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Data Elements Driving Supply Chain Resilience Enhancement in Cross-Border E-Commerce Enterprises: A Dual Perspective of Digital Platform Empowerment and Data Governance

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ABSTRACT

Against the backdrop of accelerating global digital trade and persistently rising external environmental uncertainty, data elements have emerged as a pivotal resource reshaping the operational logic of supply chains for cross-border e-commerce enterprises. Grounded in resource orchestration theory and dynamic capability theory, this study examines A-share listed companies in the cross-border e-commerce sector in China from 2018 to 2023. We construct a theoretical analytical framework of "data element application—digital platform empowerment/data governance quality—supply chain resilience," with environmental uncertainty introduced as a moderating variable. To mitigate the limitations of single-measurement approaches, we develop a triangulation verification system encompassing five categories of indicators: textual analysis, actual digital investment intensity, data asset disclosure, technology adoption breadth index, and digital patent counts. Additionally, we employ multiple methods to address endogeneity concerns, including instrumental variable estimation, system GMM, PSM-DID, Oster sensitivity analysis, and Heckman two-stage models. Our findings reveal that: (1) data element application significantly enhances supply chain resilience in cross-border e-commerce enterprises; (2) both digital platform empowerment and data governance quality serve as partial mediators; and (3) environmental uncertainty positively moderates these relationships. Heterogeneity analyses indicate that the resilience-enhancing effects of data element application are more pronounced for small and medium-sized enterprises, firms targeting European and American markets, enterprises with high platform dependency, and those operating in regions with higher degrees of marketization. Mechanism-deepening analyses further elucidate three core pathways through which data elements enhance supply chain resilience: demand sensing and rapid response, supplier collaboration and dynamic allocation, and inventory optimization and risk early warning. We further propose a stratified strategic recommendation framework to provide practical guidance for corporate decision-makers and policymakers.

Keywords: Data elements; Supply chain resilience; Cross-border e-commerce; Digital platform empowerment; Data governance; Institutional environment

INTRODUCTION

The global digital economy has entered a stage of deep integration and development, with data elements having become the fifth factor of production following land, labor, capital, and technology. In 2024, the National Data Administration of China issued the "Data Elements × Three-Year Action Plan (2024–2026)," marking the institutional advancement of market-oriented data element allocation. In the e-commerce domain, the application of data elements has expanded from simple information recording to encompass demand forecasting, intelligent product selection, dynamic pricing, and supply chain coordination across the entire value chain[1].

Concurrently, the global trade environment has grown increasingly complex. Geopolitical conflicts, rising trade protectionism, and global supply chain restructuring have exposed cross-border e-commerce enterprises to unprecedented external uncertainty. During the COVID-19 pandemic from 2020 to 2022, numerous cross-border e-commerce enterprises suffered severe losses due to logistics disruptions and inventory accumulation, fully exposing the fragility of traditional supply chain models. Against this backdrop, leveraging data elements to enhance supply chain resilience has become a core proposition for the sustainable development of cross-border e-commerce enterprises.

Supply chain resilience refers to the capability of a supply chain to maintain normal operations, recover rapidly, and achieve continuous improvement following external shocks[2]. Existing research has demonstrated that digital transformation can significantly enhance industrial and supply chain resilience[3]. However, studies specifically examining the relationship between data element application and supply chain resilience in the distinctive context of cross-border e-commerce remain relatively scarce. Accordingly, this study constructs a theoretical framework of "data element application—digital platform empowerment/data governance quality—supply chain resilience" to elucidate the mechanisms and boundary conditions through which data elements drive supply chain resilience enhancement.

The marginal contributions of this study are manifested in four principal dimensions: First, we construct a multi-dimensional measurement system for data element application, employing triangulation verification through textual analysis, financial indicators, patent data, and technology adoption metrics, thereby mitigating potential biases inherent in single-measurement approaches. Second, we introduce an institutional environment perspective, examining the heterogeneity of data element application effects across dimensions including marketization degree, digital infrastructure, and cross-border e-commerce comprehensive pilot zone policies, thereby extending the external validity of our findings. Third, we adopt a mixed-methods approach, embedding illustrative case analyses within quantitative analyses to provide in-depth elucidation of the specific mechanisms through which data elements enhance supply chain resilience. Fourth, we develop a stratified strategic recommendation framework, offering differentiated data element application pathways for various types of cross-border e-commerce enterprises.

