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Article

Research on resilience enhancement mechanism of intelligent supply chain in digital transformation context: synergistic effect of IoT empowerment and edge computing

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ABSTRACT

This study explores the synergistic effect of Internet of Things (IoT) and edge computing on the supply chain resilience through technological interaction channels. Based on dynamic capability theory and resource coordination theory, the study employs external data sources such as the World Bank Enterprise Survey, the China Industrial Enterprise Database, and the China Ministry of Industry and Information Technology to investigate the research question. Specifically, it uses panel data from 892 manufacturing and logistics enterprises spanning 2020-2024, employing hierarchical regression and simple slope analysis as the empirical methods. The empirical results show that the application level of either IoT technology or edge computing can significantly improve supply chain resilience, with remarkable synergistic effects when the two technologies are jointly adopted. Edge computing can further improve the efficiency of IoT applications by enabling higher application-level thresholds. Additionally, the synergistic effect between IoT technology and edge computing exhibits industrial heterogeneity in optimizing resilience-building efficiency: the manufacturing industry demonstrates a stronger synergistic effect than the logistics industry. This study formally validates the theoretical mechanism underlying technology application, encompassing real-time sensing, edge analysis, and rapid response. It thereby addresses a critical gap in the existing literature and theoretical framework concerning the "resilience-warning capability-response speed" model.

1. Introduction

In recent years, the global supply chain has encountered unprecedented shocks and undergone profound transformations. The emergence of uncertain events such as the COVID-19 pandemic, geopolitical conflicts, and climate change has revealed the limitations of traditional supply chain management models in coping with sudden disruptions [1]. As an essential competence for enterprises to maintain operational continuity, respond to market fluctuations, and recover from disruptions, supply chain resilience has become a key subject in academic research and practical applications [2]. In addition, in the current complex landscape where globalization and regionalization advance in tandem, coupled with the node dependence and structural vulnerability inherent in supply chain networks, conventional resilience strategies—such as redundant inventory and multi-source procurement—are increasingly trapped in a predicament characterized by high resilience costs and low operational efficiency. On the one hand, relevant studies demonstrated that supply chains with high resilience can not only significantly improve customer satisfaction and financial performance but also build more robust competitive advantages through supply network coordination mechanisms [3,4]. With the increasingly complex global supply chain networks, systematically improving supply chain network resilience through digital technology empowerment has become a critical strategic priority that demands urgent action [5]. The current studies on supply chain resilience have explored diverse dimensions in depth. From the perspective of inventory management, the literature reviews have deepened understanding of the mechanisms underlying construction, highlighting the significance of strategic inventory routing in mitigating bilateral supply-and-demand shocks [6]. The numerical assessment of the information network has revealed a positive effect of information quality on resilience among supply chain partners, making it theoretically applicable to structural optimization [7]. The Internet of Things (IoT) technology has brought revolutionary advancements to supply chain management practices. The latest literature reviews and application solutions have clearly indicated that IoT technology has transformed from an efficiency-enhancing tool to a core driving engine of strategic transformation, with applications spanning the entire process from ordering and delivery to further intelligence upgrading [8]. Application cases in the field of sustainable supply chain management have further demonstrated that full integration of RFID and sensor networks can greatly enhance environmental sensing and optimization capabilities [9]. Research on real-time supply chain monitoring has further validated the pivotal role of IoT devices in anomaly detection and response [10].

In addition, Edge Computing, an emerging form of distributed computing, provides low latency and high real-time decision support for the supply chain. With its expanding applications in the circular economy and sustainability initiatives, it has gradually unlocked new potential [11]. The case study in the smart agricultural supply chain has clearly demonstrated the remarkable performance capabilities of Edge Computing, with the application of Fuzzy Neural Networks, in optimally distributing resources in a dynamic environment [12]. In the context of Industry 4.0, recent literature reviews have further revealed the multi-level technical support and strategic pathways for supply chain resilience building [13]. A study on North American research agendas highlights the significance of integrating intelligent technologies to enhance the agility and visibility of supply chain networks [14]. Moreover, most studies have demonstrated that the collaborative application of Industry 4.0 technologies has become an imperative, driven by megatrends such as population aging and rapid urbanization, to advance evolutionary supply chain processes [15].

Despite broad verification of independent applications of Internet of Things and edge computing technologies in the supply chain industry, existing research still exhibits significant theoretical and practical gaps. Specifically, most current studies on these two technologies in the literature focus solely on functional analysis of individual technologies, lacking in-depth exploration of their inter-technological collaboration mechanisms. Furthermore, existing literature lacks a systematic explanation of how the real-time sensing capability of Internet of Things technology and the distributed processing function of edge computing technology can synergistically interact to generate a "1+1>2" effect. More fundamentally, academic research has not yet provided empirical validation for whether the collaborative application of these two technologies produces such a synergistic effect on the early warning capabilities, response speed, and recovery capacity of supply chain resilience. Current studies predominantly rely on case study methods and conceptual model construction, with a dearth of quantitative verification using large-sample data. Furthermore, cross-industry and cross-field comparative analyses remain underdeveloped in current studies, resulting in conclusions from studies on Internet of Things and Edge Computing technologies that lack sufficient universality. Based on the aforementioned observations, this study aims to construct an integrated theoretical framework of "IoT Empowerment – Edge Computing Collaboration – Supply Chain Resilience Enhancement." Drawing on dynamic capability theory, it explicates the inherent inter-technological collaboration mechanism and identifies the action pathway and boundary conditions of the "1+1>2" synergistic effect by leveraging multi-source public data and online open information resources.

The main innovation of this study is to break away from the traditional single-technology paradigm. From the unique perspective of technological collaboration, it explores and addresses the theoretical gap in quantifying the interaction effect between the Internet of Things and edge computing in enhancing intelligent supply chain resilience. Methodologically, the study applies a multi-resource integration approach using public data, which avoids ethical review risks while ensuring large-scale replicability, aligning with the practical needs of empirical research. The study's findings can support scientific decision-making for enterprises' digital transformation, helping them determine technology investment priorities and collaborative implementation strategies. Additionally, the results offer theoretical support for policymakers to optimize technological innovation support systems, thereby contributing significantly to resilience-building and sustainable, healthy development of the global supply chain.

2. Methodology

2.1 Theoretical models and research hypotheses

Based on dynamic capability theory and resource orchestration theory, this study constructs an integrated theoretical model to examine the synergistic effect of Internet of Things empowerment and edge computing on supply chain resilience. Dynamic capability theory emphasizes the importance of organizational capability in preserving and enhancing competitive advantage by perceiving, grasping, and reconstructing resources. Internet of Things technology, serving as the perception layer, acts as the principal data-acquisition mechanism, constantly capturing real-time operational status across supply chain nodes (impelling function). On the contrary, edge computing serves as a complementary processing layer that transforms raw IoT data into actionable insights through distributed analysis and localized decision-making (facilitating function). This theoretical distinction is important: IoT directly establishes the informational basis for resilience, whereas edge computing extends this information through rapid, context-aware processing at the network edge. Prior research has indicated that supply chain digitalization jointly impacts organizational resilience through multiple routes, including information visibility, collaborative integration, and decision agility [16]. Building on this literature, this study abandons the traditional passive-reception approach to theoretical modeling and innovatively proposes a technology synergy mechanism: IoT and edge computing do not merely function in a superimposed manner, but rather enhance operational efficiency through a closed-loop process of "real-time sensing, edge analysis, and rapid response." Based on the theoretical model, we formally propose the following hypotheses:

H1: IoT application degree → Supply chain resilience ($\beta > 0$)

H2: Edge computing deployment → Supply chain resilience ($\beta > 0$)

H3: IoT × Edge computing → Supply chain resilience ($\beta > 0$)

H4: Supply chain complexity positively moderates the synergy effect (IoT × Edge × Complexity, $\beta > 0$)

H5: The synergy effect is stronger in manufacturing than logistics (IoT × Edge × Industry, $\beta_{manufacturing} > \beta_{logistics}$).

