendour is a representative case of G3. Compared with G2, G3 highlights a different organizational complement to digitalization, in which relatively efficient asset utilization forms part of the configuration.

Overall, the five configurations demonstrate equifinality: high SCR is associated with multiple combinations of technological, organizational, and environmental conditions rather than with a single universally sufficient factor. In particular, both R&D-centered and digitalization-centered configurations are empirically relevant, but their association with

high SCR depends on the organizational and environmental conditions with which they are combined.

4.2.2. Analysis of the Non-High Supply Chain Resilience Configurations

The revised analysis identifies five configurations associated with non-high SCR. A notable feature of these pathways is the recurrent absence of digitalization: four of the five configurations (F1–F4) contain ~DIG, although the accompanying organizational and environmental conditions differ substantially across configurations.

F1 (~DIG * ~RD * ~HHI) combines low digitalization, low R&D investment, and low industry concentration. Shanhe Intelligent is a representative case of this configuration. This pathway reflects a combination in which both major technological conditions are absent under a relatively unconcentrated industry environment.

F2 (~DIG * ~RD * ROA * ~AT) similarly combines low digitalization and low R&D investment, but these technological conditions coexist with relatively high profitability and low asset turnover. Laobaigan Liquor is a representative case of F2. This configuration indicates that relatively favorable profitability alone does not distinguish high-SCR cases when both digitalization and R&D investment are simultaneously limited.

F3 (~DIG * ~ROA * ~AT * ~HHI) combines low digitalization with relatively low profitability, low asset turnover, and low industry concentration. Taihe Intelligent is a representative case of this configuration. The pathway illustrates a pattern in which limited digitalization coexists with comparatively weak organizational conditions.

F4 (~DIG * ROA * AT * ~HHI) presents a contrasting organizational combination. Although profitability and asset turnover are relatively high, digitalization is absent, and industry concentration is low. Hualu Hengsheng is a representative case of F4. This configuration further shows that comparatively favorable organizational conditions do not, by themselves, distinguish high-resilience cases.

Finally, F5 (~RD * ROA * ~AT * ~HHI) differs from F1–F4 because digitalization is not a defining condition. Instead, the configuration combines low R&D investment with high profitability, low asset turnover, and low industry concentration. Gree Electric is a representative case of F5.

Taken together, the five non-high-SCR configurations reinforce the configurational asymmetry of supply chain resilience. Non-high SCR is not simply the inverse of the high-SCR solutions; rather, different combinations of limited technological capabilities and organizational or environmental conditions are associated with the outcome.

4.3. Robustness Checks

Robustness checks are conducted by adjusting the parameters used in truth-table construction and by examining the sensitivity of the results to alternative calibration schemes [10,11,37]. First, the case-frequency threshold is increased from 1 to 2 while the consistency threshold (0.85), PRI threshold (0.50), and baseline calibration scheme remain unchanged. The resulting configurations for both high and non-high SCR are identical to those obtained in the baseline analysis. The overall solution consistency, PRI, and coverage also remain unchanged, indicating that the findings are not sensitive to the case-frequency threshold.

Second, calibration sensitivity is examined by recalibrating the five antecedent conditions using the 90th, 50th, and 10th percentiles instead of the baseline 95th, 50th, and 5th percentiles, while retaining the baseline calibration of the SCR outcome. Under this alternative calibration, several substantive configurational patterns are preserved. For high SCR, the configuration DIG*AT*~HHI remains unchanged, while the digitalization-centered and R&D-centered patterns identified in the baseline analysis reappear in simplified or

reconfigured forms. For non-high SCR, the configurations ~DIG*~RD*ROA*~AT and ~RD*ROA*~AT*~HHI are reproduced exactly, while other pathways continue to highlight the recurrent roles of low digitalization and/or low R&D.

As an additional, more stringent sensitivity test, the antecedent conditions are recalibrated using the 75th, 50th, and 25th percentiles. Under this stronger recalibration, the exact minimized configurations change more noticeably, although the broader configurational roles of digitalization, R&D investment, organizational conditions, and industry environment remain observable. Taken together, the robustness analyses indicate that the results are highly stable to changes in the case-frequency requirement and broadly stable in their substantive interpretation across alternative calibration schemes, although individual minimized expressions show some sensitivity to more substantial changes in calibration anchors.