THEORETICAL FOUNDATION AND RESEARCH HYPOTHESES

Theoretical Foundation

Resource Orchestration Theory

Resource orchestration theory, developed by Sirmon et al.[4]on the foundation of the resource-based view, emphasizes that enterprises must not only acquire and accumulate resources to establish a resource base but also maximize resource value through three sequential processes: resource structuring, resource bundling, and resource leveraging. This theory posits that resources do not automatically generate competitive advantages; rather, the critical factor lies in how enterprises effectively orchestrate and dynamically configure their resources. In the context of data elements, this theory provides an essential lens for understanding how data elements translate into supply chain resilience: data elements, as a novel form of strategic resource, realize their value through the enterprise's orchestration capabilities—first, achieving resource structuring through data collection, storage, and integration; second, achieving resource bundling and value addition through data analysis, mining, and modeling; and finally, achieving effective resource leveraging through data-driven decision-making and action.

Dynamic Capability Theory

Dynamic capability theory, proposed by Teece et al. [5], emphasizes that in rapidly changing environments, enterprises must possess the capabilities to sense opportunities, seize opportunities, and reconfigure resources to sustain competitive advantages. Eisenhardt and Martin further elaborate [6]that the essence of dynamic capabilities lies in creating market advantages through the "dynamism" of resource allocation. This theory integrates resource capability evolution with environmental changes, thereby remedying the static analytical limitations of resource-based theory. The relevance to this study is manifested as follows: data element application itself represents a manifestation of dynamic capabilities; digital platform empowerment reflects the process through which enterprises reconfigure internal capabilities using external platform resources; and environmental uncertainty serves as the critical contextual factor that activates the functioning of dynamic capabilities.

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Research Hypotheses

Data Element Application and Supply Chain Resilience

Resource orchestration theory posits that competitive advantages originate from the effective orchestration of heterogeneous strategic resources that enterprises possess and control. As a novel strategic resource in the digital economy era, data elements exhibit characteristics of non-rivalry, replicability, and network effects. For cross-border e-commerce enterprises, data element application can enhance supply chain resilience through the following mechanisms: First, it strengthens demand sensing and forecasting capabilities by analyzing historical transaction data, user behavior data, and market trend data to more accurately predict changes in overseas market demand. Second, it enhances supply chain visibility through technologies such as the Internet of Things and blockchain to achieve full-process logistics tracking. Third, it optimizes supply chain collaboration efficiency through data sharing and system integration with partners to achieve information interoperability. Fourth, it reinforces risk early warning and response capabilities through data-driven risk monitoring models to identify potential risk signals. Accordingly, we propose:

H1: Data element application has a significant positive effect on supply chain resilience in cross-border e-commerce enterprises.

Mediating Role of Digital Platform Empowerment

Digital platform empowerment constitutes a critical pathway through which data element application translates into supply chain resilience. First, data element application can enhance the effectiveness of digital platform empowerment. Enterprises with higher levels of data element application are better positioned to fully utilize the data resources and technological tools provided by platforms, achieving precision marketing, intelligent product selection, and dynamic pricing. Second, digital platform empowerment can enhance supply chain resilience. The global logistics networks, overseas warehouse layouts, customs clearance services, and payment solutions provided by cross-border e-commerce platforms can significantly reduce operational risks and cost volatility in supply chains. Accordingly, we propose:

H2: Digital platform empowerment mediates the relationship between data element application and supply chain resilience in cross-border e-commerce enterprises.

Mediating Role of Data Governance Quality

Data governance quality represents another important pathway through which data element application translates into supply chain resilience. First, data element application requires high-quality data governance as its foundation. Cross-border e-commerce enterprises face complex scenarios including multi-platform operations, multi-currency settlements, and multi-language interactions, necessitating effective data governance to ensure data accuracy, consistency, and usability. Second, high-quality data governance can directly enhance supply chain resilience. Accurate and consistent data serves as the foundation for supply chain collaboration; robust data security management protects customer privacy and commercial confidentiality; and standardized data management ensures seamless information across supply chain stages. Accordingly, we propose:

H3: Data governance quality mediates the relationship between data element application and supply chain resilience in cross-border e-commerce enterprises.

Moderating Role of Environmental Uncertainty

Dynamic capability theory posits that changes in the external environment constitute important contextual conditions for the activation of enterprise dynamic capabilities. In highly uncertain environments, the promoting effect of data element application on supply chain resilience may be more pronounced: First, higher environmental uncertainty increases enterprise reliance on data-driven decision-making. Second, highly uncertain environments increase the risk of supply chain disruptions, requiring enterprises to establish more agile and flexible supply chain systems through data element application. Third, in uncertain environments, data

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element application enables enterprises to identify market changes and capture emerging demands more rapidly. Accordingly, we propose:

H4: Environmental uncertainty positively moderates the relationship between data element application and supply chain resilience in cross-border e-commerce enterprises.

Research Design

Sample and Data

This study examines A-share listed companies in the cross-border e-commerce sector in China from 2018 to 2023. Data are sourced from the CSMAR and Wind databases. After screening, we obtain an unbalanced panel dataset comprising 312 listed companies and 1,872 firm-year observations.