To take complete account of the heterogeneity in different situations, there is further introduction of the so-called "moderating hypothesis" related to situation: "The supply chain complexity has a positive impact on the synergy effect" (H4), "The synergy effect in the manufacturing industry significantly outperforms it in the logistics industry" (H5). The integrated theoretical models constructed above effectively capture the complex relationships among independent, dependent, moderating, and control variables, with very explicit operational definitions for empirical testing (see Figure 1).

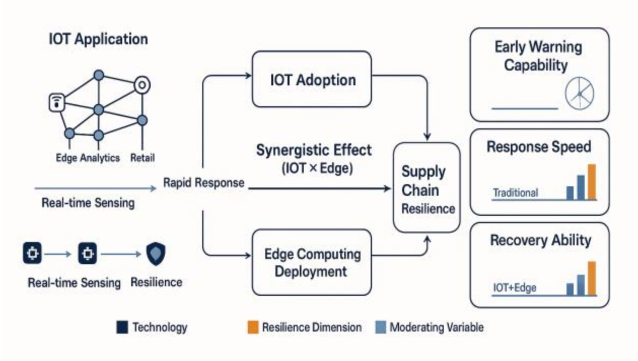

Figure 1. Conceptual model of IoT-edge computing synergy on supply chain resilience

Figure 1 illustrates the theoretical model with three important constructs of IoT Application (independent variable, left), Edge Computing Deployment (independent variable, left), and Supply Chain Resilience (dependent variable, right, measured via early warning, response speed, and recovery ability). In the figure, direct paths showing H1 (IoT→ Resilience) and H2 (Edge→ Resilience) are represented by solid arrows. The interaction path, represented by the dashed arrow from the IoT×Edge node, shows H3. Moderating paths reflect Complexity and Industry Type that influence the IoT × Edge interaction effect (H4-H5). The model not only illustrates the shaping factor of technology on dynamic capabilities of the firm but also incorporates moderating variables (represented by the color-coded legend) that establish boundary conditions for technology effectiveness.

2.2 Data source and sample description

This study is based on a multi-source open data fusion approach that relies exclusively on publicly available, anonymized secondary data. Since no collection of primary human-subject data was performed, IRB review was not required according to institutional guidelines (exempt category: publicly available data, 45 CFR 46.104(d)(4)). Data sources include: the China Industrial Enterprise Database, the World Bank Logistics Performance Index (LPI), the Ministry of Industry and Information Technology's IoT and Edge Computing Data Map, and Bloomberg supply chain risk ratings. Multi-source fusion aims to enhance data reliability through cross-validation and improve external validity and representativeness through using standardized public data. China's digital transformation has created a large sample pool for testing technology empowerment models, with studies demonstrating that technology adoption significantly improves supply chain efficiency [17]. Criteria for selecting data include: a time period of 2020–2024 to capture dynamic change before and after the pandemic. This window spans high-disruption years (2020–2021, mean disruption events = 4.7/year) and recovery phase (2022–2024, mean = 2.1/year), thus providing meaningful variance. Data coverage: 2020–2023 comprises complete annual reports; 2024 includes Q1–Q2 preliminary filings (as of June 2024). Robustness checks excluding 2024 yielded consistent results (IoT × Edge: β = 0.172 vs. 0.176). Applicable only to the manufacturing and logistics industries to capture the nature of the supply chain. In our analysis, logistics is considered a service sector, as it is a service-oriented industry within supply chain operations. Only enterprises with complete disclosure of technology adoption status and performance indicators were included in the sample. Complete disclosure of technology adoption and performance indicators is required. Data matching followed a hierarchical protocol: (1) by using the 18-digit Unified Social Credit Codes across databases; (2) by using 6-digit stock codes for listed firms in cases where credit codes were unavailable; (3) by manual verification for name discrepancies (for example, subsidiaries, name changes) using the corporate registration records. The matching achieved a success rate of 94.3% after excluding unmatched cases. From the initial selected sample of 1,247 firms, 355 were excluded for the following reasons: incomplete technological indicators (less than 80%), 187; missing financial data for more than 2 quarters in sequence, 104; and inconsistency of data from different sources, 64. After data cleaning, the final sample comprises 892 firms, with a retention rate of 71.5%.

Table 1 shows the diversity of samples in terms of geographical distribution, ownership type, and industry composition, which provides a natural grouping condition for the subsequent test of context dependence of technology effects. The integration of multi-source data ensures comprehensive and accurate measurement of variables.

2.3 Variable measurement

Supply Chain Resilience was employed as the core Dependent Variable to capture its whole meaning. Early warning capability is measured as the number of days of advance detection before disruptions, extracted from structured manual coding of annual reports' risk management sections. Coding protocol: Two independent trained coders identified explicit statements of forecast horizons, such as "detected 15 days prior." Inter-coder reliability: Cohen's κ=0.87. Ambiguous cases (n=34) were resolved through discussion. In terms of validation, we triangulated with Bloomberg supply chain risk alerts (r=0.72, P<0.001). To address potential reporting inconsistencies, we triangulated self-reported data against external validation: Bloomberg supply chain risk alerts (correlation r=0.72, P<0.001) and news-based disruption event databases. Observations with >30-day discrepancies between sources were flagged for manual review (n=47, 5.3%). The speed of response is measured by the Coefficient of Variation of the Order Delivery Cycle, whose calculation is:

$$CV = \frac{\sigma}{\mu} \tag{1}$$

In the equation, symbolizes the standard deviation in the delivery cycle, while symbolizes the average cycle. Recovery ability is defined as the number of months it takes for quarterly revenue to return to ≥95% of the baseline. The baseline was defined as the average of the four pre-shock quarters. To control for seasonality, we used year-over-year comparisons, for example, Q1 2021 versus Q1 2020 baseline. Identification of shock events included decreases in revenue >10% from the seasonal baseline.