4.4. Temporal Stability and Annual Coverage of Configurational Pathways

To examine temporal stability, the panel structure of the data is incorporated following García-Castro and Ariño [38]. The pooled analysis is based on 300 firm-year observations from 60 firms during 2019–2023. The between-group adjusted distance captures variation in configuration consistency across annual cross-sections, whereas the within-group adjusted distance captures firm-level heterogeneity in the same set relationship over time. Smaller distances indicate greater stability at the corresponding level.

As shown in Table 5, the between-group adjusted distances range from 0.028 to 0.127 for high-SCR configurations and from 0.043 to 0.077 for non-high-SCR configurations, suggesting reasonable temporal stability. By contrast, the within-group adjusted distances range from 0.209 to 0.271 and from 0.245 to 0.286, respectively, indicating appreciable firm-level heterogeneity. Thus, the pooled solutions represent recurring configurational patterns rather than relationships that operate uniformly across all firms.

Annual consistency shows that G2 and G3 remain comparatively stable, whereas G1, G4, and G5 are generally more consistent in the later years. The full annual consistency and raw-coverage results are reported in Supplementary Table S2.

Figure 2 shows distinct changes in the annual raw coverage of the five high-SCR configurations. G1 declines from 0.550 in 2019 to 0.428 in 2023, whereas G2 increases from 0.381 to 0.483. G3 peaks in 2021 and subsequently declines, G4 shows an overall downward trend with a slight recovery in 2023, and G5 remains relatively stable. These patterns indicate changes in the relative empirical relevance of different configurations over time rather than a deterministic temporal transition.

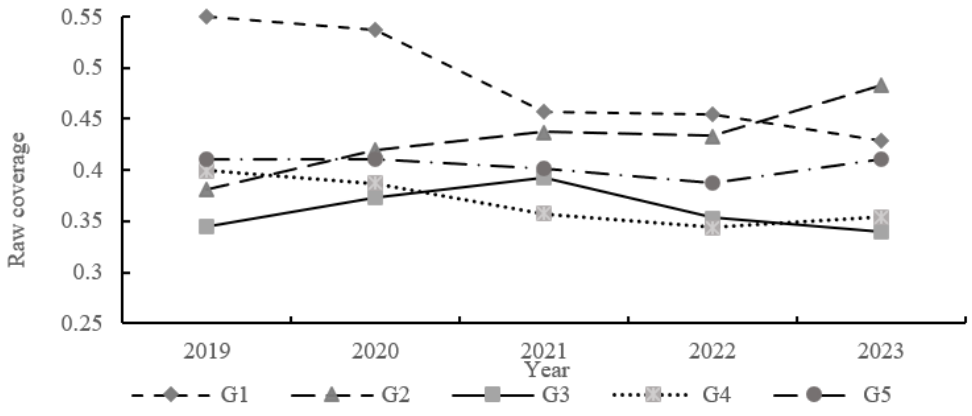


Figure 2. Annual Raw Coverage of High-SCR Configurations, 2019–2023.

5. Discussion

5.1. Configurational Interpretation of SCR

This study shows that supply chain resilience (SCR) in Chinese manufacturing firms is better understood as a configurational outcome rather than the result of any single antecedent condition. Consistent with the configurational logic of QCA and the TOE framework, none of the five conditions—digitalization (DIG), R&D investment (RD), return on assets (ROA), asset turnover (AT), and industry concentration (HHI)—emerges as a necessary condition for high SCR. This suggests that high SCR is associated with different combinations of technological, organizational, and environmental conditions.

The sufficiency analysis identifies five configurations associated with high SCR. G1, G4, and G5 are mainly characterized by R&D investment, whereas G2 and G3 are centered on digitalization. Their organizational and environmental conditions differ, indicating that neither R&D nor digitalization is sufficient on its own. Instead, high resilience is associated with multiple combinations of technological, organizational, and environmental conditions. This finding is consistent with prior studies emphasizing the importance of digital capability, innovation investment, and broader supply chain capabilities in resilience development [4,8,25,26].