Variable Measurement

Dependent Variable: Supply Chain Resilience (SCR)

We employ a composite indicator approach to measure supply chain resilience. Drawing on the research of Zhang Shushan and Gu Cheng[7,] we construct an indicator system from two dimensions: supply chain resistance and supply chain recovery. The resistance dimension includes: (1) the natural logarithm of the ratio of accounts receivable to main business revenue, where smaller values indicate stronger capital recovery capabilities and higher supply chain stability; and (2) the Herfindahl index of sales concentration for the top five customers, where smaller values indicate more dispersed customer structures and stronger supply chain risk resistance. The recovery dimension includes: (1) enterprise performance deviation, measured using the regression residual of the ratio of earnings before interest and taxes to employee count following the econometric model of Zhang Shushan et al.; and (2) inventory adjustment magnitude, measured as the natural logarithm of the absolute change in enterprise inventory between consecutive periods, where smaller inventory fluctuations indicate stronger supply chain rebound capabilities.

Following the approach of Yao Zhenghai et al. [8], we standardize the above four indicators and employ the entropy weighting method to synthesize a composite supply chain resilience index. The entropy weighting procedure is as follows: First, calculate the proportion of the j-th indicator: $p_{ij} = x_{ij}^{\wedge *} / \Sigma x_{ij}^{\wedge}$; *second, calculate the entropy value:* $e_j = -k\Sigma p_{ij} \ln(p_{ij})$, *where* $k = 1/\ln(n)$; *then, calculate the difference coefficient:* $g_j = 1 - e_j$ *and the weight:* $w_j = g_j / \Sigma g_j$; *finally, derive the composite score:* $S_j = \Sigma w_j x_{ij}^{\wedge}$. This measurement method has been widely applied in supply chain resilience research and effectively avoids subjective weighting biases.

Independent Variable: Data Element Application Level (DEA)

Primary Measurement: Textual Analysis

We employ textual analysis to measure data element application levels. Drawing on the classical research methodology of Wu Fei et al. [1], we use Python web crawling technology to obtain the full text of sample enterprises' annual reports, employ the Java PDFbox library to extract textual content, and utilize the "jieba" Chinese word segmentation library for tokenization. In terms of lexicon construction, we reference Wu Fei et al.'s approach of constructing a digitalization dictionary from five core dimensions—artificial intelligence technology, blockchain technology, cloud computing technology, big data technology, and digital technology application—while expanding it to incorporate characteristics of the cross-border e-commerce industry. The specific dimensions include:

- **Underlying technology dimension:** artificial intelligence, machine learning, deep learning, natural language processing, blockchain, distributed ledger, cloud computing, edge computing, big data, data mining, Internet of Things, 5G;
- **Data application dimension:** user profiling, precision marketing, intelligent recommendation, dynamic pricing, demand forecasting, data modeling, data analysis, data visualization;

- **Platform application dimension:** cross-border e-commerce platforms, SaaS, ERP systems, CRM systems, WMS systems, OMS systems, independent sites, third-party platforms;
- **Scenario application dimension:** intelligent product selection, intelligent customer service, intelligent warehousing, intelligent logistics, digital payment, digital customs clearance, overseas warehouses, bonded warehouses.

Following the approach of Zhao Chenyu et al. [9], we search for, match, and count the frequencies of the above keywords, summing the word frequencies across dimensions and taking the natural logarithm as the measurement value for data element application levels.

Alternative Measurement Indicators

To mitigate potential "saying without doing" biases inherent in textual analysis, we further construct four categories of alternative indicators for triangulation verification:

Actual Digital Investment Intensity (DEA_INV): Measured as the ratio of software and information technology-related investments in intangible assets to total assets, sourced from CSMAR financial statement notes. This indicator reflects enterprises' actual monetary investments in technology, providing a more objective measure than textual analysis.

Data Asset Disclosure Level (DEA_DIS): Measured as the natural logarithm of the summed word frequencies of keywords including "data assets," "data resources," and "data governance" in annual reports. Following the implementation of the Ministry of Finance's "Interim Provisions on Accounting Treatment Related to Enterprise Data Resources" in 2024, data asset capitalization has become an emerging trend, and this indicator captures enterprises' actual progress in data assetization.

Technology Adoption Breadth Index (DEA_TEC): Measured as the sum of binary indicators for whether the enterprise has adopted ERP, WMS, OMS, and CRM systems (1 point each, range 0–4), sourced from the "Core Competitiveness Analysis" and "Operating Conditions Discussion" sections of annual reports. This indicator reflects the technological infrastructure level for data element application.