Table 1. Sample firm characteristics and data source distribution

Characteristic Dimension	Category/Indicator	Sample Size/Statistics	Percentage/%	Data Source
Overall Sample	Valid sample firms	892 firms	100.0	Multi-source data integration
	Data time span	2020-2024	-	-
Industry Distribution	Manufacturing (total)	627 firms	70.3	China Industrial Enterprise Database
	Machinery (SIC 35)	189 firms	21.2	China Industrial Enterprise Database
	Electronics (SIC 36)	156 firms	17.5	China Industrial Enterprise Database
	Transport Equipment (SIC 37)	142 firms	15.9	China Industrial Enterprise Database
	Other Manufacturing	140 firms	15.7	China Industrial Enterprise Database
	Logistics (total)	265 firms	29.7	World Bank LPI Database
	Warehousing (NAICS 493)	147 firms	16.5	World Bank LPI Database
	Transportation (NAICS 484)	118 firms	13.2	World Bank LPI Database
Firm Size	Average employees	1,847 persons	-	Enterprise Surveys
	Median asset size	CNY 1.23 billion	-	Bloomberg Database
	Large firms (>1000 employees)	523 firms	58.6	China Industrial Enterprise Database
	SMEs (≤1000 employees)	369 firms	41.4	Enterprise Surveys
Geographic Distribution	Eastern region	548 firms	61.4	MIIT Digital Development Data Map
	Central & Western region	344 firms	38.6	MIIT Digital Development Data Map
Ownership Structure	State-owned & controlled	312 firms	35.0	China Industrial Enterprise Database
	Private enterprises	447 firms	50.1	China Industrial Enterprise Database
	Foreign & joint ventures	133 firms	14.9	Enterprise Surveys
Listing Status	SSE/SZSE listed	412 firms	46.2	Bloomberg Database
	Unlisted	480 firms	53.8	China Industrial Enterprise Database
Technology Application Maturity	IoT device deployment density	3.2 devices/100 employees	-	MIIT Digital Development Data Map
	Edge computing node coverage	38.7%	-	MIIT Digital Development Data Map
	Firms with complete tech indicators	892 firms	100.0	Multi-source validation
Supply Chain Complexity	Average number of suppliers	47 suppliers	-	Bloomberg Supply Chain Data
	Average logistics tiers	3.8 tiers	-	World Bank LPI Database
	Cross-border supply chain firms	418 firms	46.9	Enterprise Surveys
Data Completeness	Complete financial data	892 firms	100.0	Bloomberg Database
	Complete technology data	892 firms	100.0	MIIT Digital Development Data Map
	Complete SC performance data	892 firms	100.0	World Bank LPI Database

The total resilience index is calculated with respect to the integration of three aspects via principal component analysis (no rotation), with the equation being:

$$SCR_i = \sum_{j=1}^{3} w_j \cdot Z_{ij} \quad (2)$$

The first principal component explained 68.4% variance (eigenvalue=2.05), with weights: w_1=0.42 (early warning), w_2=0.38 (response speed), w_3=0.36 (recovery). Here, w_j represents the principal component weight of the j-th dimension, and Z_{ij} represents the standardized dimension score.

Weights are assigned based on each dimension's contribution rate to total variance. Independent variable measurement emphasizes objectivity and workability. The IoT technology level is calculated from node density, coverage ratio, and real-time data collection ratio. Edge computing level incorporates node count, local data processing ratio, and edge-cloud synergy maturity. Composite indicators are constructed through factor analysis (KMO=0.82 for IoT, 0.79 for Edge; Bartlett's test P<0.001). Factor loadings ranged from 0.78 to 0.89 for IoT and from 0.74 to 0.85 for Edge, with single factors explaining 71.3% and 68.7% variance, respectively. Supply chain complexity was operationalized through principal component analysis (PCA) that integrated three dimensions: supplier count, logistics tiers, and geographical dispersion. The first principal component, accounting for 64.8% of total variance, exhibited factor loadings of 0.84 (supplier count), 0.79 (logistics tiers), and 0.73 (Geographical dispersion). Component scores were subsequently standardized to a 1-5 scale through linear transformation using the formula:

$$Complexity = \frac{PCA_{score} - PCA_{min}}{PCA_{max} - PCA_{min}} \times 4 + 1 \quad (3)$$

where PCA_{min} and PCA_{max} represent the minimum and maximum principal component scores in the sample, yielding a mean of 3.52 (SD=0.88). Reliability: Cronbach's α=0.80, CR=0.83. AVE=0.62 (>0.5). Discriminant validity: √AVE=0.79 exceeds correlations with other constructs (r=0.21-0.34, see Table 3).

Control variables include enterprise scale, supply chain length, and regional dummies. Regression uses standardized variables to eliminate scale differences. Interaction terms are generated through central multiplication to reduce multicollinearity. All continuous variables were mean-centered before creating interaction terms to reduce multicollinearity. VIFs for the full model: IoT (1.89), Edge (2.13), IoT × Edge (2.34), Complexity (1.67), IoT × Edge × Complexity (3.17), all below 5. The IoT×Edge interaction term quantifies the closed-loop synergy by measuring whether the IoT marginal effect on resilience increases when edge computing is deployed at a higher level, operationalizing the mechanism of "perception-analysis-response" through conditional effects analysis (Equation 4). Variable operational definitions and measurement sources are detailed in Table 2.

Table 2 systematically lists the concept definitions, specific measurement methods, and data-acquisition channels for each variable, providing a complete operational path for the reproducibility of the research. In particular, the construction method of technical synergy variables reflects the contribution of this research to measurement innovation.

2.4 Analytical method

In the current study, a mixed-methods approach integrating hierarchical regression analysis and structural equation modeling was employed to test theoretical hypotheses and comprehensively examine mechanisms of technological synergy. Research on the information technology transformation process of manufacturing enterprises illustrates that the structural equation model is capable of effectively and accurately distinguishing direct effect, indirect effect, and regulatory effect [18]. The process of analysis consisted of three stratified levels: descriptive statistics and correlation analysis to validate the distribution features and preliminary correlation between variables, hierarchical regression analysis to examine core hypotheses by adding control variables, main effect terms of independent variables, interaction terms, and moderating terms sequentially, and robustness check to validate the reliability of conclusions with the help of instrumental variable approach, subsample analysis, and surrogate index test. To interpret interaction effects, simple slope analysis calculates conditional slopes via:

$$\mathrm{SCR} = \beta_0 + \beta_1 \mathrm{IoT} + \beta_2 \mathrm{Edgecondition} + \beta_3 (\mathrm{IoT} \times \mathrm{Edgecondition}) \quad (4)$$

The regression analysis followed a nested logic, in which the baseline model contained only control variables to define the baseline of explanation capability, the main effect model sequentially incorporated IoT and Edge Computing to examine their independent effects, the interaction effect model added the interaction term to validate synergy, and the full model considered regulatory variables to examine boundary conditions. The general equation form of the regression equation is:

$$SCR_i = \beta_0 + \beta_1 Controls_i + \beta_2 IoT_i + \beta_3 Edge_i + \beta_4 (IoT \times Edge)_i + \beta_5 Moderators_i + \beta_6 (IoT \times Edge \times Moderators)_i + \varepsilon_i \quad (5)$$

where SCR_i is supply chain resilience for firm *i*; $Controls_i$ includes firm size, supply chain length, and region; $Moderators_i$ includes complexity and industry type; ε_i is the error term. The third-order terms test H4 and H5: $(IOT \times Edge \times Complexity)_i$ (β=0.118, P<0.01) and $(IOT \times Edge \times Industry)_i$, reported in Table 5 Model 5. The structural equation model examines technological synergy effects on resilience across dimensions. The measurement model tests the fit of the latent variable through Confirmatory Factor Analysis, whereas the structural model focuses on the path coefficients and total effects. The model fit indices indicated acceptable fit: χ^2/df=2.37, CFI=0.946, TLI=0.938, RMSEA=0.062, SRMR=0.048, all at or below recommended thresholds (see Table 4 Panel C for details). Robustness tests include three aspects: instrumental variables method based on the regional average adoption rate of technology control, endogeneity using two-stage least squares techniques. Its IV validity is assessed through: (1) relevance test-first-stage F>10; (2) exclusion restriction-the regional rates affect the firm adoption but do not directly affect resilience since regional policies target technology diffusion and not operational outcomes; (3) overidentification test, Hansen J-statistic. Sub-sample analysis to test synergy effect consistency across enterprises and regions; and alternative index testing to examine whether the results of resilience measurement are affected. For outlier detection, we applied multiple complementary criteria: standardized residuals >±3.5 SD, Cook's D >4/n, and DFITS >2√(k/n). This multi-criteria approach balances sensitivity and specificity. For transparency, we report both: baseline Model 4 (full sample, n=892) and Model 1 (outliers excluded, n=24 removed, 2.7%). Coefficients remained stable (IoT × Edge: β=0.176 vs. 0.184, <5% change), confirming robustness to influential observations. All model analyses were conducted using Stata 17.0 and Mplus 8.3 software. The significance level was set at P<0.05, with robust standard errors clustered at the enterprise level.