From an RBV perspective, these patterns suggest that R&D and digitalization represent different capability bases whose relevance depends on how they are combined with firms' financial and operational resources.

5.2. Configurational Asymmetry and Pathway Heterogeneity

The results reveal configurational asymmetry between high and non-high SCR. The non-high-SCR configurations are not simple reversals of the high-SCR pathways. Low digitalization appears in four of the five non-high-SCR configurations, while low R&D investment is also present in several pathways. However, these technological conditions are combined with different organizational and environmental conditions.

Digitalization also appears in different high-SCR configurations. G2 combines high digitalization with low ROA and low HHI, whereas G3 combines high digitalization with high asset turnover and low HHI. This suggests that the role of digitalization varies across configurations rather than following a single pattern. This extends previous research on the positive role of supply chain digitalization in resilience [6,8] by showing that its empirical relevance depends on the organizational and environmental conditions with which it is combined. The contrast between G2 and G3 further suggests that digitalization may play different roles across organizational conditions, being associated with resilience under relatively constrained profitability in G2 and complementing high operational efficiency in G3.

5.3. Temporal Evolution of Configurational Pathways

The temporal analysis shows that the relative empirical relevance of the high-SCR configurations varies across 2019–2023. G1 exhibits an overall decline in raw coverage, whereas G2 increases from 0.381 in 2019 to 0.483 in 2023. G3 reaches its highest coverage in 2021 and subsequently declines; G4 shows an overall downward trend with a slight recovery in 2023; and G5 remains comparatively stable over the observation period.

These patterns indicate that the prominence of different resilience configurations changes over time rather than following a uniform transition. In particular, the higher coverage of G2 in the later period suggests that the digitalization-centered configuration becomes more empirically relevant within the observed sample. However, the results do not establish that digitalization replaces R&D- or resource-based pathways, which remain present throughout the study period. Moreover, because coverage changes are

descriptive and the observation period includes both pandemic-related disruptions and the subsequent recovery period, they should not be interpreted as direct causal responses to specific external events.

Overall, the temporal findings support the coexistence of multiple resilience-building configurations whose relative relevance varies over time, rather than a deterministic shift from traditional resource-based pathways toward digitalization.

5.4. Theoretical Implications

This study contributes to the understanding of supply chain resilience from a configurational perspective. First, the findings show that resilience is associated with different combinations of technological, organizational, and environmental conditions rather than with the independent effect of a single factor. This supports the use of the TOE framework for examining the interdependence among multiple conditions in resilience formation.

Second, the results provide further evidence of configurational asymmetry. The configurations associated with non-high SCR are not the mirror image of those associated with high SCR. This suggests that the configurational patterns associated with weak resilience cannot be understood simply by reversing the conditions associated with high resilience.

Third, the findings provide a more detailed understanding of the role of digitalization in supply chain resilience. Digitalization is not a necessary condition for high SCR, nor does it play the same role in every configuration. Its empirical relevance depends on how it is combined with operational efficiency, financial resources, and external environmental conditions. In some configurations, digitalization works together with other organizational capabilities, while in others it may help firms respond to resource constraints. The temporal results further show that the importance of such digitally enabled configurations can change over time.

From a sustainability perspective, these findings suggest that long-term supply chain continuity and adaptability depend on the alignment of digital, technological, and organizational capabilities rather than on digital investment alone.

5.5. Managerial Implications

The findings suggest that manufacturing firms should not rely on a single approach to improve supply chain resilience. Different combinations of digital capability, innovation investment, financial resources, and operational efficiency can be associated with high resilience. Firms therefore need to consider their own resource conditions and operating environments when choosing resilience-building strategies rather than simply following the same set of practices.

For firms with strong innovation capabilities, sustained R&D investment may remain relevant across different financial and operational profiles, as reflected in G1, G4, and G5. Firms with stronger digital capabilities may benefit from combining digitalization with operational efficiency and supply chain coordination. For firms facing greater resource constraints, digital technologies may also help improve information sharing and coordination and partly reduce the disadvantages caused by limited financial resources.