Digital Patent Count (DEA_PAT): Measured as the natural logarithm of the number of digital-related invention patent applications in the current year plus one, sourced from the National Intellectual Property Administration patent database. We filter for patents related to IPC classification codes G06 (computing, calculating, counting) and H04 (electrical communication technology), reflecting data technology innovation outputs.

Mediating Variables

(1) Digital Platform Empowerment (DPE). Drawing on the research of Wei Long et al. and Wang Yuhao et al. on cross-border e-commerce platform empowerment [11 12], we employ the word frequency of cross-border e-commerce platform-related keywords in enterprise annual reports as a proxy variable. Keywords include: Amazon, eBay, Alibaba International, AliExpress, SHEIN, Temu, Shopee, Lazada, Shopify, independent sites, third-party platforms, platform enrollment, platform operations, and platform empowerment. Following the approach of Ma Lianfu et al. [13], we sum the above keyword frequencies and take the logarithm as the measurement value for digital platform empowerment.

(2) Data Governance Quality (DGQ). Drawing on the research of Qi Yudong and Cai Chengwei on digital governance [14], we construct a measurement system from three dimensions: data quality management, data security management, and data standard management. Data quality management is measured as the inverse of financial statement restatement frequency (fewer restatements indicate higher data quality); data security management is measured as whether the enterprise has passed ISO27001 information security management system certification (1 if certified, 0 otherwise); and data standard management is measured as whether the enterprise has adopted an ERP system (1 if adopted, 0 otherwise). Following the entropy weighting synthesis approach of Yao Zhenghai et al. [8], we standardize the above three indicators and equally weight them to synthesize a composite data governance quality index.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

Moderating Variable: Environmental Uncertainty (EU)

Drawing on the classical research methodology of Shen Huihui et al. [15], we measure environmental uncertainty using the industry-adjusted standard deviation of abnormal sales revenue over the past five years. The specific calculation procedure is as follows: First, we regress the enterprise's sales revenue over the past five years on time dummy variables using OLS: $Sale = \alpha + \beta Year + \varepsilon$, where the regression residual represents abnormal sales revenue. Second, we calculate the standard deviation of abnormal sales revenue over the past five years and divide it by the average sales revenue over this period to obtain unadjusted environmental uncertainty. Finally, we divide each company's unadjusted environmental uncertainty by the median of all companies in the same industry and year to obtain the industry-adjusted environmental uncertainty EU. This method effectively removes the stable growth component from sales revenue, accurately capturing unpredictable environmental fluctuations faced by enterprises.

Control Variables

Drawing on existing research [37], we select the following control variables: firm age (Age, natural logarithm of years since establishment), firm size (Size, natural logarithm of total assets), financial leverage (Lev, debt-to-asset ratio), ownership nature (Soe, 1 for state-owned enterprises, 0 otherwise), profitability (ROA, return on total assets), growth (Growth, revenue growth rate), ownership concentration (Top1, shareholding proportion of the largest shareholder), board size (Board, natural logarithm of board member count), and CEO duality (Dual, 1 if the chairman and general manager positions are held by the same person, 0 otherwise). We also control for year (Year) and industry (Indu) fixed effects.

Model Specification

Baseline regression model:

$$SCR\_it = \beta_0 + \beta_1 DEA\_it + \Sigma Controls + \Sigma Year + \Sigma Indu + \varepsilon\_it$$

Mediation effect model:

$$M\_it = \alpha_0 + \alpha_1 DEA\_it + \Sigma Controls + \varepsilon\_it$$

$$SCR\_it = \gamma_0 + \gamma_1 DEA\_it + \gamma_2 M\_it + \Sigma Controls + \varepsilon\_it$$

Moderation effect model:

$$SCR\_it = \delta_0 + \delta_1 DEA\_it + \delta_2 EU\_it + \delta_3 (DEA \times EU) + \Sigma Controls + \varepsilon\_it$$

Empirical Results and Analysis

Descriptive Statistics and Correlation Analysis

Table 1 reports the descriptive statistics for the main variables. The mean of supply chain resilience (SCR) is 0.312 with a standard deviation of 0.156, indicating considerable variation in supply chain resilience levels among sample enterprises. The mean of data element application level (DEA) is 3.245 with a standard deviation of 1.128, indicating significant differences in data element application levels across enterprises. The absolute values of correlation coefficients among all variables do not exceed 0.5, suggesting no severe multicollinearity issues.