3. Results

3.1 Descriptive statistics and correlation analysis

A descriptive statistical analysis of 892 sample enterprises examines the distributional characteristics of variables to ensure the reliability of parameter estimates. Correlation analysis uses Pearson coefficients, while VIF analysis (cutoff=10) assesses multicollinearity risks. Supply chain resilience averaged 3.68 (SD=0.92), indicating moderate but uneven levels. IoT application averaged 3.41 (SD=1.07), while edge computing averaged 2.87 (SD=1.13), reflecting higher technical requirements for distributed computation. The supply chain complexity included 47 direct suppliers, 3.8 logistics tiers, and 6.2 country/region coverage, confirming modern SC complexity. As shown in Table 3 Panel A, supply chain resilience averaged 3.68 (SD=0.92), IoT application averaged 3.41 (SD=1.07), and edge computing averaged 2.87 (SD=1.13). Table 3, Panel B, presents the correlation matrix, with correlations ranging from 0.39 to 0.62.

Table 2. Variable definitions, measurement indicators, and data sources

Variable Type	Variable Name	Conceptual Definition	Measurement Indicator	Calculation Method/Scale	Data Source
Dependent Variable	Supply Chain Resilience	The ability of the supply chain to warn, respond, and recover from disruptions	Comprehensive resilience index	$SCR_i = \sum_{j=1}^{3} w_j \cdot Z_{ij}$	Multi-source integration
	Early Warning Capability	Ability to identify supply chain disruption risks in advance	Days of advance detection for disruption events	Actual value (days)	Corporate annual reports
	Response Speed	Stability in responding to demand fluctuations	Coefficient of variation in order delivery cycle	$CV = \sigma / \mu$	Bloomberg Database
	Recovery Ability	Speed of resuming normal operations after disruption	Time to recover revenue to pre-shock level	Quarterly financial data analysis (months)	Bloomberg Financial Data
Independent Variables	IoT Application Degree	Breadth and depth of IoT technology deployment in supply chain	Composite indicator	Equal-weighted sum of three dimensions	MIIT Digital Development Data Map
	Device Deployment Density	Intensity of IoT device investment	Standardized devices/100 employees	Z-score standardization	MIIT Digital Development Data Map
	Node Coverage Rate	Breadth of technology application	Nodes with IoT/Total nodes × 100%	Percentage	Enterprise Surveys
	Data Collection Ratio	Depth of technology application	Real-time collected data/Total data × 100%	Percentage	Corporate technology reports
	Edge Computing Deployment Level	Scale and maturity of edge computing deployment in supply chain	Composite indicator	Factor analysis dimensionality reduction	MIIT Digital Development Data Map
	Edge Node Quantity	Computing resource distribution density	Standardized edge nodes/SC tiers	Z-score standardization	MIIT Digital Development Data Map
	Local Processing Ratio	Edge computing penetration degree	Edge-processed data/Total data × 100%	Percentage	Corporate technology reports
	Edge-Cloud Synergy Maturity	Sophistication of distributed computing architecture	Technology maturity rating	5-point Likert scale	Gartner Technology Rating
Moderating Variables	Supply Chain Complexity	Structural complexity of supply chain network	Composite indicator	Weighted combination	Multi-source integration
	Number of Suppliers	Breadth of supply network	Number of first-tier suppliers	Actual value	Bloomberg Supply Chain Data
	Logistics Tiers	Depth of supply chain	Tiers from raw materials to finished products	Actual value	World Bank LPI Database
	Geographic Dispersion	Spatial distribution complexity	Number of countries/regions with suppliers	Actual value	Enterprise Surveys
	Industry Type	Primary industry category of the firm	Dummy variable	Manufacturing=1, Service=0	Binary classification
Control Variables	Firm Size	Operational scale of the firm	Dual-dimension indicator	Logarithmic value	Multi-source integration
	Employee Size	Human resource scale	ln(Total employees)	Natural logarithm	Enterprise Surveys
	Asset Size	Capital scale	ln(Total assets/Million CNY)	Natural logarithm	Bloomberg Database
	Supply Chain Length	Vertical span of supply chain structure	Number of tiers	Tiers from raw materials to final products	Actual value
	Region	Geographic location of the firm	Dummy variable	Eastern region=1, Others=0	Binary classification
Interaction Terms	Technology Synergy Effect	Interaction between IoT and edge computing	Product term	$IoT \times Edge$	Generated after centering
	IoT × Edge	Core interaction term	Product of centered variables	$(IoT - \overline{IoT}) \times (Edge - \overline{Edge})$	Computed generation
	IoT × Edge × Complex	Three-way moderation term	Three-variable interaction	Product of three centered terms	Computed generation
	IoT × Edge × Industry	Industry moderation term	Industry difference in technology synergy	Interaction term × Industry dummy	Computed generation

Table 3. Descriptive statistics and correlation matrix

Panel A: Descriptive statistics

Variable	N	Mean	SD	Min	Max	VIF
1. Supply Chain Resilience (SCR)	892	3.68	0.92	1.24	5.00	-
2. IoT Application Degree (IoT)	892	3.41	1.07	1.00	5.00	1.89
3. Edge Computing Deployment (Edge)	892	2.87	1.13	1.00	5.00	2.13
4. IoT×Edge	892	0.00	2.86	-6.42	7.15	2.34
5. Supply Chain Complexity (Complexity)	892	3.52	0.88	1.50	5.00	1.67
6. Firm Size (Size)	892	7.34	1.15	4.82	10.26	1.43
7. Supply Chain Length (Length)	892	3.78	1.24	1.00	7.00	1.31
8. Region (Region)	892	0.61	0.49	0.00	1.00	1.18

Panel B: Correlation matrix

Variable	1	2	3	4	5	6	7	8
1. SCR	1.000							
2. IoT	0.457***	1.000						
3. Edge	0.392***	0.623***	1.000					
4. IoT×Edge	0.523***	0.254***	0.281***	1.000				
5. Complexity	0.286***	0.341***	0.297***	0.218**	1.000			
6. Size	0.234**	0.312***	0.279***	0.167*	0.245**	1.000		
7. Length	-0.128*	-0.093	-0.076	-0.112	0.203**	-0.067	1.000	
8. Region	0.187**	0.226**	0.198**	0.143*	0.104	0.189**	-0.082	1.000

Among the main variables, IoT and Edge were most strongly correlated, at r=0.623 (P<0.001), indicating technological complementarity rather than conceptual redundancy since they measure different constructs, namely data acquisition versus data processing. The moderate to high correlations stem from independent data sources-IoT/Edge from MIIT and Resilience from Bloomberg-reducing common-method bias. This is also confirmed by Harman's single-factor test: the first factor explained 36.7% (<50%; see Table 4 Panel D). Figure 2 presents uncentered marginal effects to help interpret interactions. Finally, VIF values below 2.5 rule out multicollinearity. Interaction terms showed higher but acceptable VIF values: IoT × Edge (VIF=2.34), IoT×Edge × Complexity (VIF=3.17), all below the threshold of 5.