At the same time, the results do not suggest that R&D-centered configurations have become irrelevant. These configurations remain empirically relevant during the study period, although their relative coverage changes over time. Firms should therefore avoid treating digitalization and innovation investment as mutually exclusive choices. A more practical approach is to align digital investment, R&D activities, operational efficiency, and resource conditions with changes in the external environment.

From a sustainability perspective, such flexibility can help manufacturing firms maintain operational continuity while improving their ability to adapt to uncertainty over the

longer term. Digital technology is therefore more useful when it is integrated into broader supply chain and organizational practices rather than adopted as a standalone solution.

6. Conclusions

This study examines the configurational patterns associated with supply chain resilience (SCR) in Chinese manufacturing firms from 2019 to 2023 using dynamic QCA. The results show that no single condition is necessary for high SCR. Instead, five alternative configurations are identified, showing that high SCR is associated with different combinations of technological, organizational, and environmental conditions.

Among the high-SCR configurations, G1, G4, and G5 contain high R&D investment as a defining condition, whereas G2 and G3 contain high digitalization. This suggests that neither digitalization nor R&D alone is sufficient for high resilience. Their empirical relevance varies with the accompanying ROA, asset-turnover, and industry-concentration conditions. The five non-high-SCR configurations also differ from the high-SCR pathways, showing clear configurational asymmetry.

The temporal analysis shows that the relevance of these configurations changes over time. G1 shows an overall decline in coverage, while G2 becomes more prominent in the later years. Other pathways remain relatively stable or show mixed changes. These results suggest variation in the relative importance of different configurations rather than a uniform shift toward digitalization.

Overall, the findings show that there is no single best way to build supply chain resilience. Firms therefore need to align digital capability, innovation investment, organizational resources, and operating conditions with their own circumstances to support resilient and sustainable supply chain operations.

7. Limitations and Future Research

Despite its contributions, this study has several limitations. First, the sample is limited to Chinese listed manufacturing firms and was constructed through a purposive sampling procedure. Although the sample covers different manufacturing subsectors, it may still overrepresent relatively large and digitally active firms. Future research could extend the analysis to larger and more representative samples, including small and medium-sized enterprises and firms from other industries.

Second, the study covers the period from 2019 to 2023, during which manufacturing supply chains experienced considerable environmental uncertainty and external disruptions. Although this period provides an appropriate context for examining supply chain resilience, the findings may not fully reflect resilience-building mechanisms under more stable conditions. Future studies could extend the observation period to examine whether the identified configurations remain stable over time.

Third, although DQCA captures both configurational relationships and temporal changes, it does not directly reveal the underlying behavioral and decision-making processes through which firms develop resilience. Future research could combine configurational analysis with case studies, interviews, or survey-based approaches to provide a more detailed understanding of these mechanisms.

Finally, this study focuses on five technological, organizational, and environmental conditions. Future research could incorporate additional factors such as supply chain collaboration, institutional support, green finance, or more specific digital technologies to further examine how different conditions interact in shaping supply chain resilience. Future research could also compare alternative proxies and weighting schemes for the multidimensional SCR measure.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su182110983/s1. Table S1: Digitalization-Related Keyword Dictionary; Table S2: Annual Consistency and Raw Coverage of High- and Non-High-SCR Configurations, 2019–2023.

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Abbreviations

The following abbreviations are used in this manuscript:

TOE	Technology–Organization–Environment
QCA	Qualitative Comparative Analysis
DQCA	Dynamic Qualitative Comparative Analysis
SCR	Supply Chain Resilience
RBV	Resource-Based View
DIG	Digitalization Level
RD	R&D Investment
R&D	Research and Development
ROA	Return On Assets
AT	Asset Turnover
HHI	Herfindahl–Hirschman Index
PRI	Proportional Reduction in Inconsistency
CSMAR	China Stock Market & Accounting Research Database
ST	Special Treatment
*ST	Special Treatment (firms subject to delisting risk warning)

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