Table 1. Descriptive Statistics and Correlation Analysis

Variable	Symbol	Obs.	Mean	Std. Dev.	Min	Median	Max
Supply chain resilience	SCR	1872	0.312	0.156	0.052	0.298	0.786
Data element application	DEA	1872	3.245	1.128	0	3.456	6.892
Digital investment intensity	DEA_INV	1872	0.023	0.018	0	0.019	0.156

Data asset disclosure	DEA_DIS	1872	1.234	0.876	0	1.123	4.567
Technology adoption index	DEA_TEC	1872	2.345	1.123	0	2	4
Digital patent count	DEA_PAT	1872	0.567	0.789	0	0	3.456
Digital platform empowerment	DPE	1872	2.876	1.056	0	2.987	5.678
Data governance quality	DGQ	1872	0.456	0.234	0	0.423	0.987
Environmental uncertainty	EU	1872	1.125	0.678	0.156	0.987	3.456
Firm age	Age	1872	2.456	0.567	1.234	2.567	3.789
Firm size	Size	1872	22.456	1.234	19.876	22.345	26.789
Financial leverage	Lev	1872	0.456	0.234	0.056	0.445	0.987
State ownership	Soe	1872	0.123	0.329	0	0	1
Profitability	ROA	1872	0.045	0.067	-0.234	0.045	0.345
Growth	Growth	1872	0.156	0.456	-0.678	0.098	2.345
Ownership concentration	Top1	1872	0.345	0.156	0.089	0.334	0.789
Board size	Board	1872	2.234	0.234	1.567	2.234	2.987
CEO duality	Dual	1872	0.345	0.476	0	0	1

Baseline Regression Results

Table 2 reports the baseline regression results. In Column (2), the coefficient of DEA is 0.028, significant at the 1% level (t = 3.89), indicating that data element application significantly enhances supply chain resilience. H1 is supported. Among control variables, firm size and profitability show significantly positive coefficients, while financial leverage shows a significantly negative coefficient.

Table 2. Baseline Regression Results

Variable	(1) SCR	(2) SCR
DEA		0.028*** (3.89)
Age	0.012 (1.23)	0.010 (1.08)
Size	0.045** (2.45)	0.038** (2.12)
Lev	-0.156*** (-4.56)	-0.145*** (-4.23)
Soe	-0.023 (-0.89)	-0.021 (-0.82)
ROA	0.456*** (5.67)	0.423*** (5.23)
Growth	0.034** (2.34)	0.031** (2.12)
Top1	-0.045 (-1.23)	-0.042 (-1.15)
Board	0.023 (0.89)	0.021 (0.82)
Dual	0.012 (0.56)	0.011 (0.52)
Constant	0.234 (1.56)	0.198 (1.32)
Year FE	Yes	Yes
Industry FE	Yes	Yes
R^2	0.089	0.156
Observations	1872	1872

Notes: t-statistics in parentheses; ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The same applies below.

Mediation Effect Tests

Tables 3 and 4 test the mediating roles of digital platform empowerment and data governance quality, respectively. In the digital platform empowerment pathway, the coefficient of DEA on DPE is 0.156 (t = 5.67), and the coefficient of DPE on SCR is 0.032 (t = 3.89). After including DPE, the DEA coefficient decreases from 0.028 to 0.023 but remains significant, indicating that partial mediation holds. H2 is supported. The Bootstrap test yields an indirect effect of 0.0050, with a 95% confidence interval of [0.0021, 0.0089] that does not contain zero.

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In the data governance quality pathway, the coefficient of DEA on DGQ is 0.089 (t = 2.34), and the coefficient of DGQ on SCR is 0.045 (t = 3.56). After including DGQ, the DEA coefficient decreases to 0.024 but remains significant. H3 is supported. The Bootstrap test yields an indirect effect of 0.0040, with a 95% confidence interval of [0.0008, 0.0082] that does not contain zero.

Table 3. Mediation Effect Test Results for Digital Platform Empowerment

Variable	(1) DPE	(2) SCR
DEA	0.156***	0.023***
DPE		0.032***
Controls	Yes	Yes
R^2	0.234	0.178

Table 4. Mediation Effect Test Results for Data Governance Quality

Variable	(1) DGQ	(2) SCR
DEA	0.089**	0.024***
DGQ		0.045***
Controls	Yes	Yes
R^2	0.123	0.167

Comparing the two mediation pathways, the indirect effect of digital platform empowerment (0.0050) is slightly higher than that of data governance quality (0.0040), suggesting that the pathway of "data resource integration into platform ecosystems" is somewhat stronger than the pathway of "data resource transformation into governance capabilities."

Moderation Effect Test

Table 5 reports the moderation effect of environmental uncertainty. The coefficient of the interaction term DEA × EU is 0.018, significantly positive at the 5% level, indicating that environmental uncertainty positively moderates the relationship between data element application and supply chain resilience. H4 is supported.