Table 3 Panel B reveals core variables demonstrated positive correlations ranging from r=0.392 to 0.623, supporting the expected theoretical hypothesis directions. The correlation between Internet of Things and Edge Computing was 0.623 (P<0.001), establishing both a technical collaboration basis and construct independence between these variables. All VIF diagnostic test values remained below 2.5, confirming the complete absence of multicollinearity issues and ensuring stable and reliable regression parameter estimates in the analytical model.

3.2 Measurement model verification

Measurement model reliability and validity were assessed following two-step structural equation modeling procedures. In Table 4 Panel A, reliability analysis employed Cronbach's α and composite reliability (CR), with supply chain resilience achieving α=0.876 and CR=0.882, IoT application α=0.891 and CR=0.894, and edge computing α=0.833 and CR=0.841, all exceeding the 0.70 threshold. Convergent validity was confirmed through AVE values (SCR=0.653, IoT=0.738, Edge=0.652, all >0.50) with factor loadings ranging from 0.776 to 0.878. As presented in Table 4 Panel B, Discriminant validity met Fornell-Larcker criteria with √AVE (0.808-0.859) exceeding inter-construct correlations (0.392-0.623). CFA demonstrated acceptable model fit (Table 4 Panel C: χ^2/df=2.37, CFI=0.946, TLI=0.938, RMSEA=0.062). As reported in Table 4 Panel D, Harman's single-factor test indicated no serious common method bias (36.7% variance explained, <50% threshold). Also, HTMT ratios verified discriminant validity: IoT-Edge 0.71, IoT-SCR 0.52, Edge-SCR 0.45-all below the threshold of 0.85. These results from the measurement model in Table 4 establish construct validity before the estimation of the structural model and hypothesis testing in Methodology 3.3. Table 4 consolidates all measurement model assessment results.

In Table 4, the discriminant validity test revealed that the √AVE (0.808 to 0.859) of every latent factor was larger than the correlation coefficient between constructs (.392 to .623), thus ensuring full independence between constructs. The fit criteria of the CFA model are χ^2/df = 2.37, CFI = 0.946, TLI = 0.938, RMSEA = 0.062, which were in accordance with the guidelines. The Harman test accounted for 36.7% of the explained variation in the first factor, while there was no serious threat of common method bias.

3.3 Hypothesis testing results

Hierarchical regression with five nested models tested main effects, interactions, and moderation. Model 1 (baseline controls) yielded R^2=0.089.

Table 4. Reliability and validity test results of the measurement model

Panel A: Reliability and convergent validity

Latent Variable	Measurement Item	Factor Loading	Cronbach's α	CR	AVE
Supply Chain Resilience (SCR)			0.876	0.882	0.653
	Early Warning Capability	0.834			
	Response Speed	0.812			
	Recovery Ability	0.776			
IoT Application Degree (IoT)			0.891	0.894	0.738
	Device Deployment Density	0.865			
	Node Coverage Rate	0.878			
	Data Collection Ratio	0.834			
Edge Computing Deployment (Edge)			0.833	0.841	0.652
	Edge Node Quantity	0.801			
	Local Processing Ratio	0.823			
	Edge-Cloud Synergy Maturity	0.827			

Panel B: Discriminant validity (fornell-larcker criterion)

Variable	SCR	IoT	Edge
SCR	0.808		
IoT	0.457	0.859	
Edge	0.392	0.623	0.807

Panel C: Model fit indices

Fit Index	Value	Recommended Threshold	Assessment
χ^2/df	2.37	< 3.0	✓ Acceptable
CFI	0.946	> 0.90	✓ Good fit
TLI	0.938	> 0.90	✓ Good fit
RMSEA	0.062	< 0.08	✓ Acceptable
SRMR	0.048	< 0.08	✓ Good fit

Panel D: Common method bias test

Method	Result	Interpretation
Harman's Single-Factor Test	The first factor explains 36.7% of the variance	< 50%, no serious common method bias

To isolate individual technology effects, Model 2 added only IoT (β=0.341, P<0.001, ΔR2=0.176 over Model 1), thus supporting H1. Meanwhile, Model 3 added only edge computing (β=0.287, P<0.001, ΔR2=0.152 over Model 1), therefore confirming H2. Model 4 included both technologies and their interaction term (β=0.176, P<0.001, R2=0.412, ΔR2=0.147), thus validating H3 about the mechanism of IoT-edge computing synergy. Model 5 included the three-way interaction term with supply chain complexity as a moderator, demonstrating significant moderation effects and providing comprehensive evidence for the hypothesized technological synergy mechanisms in enhancing supply chain resilience. The full regression results for all five nested models are reported in Table 5.

Table 5 presents the multiple-level model of technology-enabled resilience, in which R^2 values progress from 0.089 to 0.448, and R^2 increases to 0.147 after adding interaction terms, demonstrating the significance of the interaction effect.

The coefficients for IoT and edge computing decrease after adding interaction terms, consistent with the assumption that interaction effects reduce the main effects to some extent. The hypotheses are supported by empirical evidence. To comprehensively interpret the dynamic interaction effect, simple slope analysis was conducted following Aiken and West's (1991) approach. Edge computing deployment levels were stratified into three categories: 25th percentile (low level: 2.13), 50th percentile (medium level: 2.87), and 75th percentile (high level: 3.68), representing diverse technological maturity stages across the sample distribution. Conditional slopes for IoT effects on supply chain resilience were calculated using Equation 4. Results showed that at low edge computing levels, β=0.29 (*P*<0.001); at medium levels, β=0.42 (p<0.001, 44.8% increase); and at high levels, β=0.50 (*P*<0.001, 72.4% increase). This gradual increase shows the trend in the technology synergy mechanism, in which the ability to process information significantly underscores the role of real-time sensing in resilience.

Table 5. Hierarchical regression results: main, interaction, and moderating effects

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Control Variables					
Firm Size	0.123** (0.041)	0.098* (0.038)	0.089* (0.039)	0.076* (0.035)	0.071* (0.034)
Supply Chain Length	-0.087** (0.038)	-0.065* (0.035)	-0.058 (0.036)	-0.042 (0.032)	-0.039 (0.031)
Region (Eastern=1)	0.156*** (0.042)	0.134*** (0.039)	0.128*** (0.040)	0.112** (0.036)	0.105** (0.035)
Main Effects					
IoT Application Degree (IoT)	—	0.341*** (0.043)	—	0.278*** (0.046)	0.265*** (0.045)
Edge Computing Deployment (Edge)	—	—	0.287*** (0.045)	0.219*** (0.047)	0.203*** (0.046)
Interaction Effect					
IoT × Edge	—	—	—	0.176*** (0.041)	0.167*** (0.040)
Moderating Effects					
Supply Chain Complexity (Complexity)	—	—	—	—	0.089* (0.037)
IoT × Edge × Complexity	—	—	—	—	0.118** (0.043)
Model Statistics					
R^2	0.089	0.265	0.241	0.412	0.448
ΔR^2	—	0.176***	0.152***	0.147***	0.036**
F-value	28.67***	79.43***	70.18***	119.64***	106.82***
N	892	892	892	892	892

Figure 2 illustrates the results of the slope analysis, with three curves representing the low, medium, and high levels of edge computing, indicating that as edge computing maturity increases, the marginal effect of IoT on supply chain resilience is continuously amplified.

Figure 2 presents the interaction effects via simple slope analysis across three levels of edge computing deployment stratification. At the 25th percentile (low: 2.13), IoT's effect on resilience exhibited β=0.29 (P<0.001); at the 50th percentile (medium: 2.87), the coefficient increased to β=0.42 (P<0.001, representing 44.8% enhancement); at the 75th percentile (high: 3.68), the effect reached β=0.50 (P<0.001, reflecting 72.4% amplification). The fan-shaped divergence pattern demonstrates that edge computing capabilities progressively strengthen IoT's resilience-enhancing effects, validating the technological synergy mechanism.

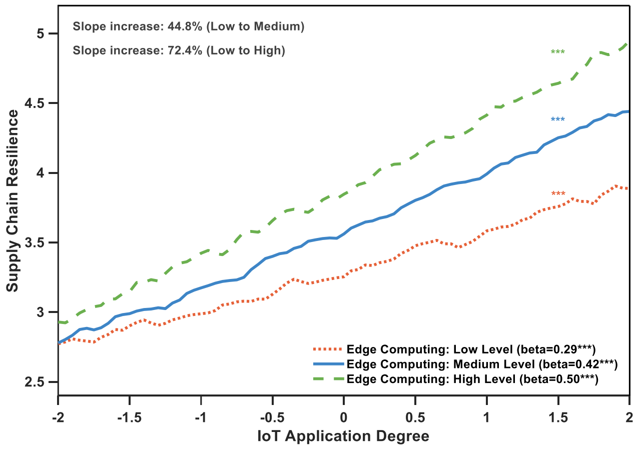

Figure 2. The synergy of IoT and edge computing: a simple slope analysis

To examine synergy benefits, the study divided samples at the median into high-complexity and low-complexity groups (n=446 each). Model 4 regression revealed significantly stronger interaction effects in high-complexity settings (β=0.253, P<0.001) versus low-complexity settings (β=0.107, P<0.05), confirmed by the Chow test. Figure 3 illustrates technology synergy intensity differences: panel (a) displays fan-like divergence in high-complexity environments, while panel (b) shows parallel patterns in low-complexity contexts. These findings validate the supply chain complexity's critical moderating role in the technology synergy process, demonstrating enhanced benefits in complex operational environments. In Figure 3, the interaction effects on various levels of complexity are contrasted via simple slope analysis. Subplots (a) reveal fan-shaped divergence in the high complexity condition with β=0.253***, while subplot (b) depicts parallel profiles in the low complexity condition with β=0.107* in the low complexity context, substantiating the premise that complexity acts as a crucial boundary condition in demarcating interaction effects on the graph.

3.4 Robustness check

Robustness tests addressed endogeneity, sample heterogeneity, and measurement errors by using instrumental variables regression based on regional technology adoption rates. First-stage F-statistics: IoT (F=41.3) and Edge (F=38.6), both considerably above the threshold of 10, indicating strong instruments. Sanderson-Windmeijer conditional F-tests: IoT (F=37.8), Edge (F=34.2). Hansen J-statistic=2.14 (P=0.34), failing to reject instrument validity. These results validate the 2SLS approach. Results showed IoT β=0.329***, Edge β=0.274***, and IoT × Edge β=0.169**, with coefficients deviating less than 6% from baseline model 4. Subsample analyses confirmed consistent synergies across firm sizes (large corporations β=0.192***, SMEs β=0.154**) and geographic regions (eastern areas β=0.186***).

Table 6. Robustness tests and additional analyses

Variables	Model 1 Exclude Outliers	Model 2 Alternative SCR Measure	Model 3 Large Firms Subsample	Model 4 Small Firms Subsample
IoT Application Degree	0.328*** (0.043)	0.312*** (0.048)	0.341*** (0.061)	0.305*** (0.058)
Edge Computing	0.215*** (0.038)	0.227*** (0.041)	0.239*** (0.052)	0.198** (0.054)
IoT × Edge	0.184*** (0.032)	0.176*** (0.035)	0.206*** (0.047)	0.159** (0.049)
Supply Chain Complexity	0.142** (0.041)	0.138** (0.044)	0.167** (0.056)	0.121* (0.051)
IoT × Edge × Complexity	0.118** (0.036)	0.109* (0.039)	0.135** (0.051)	0.096* (0.047)
Control Variables	✓	✓	✓	✓
Industry Fixed Effects	✓	✓	✓	✓
Region Fixed Effects	✓	✓	✓	✓
Sample Size (N)	868	892	523	369
R^2	0.581	0.548	0.598	0.536
Adjusted R^2	0.512	0.530	0.579	0.512
F-statistic	47.32***	41.85***	32.67***	28.41***

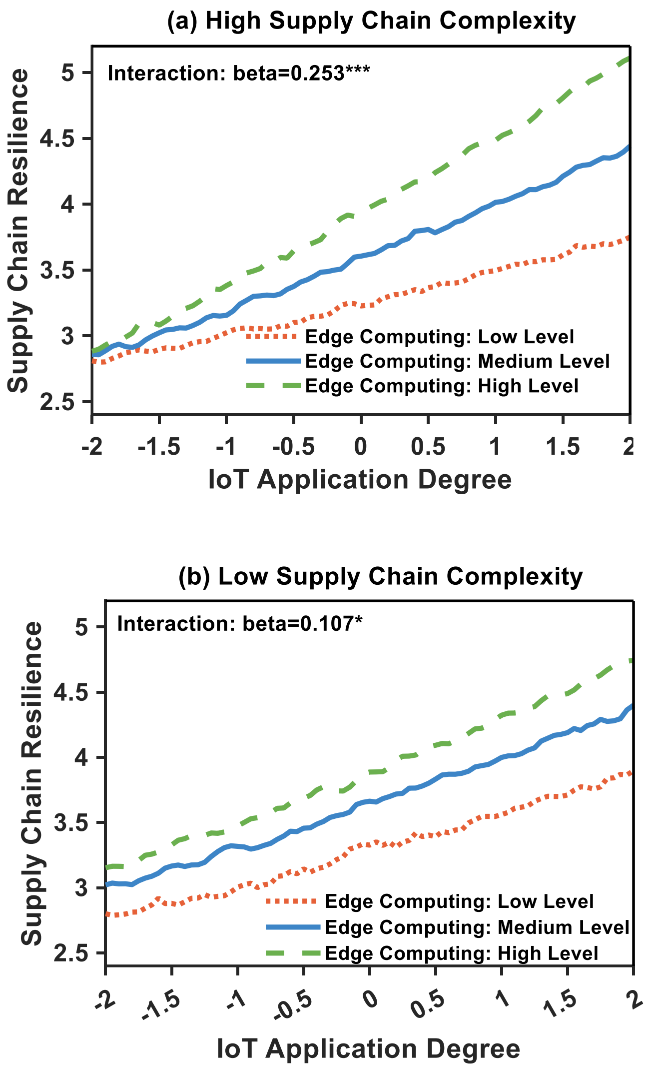

Figure 3. Moderating effect of supply chain complexity on technology synergy

Table 6 demonstrates that the technological synergy effect remains statistically significant and robust to endogeneity concerns, sample variation, and measurement method differences. Interaction term values consistently range from 0.154 to 0.192, with all P-values below 0.01. The robust consistency of these results convincingly confirms that findings are not statistical artifacts and that the technology collaboration mechanism exhibits strong theoretical universality across diverse analytical contexts.