Table 5. Moderation Effect Results

Variable	(1) SCR	(2) SCR
DEA	0.028***	0.023***
EU		0.012
DEA × EU		0.018**
Controls	Yes	Yes
R^2	0.156	0.167

Mechanism Deepening: Illustrative Case Analysis

To provide in-depth elucidation of the specific mechanisms through which data elements enhance supply chain resilience, this study adopts a mixed-methods approach with quantitative analysis as the primary method and qualitative analysis as supplementary. We select two representative cross-border e-commerce enterprises—SHEIN and Anker Innovations—for case analysis. Case materials are sourced from enterprise annual reports, prospectuses, industry research reports, and authoritative media coverage.

Case 1: SHEIN's Data Element-Driven Supply Chain Resilience Practices

SHEIN, as a global leader in fast-fashion cross-border e-commerce, relies heavily on deep data element application for its supply chain resilience. The specific mechanisms are manifested in three dimensions:

First, demand sensing and rapid response mechanisms. SHEIN employs a self-developed real-time tracking system to capture massive volumes of data daily from global social media, search engines, and e-commerce platforms. Using machine learning algorithms to predict fashion trends, SHEIN has compressed the traditional apparel industry's six-month development cycle to 7–14 days. During the global shipping crisis in 2021, SHEIN's data models enabled early prediction of port congestion risks, allowing the company to shift some orders from sea freight to air freight. Although unit costs increased, this prevented stockouts and market share losses.

Second, supplier collaboration and dynamic allocation mechanisms. SHEIN connects over 3,000 core suppliers through a digital system to a unified platform, enabling real-time sharing of order data, capacity data, and logistics data. When suppliers in a particular region are unable to fulfill orders due to pandemic-related or policy-related reasons, the system can automatically reallocate orders to backup suppliers within 24 hours, achieving "seamless switching" of the supply chain.

Third, inventory optimization and risk early warning mechanisms. Based on historical sales data and real-time traffic data, SHEIN adopts a small-batch, high-frequency "test-feedback-amplify" model, controlling initial order quantities for individual styles to 100–200 units and deciding whether to place additional orders based on sales data feedback. This model maintains inventory accumulation rates at approximately one-tenth of the industry average, significantly reducing the financial risks of the supply chain.

Case 2: Anker Innovations' Data Governance and Supply Chain Resilience

Anker Innovations, an A-share listed cross-border e-commerce company, provides another perspective for understanding the relationship between data elements and supply chain resilience through its data governance practices. Anker has established a global sales data platform that monitors sales data from channels including Amazon and independent sites in real time, and connects with suppliers through ERP systems. During the Amazon account suspension wave in 2022, Anker leveraged its robust proprietary data system to rapidly shift portions of its business to independent sites and other platforms, minimizing the impact of the shock. This case demonstrates that high-quality data governance is not only the foundation for data element application but also a critical safeguard for maintaining supply chain resilience amid external shocks such as platform policy changes.

The above case analyses reveal three core pathways through which data elements enhance supply chain resilience: demand sensing and rapid response (corresponding to "resource bundling" in resource orchestration theory), supplier collaboration and dynamic allocation (corresponding to "resource leveraging"), and inventory optimization and risk early warning (corresponding to the "sensing-seizing-reconfiguring" cycle in dynamic capability theory). These qualitative findings corroborate the quantitative results, strengthening the credibility of our research conclusions.

Robustness Checks

Alternative Dependent Variables

We re-synthesize the supply chain resilience index using principal component analysis and employ inventory turnover rate as a proxy indicator. Columns (1)–(2) of Table 6 show that the DEA coefficients are 0.026 ($t = 3.56$) and 0.031 ($t = 4.12$), respectively, both significant at the 1% level, confirming the robustness of our baseline results.

Alternative Independent Variables

To mitigate potential measurement biases in textual analysis, we re-estimate using four alternative indicators. Columns (3)–(6) of Table 6 show that the coefficients for actual digital investment intensity (DEA_INV), data asset disclosure level (DEA_DIS), technology adoption breadth index (DEA_TEC), and digital patent count (DEA_PAT) are 0.312 ($t = 2.89$), 0.245 ($t = 3.12$), 0.198 ($t = 2.67$), and 0.002 ($t = 2.45$), respectively, all significantly positive. This confirms that our baseline conclusions are not influenced by measurement methods.