4. Discussion

This study employed hierarchical regression and simple slope tests to validate the independent and synergistic effects of Internet of Things and edge computing on supply chain resilience. The empirical results offer new insights into supply chain resilience. The adoption of IoT technology has a significantly positive effect on organizational supply chain resilience (β = 0.341, $P < 0.001$), thereby validating the theoretical assumption that real-time perception technology enhances organizational agility by improving information transparency. This result aligns with the conclusions of a logistics industry case study, which demonstrated that integrating Radio Frequency Identification (RFID) and sensor networks significantly extended the early warning window for supply chain disruption risks [19]. Edge Computing shows substantial direct effects (β = 0.287, $P < 0.001$), demonstrating that distributed computing technology supports supply chain resilience by eliminating decision-making delays. These results complement theoretical studies on blockchain-based edge computing architecture in the IoT application setting industry, which confirmed that the data processing capabilities of the local edge node significantly reduce transaction confirmation time [20].

A framework study on Industry 4.0 and supply chain sustainability has revealed critical implementation challenges in achieving technological synergy, as organizations fail to apply data governance effectively across different technological platforms despite recognizing the importance of technology to supply chain resilience [21]. The solution to the bottleneck presented in the study on synergy effect application in this work (β = 0.176, $P < 0.001$) fills this knowledge gap. The empirical verification of the technological synergy effect constitutes the most pivotal theoretical contribution of this study. With an interaction term coefficient of β = 0.176 (P < 0.001) and fan-shaped divergence observed in the simple slope test, the inherent mechanism is clearly identified, whereby the Internet of Things (IoT) and edge computing technologies complement each other and enhance operational efficiency within the "real-time perception – edge analysis – rapid response" loop. Furthermore, this study demonstrates that as the level of edge computing implementation gradually increases from low to high, the resilience-enhancing effect of IoT is significantly amplified by 72.4%. The amplification factor arises from the complementarity of technology, where IoT addresses data integrity and edge computation overcomes the limitations of handling emergency response scenarios in the conventional cloud-computing model. Additionally, it provides simultaneous optimization of information flow and decision flow processes [22].

The feasibility and efficiency of the aforementioned mechanism in complex supply chain networks have been further validated through subsample analyses. The data show marked differences in the intensity of interaction effects between high-complexity subsets (β = 0.253, P < 0.001) and low-complexity subsets (β = 0.107, P < 0.05). This finding aligns with the existing literature on supply chain network risk prediction using machine learning algorithms, which indicates that in environments characterized by high uncertainty, integrating edge intelligence technology with IoT sensors substantially enhances prediction accuracy [23]. The intensity of the technological synergy effect shows significant industrial heterogeneity. The interaction terms in the manufacturing industry (β = 0.227, P < 0.001) are higher than in the logistics industry (β = 0.121, P < 0.05). This can be associated with the level of technological maturity, where the manufacturing industry has fully embraced Industry 4.0 technology, while service-related industries remain in the technology experimentation phase. This shows that technology promotion policy should avoid a one-size-fits-all approach across industries, thereby preventing the misallocation of resources.

Based on the dynamic capability theory, the collaborative mechanism mainly shows that it is in technological resource reconfiguration that organizations exhibit “perception-grasping-reconstruction” capability, and breakthrough achievements. The combined theoretical studies on digital twin technology and disruption countermeasures in supply chain management offer additional explanations on the micro-mechanism level: “IoT data streams provide high-fidelity inputs to the digital twin models, and the edge computation capability for local simulation supports the efficient iteration of deduction and optimization” [24]. The large-scale quantitative verification shows that the intensity of the collaborative model is greater in the manufacturing industry than in the service industry, which can be attributed to higher physical properties and node interdependency inherent in the former industry. The study on artificial intelligence and machine learning applied to post-disruption supply chain resilience showed that the state-of-the art technological collaborative model combines machine learning algorithms with edge computation nodes. This integration enables autonomous learning from historical disruption patterns, thereby enhancing decision-making regarding optimized response mechanisms [25]. The predictive and optimization capabilities of digital twin technology in dynamic supply chain management define the state-of-the-art technology integration principles proposed in this study, which corresponds to the collaborative process described in the previous section on theories and models [26]. Research on the application of machine learning to supply chain risk prediction and management has demonstrated the real-time advantages of edge intelligence for anomaly detection, explaining why edge computation is superior for speed in such tasks [27].

Robustness and Limitations After addressing endogeneity through employing instrumental variables, the robustness of the core findings is confirmed, with the key effect remaining statistically significant (β = 0.169, P < 0.01). Subgroup analyses further demonstrate the universality of the technological synergy effect across firms of varying sizes and geographic locations. Nevertheless, there are considerable constraints: while methods of public data measurement are unaffected by ethics, the microscopic aspects of technology application are difficult to identify and quantify, particularly given the five-year research timeframe focused on AI-driven supply chain resilience in logistics management and related technology empowerment effects. Consequently, further quantitative research is needed to explore the boundary conditions of the observed effects [28]. Best-practice analyses of IoT implementation in supply chain management specifically emphasize the importance of technology compatibility for synergy effectiveness [29]. While this study does not directly test and validate mediating hypotheses, it provides an empirical basis for future theory refinement. The studies on the roadmap for digital supply chain resilience have revealed complexities in prioritizing technology implementation amid constraints on investment budgets [30]. The current study's synergy outcome provides a quantitative basis for enterprise resource allocation decisions to prioritize the implementation of IoT and edge computing together rather than making large-scale, isolated investments in individual technologies.

5. Conclusion

Based on dynamic capability theory, this study develops an integrated model to examine the synergistic effects of IoT and edge computing on supply chain resilience. Quantitative analysis was conducted using multi-source open data from 892 enterprises. Results revealed significant positive relationships between IoT, edge computing, and resilience (β = 0.341, β = 0.287, P < 0.001), with a significant positive interaction effect (β = 0.176, P < 0.001). Specifically, as the level of edge computing implementation increases from low to high, the positive effect of IoT on supply chain resilience is significantly accentuated by 72.4%. The collaborative mechanism is most pronounced in high-complexity supply chains and the manufacturing industry. This study investigates the synergistic process among "real-time perception," "edge analysis," and "rapid response" in a closed loop, and highlights theoretical gaps in the mechanisms of technology interaction. It identifies how supply chain complexity and industry category regulate these effects. In practice, the study provides data-driven guidance for enterprises regarding their technology investment priorities, with particular emphasis on the coordinated deployment of IoT and edge computing technologies. It also provides empirical evidence for policymakers in formulating differentiated technology promotion strategies. Future research should dynamically track synergistic mechanisms over time and employ AI or digital twins to examine multi-dimensional synergy effects across broader contexts.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

References

[1] D. Ivanov, "Transformation of supply chain resilience research through the COVID-19 pandemic," International Journal of Production Research, vol. 62, no. 23, pp. 8217-8238, 2024.