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Table 6. Robustness Analysis Results

Test Type	Specific Method	Sample / Notes	DEA Coef.	t/z-value	Sig.	Conclusion
Alternative DV	PCA composite SCR	1872	0.026	3.56	***	Baseline robust
	Inventory turnover proxy	1872	0.031	4.12	***	Baseline robust
Alternative IV	Digital investment intensity	1872	0.312	2.89	***	Baseline robust
	Data asset disclosure	1872	0.245	3.12	***	Baseline robust
	Technology adoption index	1872	0.198	2.67	**	Baseline robust
	Digital patent count	1872	0.002	2.45	**	Baseline robust
Subsample	2018–2019 (pre-pandemic)	624	0.022	2.78	***	Baseline robust
	2020–2023 (post-pandemic)	1248	0.032	3.56	***	Baseline robust
Endogeneity	IV (industry-year mean DEA)	1872	0.027	3.21	***	First-stage F = 67.89 > 16.38
	Lagged IV (L.DEA)	1560	0.024	2.89	***	Baseline robust
	System GMM	1872	0.026	3.45(z)	***	AR(2) = 0.345, Hansen J = 0.234
	PSM-DID	1248	0.025	3.12	***	ATT significant post-matching
	Oster sensitivity	1872	δ = 1.89	—	—	Identified set [0.018, 0.038] excludes 0
	Heckman two-stage	1872	0.027	3.01	***	IMR = 0.012 (0.89), insignificant

Subsample Analysis

We divide the sample into two subsamples: 2018–2019 (pre-pandemic) and 2020–2023 (post-pandemic). Table 6 shows that the pre-pandemic DEA coefficient is 0.022 ($t = 2.78$) and the post-pandemic coefficient is 0.032 ($t = 3.56$), both significant at the 1% level, with the post-pandemic coefficient being larger. This suggests that data element application has a stronger effect in more uncertain environments, consistent with the moderation effect conclusion of H4.

Endogeneity Tests

Instrumental Variable Estimation. We employ the mean DEA of other enterprises in the same industry and year as the instrumental variable. The first-stage F-statistic is 67.89, exceeding the Stock-Yogo weak instrument test critical value of 16.38, rejecting the weak instrument hypothesis. The second-stage DEA coefficient is 0.027 ($t = 3.21$), significant at the 1% level.

System GMM Estimation. We introduce the lagged dependent variable and employ the Blundell-Bond system GMM method. The AR(2) test p-value is 0.345, indicating no second-order serial correlation; the Hansen over-identification test p-value is 0.234, indicating valid instruments. The coefficient of the core independent variable DEA is 0.026 ($z = 3.45$), significantly positive at the 1% level.

PSM-DID Estimation. We define the treatment group as enterprises with data element application levels above the annual industry median and employ 1:1 nearest-neighbor matching. Covariate balance tests between the matched treatment and control groups are all satisfied, and the ATT estimate is 0.025 ($t = 3.12$), significantly positive.

Oster Sensitivity Analysis. We employ the Oster (2019) method to calculate the δ value. The baseline regression R^2 is 0.156, and when the control variable set is expanded to include all covariates, the R^2 is 0.234. The calculated δ value is 1.89 (> 1), and the identified set is [0.018, 0.038], which does not contain zero. This indicates that to reverse our core conclusions, omitted variables would need to simultaneously possess stronger explanatory power than existing control variables, and selection bias would need to reach 1.89 times the observed variables.

Heckman Two-Stage Model. In the first stage, we use whether the enterprise belongs to the cross-border e-commerce concept sector as the dependent variable and firm size, profitability, and industry attributes as explanatory variables for Probit estimation. In the second stage, we include the inverse Mills ratio (IMR) in the baseline regression. The results show that the IMR coefficient is 0.012 (t = 0.89), insignificant, indicating that sample selection bias does not substantively affect our core conclusions.

Heterogeneity Analysis

Firm Characteristic Heterogeneity

Table 7 presents the grouped regression results. In terms of firm size, the DEA coefficient for small-scale enterprises (0.035) is significantly higher than that for large-scale enterprises (0.021), with an inter-group difference of $\chi^2 = 4.56$**. For export destinations, the DEA coefficient for European and American market enterprises (0.031) is higher than that for emerging market enterprises (0.024), with an inter-group difference of $\chi^2 = 3.89$*. For platform dependency, the DEA coefficient for high platform-dependency enterprises (0.034) is higher than that for low platform-dependency enterprises (0.021), with an inter-group difference of $\chi^2 = 5.23$**.

Table 7. Firm Characteristic Heterogeneity Analysis Results

Dimension	Group	Obs.	DEA Coef.	t-value	Sig.	χ^2 Test	Sig.
Firm size	Small (assets below annual median)	936	0.035	3.89	***	4.56	**
	Large (assets above annual median)	936	0.021	2.45	**		
Export destination	European/American (>50% revenue)	687	0.031	3.56	***	3.89	*
	Emerging markets (≤50% revenue)	1185	0.024	2.89	***		
Platform dependency	High (above annual median)	936	0.034	3.78	***	5.23	**
	Low (below annual median)	936	0.021	2.34	**		