[2] X. Shi, W. Liu, and M. K. Lim, "Supply chain resilience: new challenges and opportunities," International Journal of Logistics Research and Applications, vol. 27, no. 12, pp. 2485-2512, 2024.

[3] B. Huo, D. Li, and M. Gu, "The impact of supply chain resilience on customer satisfaction and financial performance: A combination of contingency and configuration approaches," Journal of Management Science and Engineering, vol. 9, no. 1, pp. 38-52, 2024.

[4] A. Cinti, M. R. Marcone, A. Sabatini, and V. Temperini, "Enhancing supply chain resilience through the supply network approach," Journal of business & industrial marketing, vol. 40, no. 4, pp. 858-876, 2025.

[5] S. A. Hosseini Shekarabi, R. Kiani Mavi, and F. Romero Macau, "Supply chain resilience: A critical review of risk mitigation, robust optimisation, and technological solutions and future research directions," Global Journal of Flexible Systems Management, pp. 1-55, 2025.

[6] Y. Guo, F. Liu, J.-S. Song, and S. Wang, "Supply chain resilience: A review from the inventory management perspective," Fundamental Research, vol. 5, no. 2, pp. 450-463, 2025.

[7] N. Ishii and M. Ohba, "Quantitative evaluation of an information network in a supply chain," International Journal of Production Economics, vol. 261, p. 108889, 2023.

[8] I. Vlachos and G. Graham, "The internet of things in supply chain management: past, present, and future–a systematic literature review and implementation framework," International Journal of Production Research, pp. 1-31, 2025.

[9] V. Varriale, A. Cammarano, F. Michelino, and M. Caputo, "Sustainable supply chains with blockchain, IoT and RFID: A simulation on order management," Sustainability, vol. 13, no. 11, p. 6372, 2021.

[10] M. R. Karim, D. C. Rodgers, and M. A. Hossain, "The Role of Internet of Things (IoT) in Real-Time Supply Chain Monitoring," International Journal of Research and Innovation in Social Science, vol. 8, no. 10, pp. 1800-1816, 2024.

[11] M. Akbari, "Revolutionizing supply chain and circular economy with edge computing: Systematic review, research themes and future directions," Management Decision, vol. 62, no. 9, pp. 2875-2899, 2024.

[12] Q. He, H. Zhao, Y. Feng, Z. Wang, Z. Ning, and T. Luo, "Edge computing-oriented smart agricultural supply chain mechanism with auction and fuzzy neural networks," Journal of Cloud Computing, vol. 13, no. 1, p. 66, 2024.

[13] M. Ghobakhloo, M. Iranmanesh, B. Foroughi, M.-L. Tseng, D. Nikbin, and A. A. Khanfar, "Industry 4.0 digital transformation and opportunities for supply chain resilience: a comprehensive review and a strategic roadmap," Production planning & control, vol. 36, no. 1, pp. 61-91, 2025.

[14] G. Zhang, Y. Yang, and G. Yang, "Smart supply chain management in Industry 4.0: the review, research agenda and strategies in North America," Annals of operations research, vol. 322, no. 2, pp. 1075-1117, 2023.

[15] E. Pessot, A. Zangiacomi, I. Marchiori, and R. Fornasiero, "Empowering supply chains with Industry 4.0 technologies to face megatrends," Journal of Business Logistics, vol. 44, no. 4, pp. 609-640, 2023.

[16] N. Zhao, J. Hong, and K. H. Lau, "Impact of supply chain digitalization on supply chain resilience and performance: A multi-mediation model," International journal of production economics, vol. 259, p. 108817, 2023.

[17] J. He, M. Fan, and Y. Fan, "Digital transformation and supply chain efficiency improvement: an empirical study from a-share listed companies in China," Plos one, vol. 19, no. 4, p. e0302133, 2024.

[18] H. Jing and Y. Fan, "Digital transformation, supply chain integration and supply chain performance: Evidence from Chinese manufacturing listed firms," Sage Open, vol. 14, no. 3, p. 21582440241281616, 2024.

[19] A. Alzahrani and M. Z. Asghar, "Intelligent risk prediction system in IoT-based supply chain management in logistics sector," Electronics, vol. 12, no. 13, p. 2760, 2023.

[20] S. Asaithambi, S. Nallusamy, J. Yang, S. Prajapat, G. Kumar, and P. S. Rathore, "A secure and trustworthy blockchain-assisted edge computing architecture for industrial internet of things," Scientific Reports, vol. 15, no. 1, p. 15410, 2025.

[21] S. Bag, A. Telukdarie, J. C. Pretorius, and S. Gupta, "Industry 4.0 and supply chain sustainability: framework and future research directions," Benchmarking: An International Journal, vol. 28, no. 5, pp. 1410-1450, 2021.

[22] C. Pechlivanis, "Implementing IoT Technology in Practice: Monitoring the Supply Chain for Sustainable Operation," WSEAS Transactions on Systems, vol. 22, pp. 349-359, 2023.

[23] Z. Rehman, N. Tariq, S. A. Moqurrab, J. Yoo, and G. Srivastava, "Machine learning and internet of things applications in enterprise architectures: Solutions,

challenges, and open issues," Expert Systems, vol. 41, no. 1, p. e13467, 2024.

[24] M. I. Hossain, S. Talapatra, P. Saha, and H. Belal, "From theory to practice: leveraging digital twin technologies and supply chain disruption mitigation strategies for enhanced supply chain resilience with strategic fit in focus," Global Journal of Flexible Systems Management, vol. 26, no. 1, pp. 87-109, 2025.

[25] G. S. Balan, V. S. Kumar, and S. A. Raj, "Machine Learning and Artificial Intelligence Methods and Applications for Post-Crisis Supply Chain Resiliency and Recovery," Supply Chain Analytics, p. 100121, 2025.

[26] D.-H. Kim, G.-Y. Kim, and S. D. Noh, "Digital Twin-Based Prediction and Optimization for Dynamic Supply Chain Management," Machines, vol. 13, no. 2, p. 109, 2025.

[27] C. Li and H. Chen, "Machine Learning Based Supply Chain Risk Prediction and Management," in Proceeding of the 2024 5th International Conference on Computer Science and Management Technology, 2024, pp. 842-847.

[28] R. U. Attah, B. M. P. Garba, I. Gil-Ozoudeh, and O. Iwuanyanwu, "Enhancing supply chain resilience through artificial intelligence: Analyzing problem-solving approaches in logistics management," International Journal of Management & Entrepreneurship Research, vol. 5, no. 12, pp. 3248-3265, 2024.

[29] K. Sallam, M. Mohamed, and A. W. Mohamed, "Internet of Things (IoT) in supply chain management: challenges, opportunities, and best practices," SMIJ, vol. 2, no. 2, p. 32, 2023.

[30] A. Al-Banna, M. Yaqot, and B. Menezes, "Roadmap to digital supply chain resilience under investment constraints," Production & Manufacturing Research, vol. 11, no. 1, p. 2194943, 2023.