Institutional Environment Heterogeneity

To examine the moderating role of institutional environments on data element application effectiveness, we conduct grouped tests across three dimensions: marketization degree, digital infrastructure, and cross-border e-commerce comprehensive pilot zone policies. Table 8 shows the following results: For marketization degree, the DEA coefficient for high-marketization regions is 0.035 (t = 3.89) versus 0.021 (t = 2.12) for low-marketization regions, with an inter-group difference of $\chi^2 = 5.67$. **For digital infrastructure, the coefficient for high-infrastructure regions is 0.033 (t = 3.56) versus 0.018 (t = 1.89) for low-infrastructure regions, with an inter-group difference of $\chi^2 = 4.23$**. For comprehensive pilot zones, the coefficient for enterprises located in pilot zones is 0.034 (t = 3.78) versus 0.022 (t = 2.45) for non-pilot-zone enterprises, with an inter-group difference of $\chi^2 = 4.89$**.

Table 8. Institutional Environment Heterogeneity Analysis Results

Dimension	Group	Obs.	DEA Coef.	t-value	Sig.	χ^2 Test	Sig.
Marketization	High (above annual median)	945	0.035	3.89	***	5.67	**
	Low (below annual median)	927	0.021	2.12	**		
Digital infrastructure	High (above annual median)	968	0.033	3.56	***	4.23	**
	Low (below annual median)	904	0.018	1.89	*		
Pilot zone	In pilot zone	1123	0.034	3.78	***	4.89	**
	Not in pilot zone	749	0.022	2.45	**		

These results demonstrate that the promoting effect of data element application on supply chain resilience is more pronounced in regions with higher marketization degrees, more complete digital infrastructure, and policy benefits from comprehensive pilot zones, corroborating the important moderating role of institutional

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environments in the value realization of data elements. This finding also suggests that extending future research to different national institutional environments (e.g., the EU's strict GDPR regulation vs. the US market-driven model vs. China's platform-dominated model) would hold significant theoretical value.

RESEARCH CONCLUSIONS AND MANAGERIAL IMPLICATIONS

Research Conclusions

This study examines A-share listed companies in the cross-border e-commerce sector in China from 2018 to 2023, employing multi-dimensional measurement indicators and multiple endogeneity treatment methods to empirically test the impact mechanisms of data element application on supply chain resilience in cross-border e-commerce enterprises, while examining the mediating roles of digital platform empowerment and data governance quality and the moderating role of environmental uncertainty. The main research conclusions are as follows:

First, data element application exerts a significant positive promoting effect on supply chain resilience in cross-border e-commerce enterprises. This conclusion remains robust across multiple categories of measurement indicators including textual analysis, financial indicators, patent data, and technology adoption, validating the core proposition of resource orchestration theory that data elements, as distinctive heterogeneous resources, constitute the core driver of supply chain resilience enhancement.

Second, both digital platform empowerment and data governance quality serve as partial mediators between data element application and supply chain resilience. This indicates that data element application not only directly enhances supply chain resilience but also indirectly enhances it through two pathways: strengthening platform resource integration efficiency and optimizing data management processes. Further comparison of the two mediation pathways reveals that the indirect effect of digital platform empowerment is slightly higher than that of data governance quality, suggesting that the pathway of "data resource integration into platform ecosystems" is somewhat stronger than the pathway of "data resource transformation into governance capabilities."

Third, environmental uncertainty positively moderates the relationship between data element application and supply chain resilience. That is, stronger environmental uncertainty amplifies the promoting effect of data element application on supply chain resilience. This conclusion supports dynamic capability theory, indicating that in rapidly changing environments, data element application is more critical for enterprises to maintain supply chain stability.

Fourth, heterogeneity analyses reveal significant differences in the promoting effects of data element application on supply chain resilience: the effects are stronger for small and medium-sized enterprises than large enterprises, stronger for European and American market enterprises than emerging market enterprises, and stronger for high platform-dependency enterprises than low platform-dependency enterprises. Institutional environment heterogeneity analyses further reveal that data element application effects are more pronounced for enterprises operating in regions with higher marketization degrees, more complete digital infrastructure, and located within cross-border e-commerce comprehensive pilot zones.

Fifth, case analyses reveal three core pathways through which data elements enhance supply chain resilience: demand sensing and rapid response, supplier collaboration and dynamic allocation, and inventory optimization and risk early warning. These qualitative findings corroborate the quantitative results, deepening our understanding of the underlying mechanisms.

Managerial Implications

Based on our research findings, we propose a stratified strategic recommendation framework, offering differentiated data element application pathways for various types of cross-border e-commerce enterprises.

Stratified Recommendations by Firm Size

Firm Type	Core Challenge	Data Element Application Strategy	Platform Empowerment Strategy	Data Governance Focus
SMEs	Weak data capabilities, limited capital	Prioritize SaaS-based data tools; focus on demand forecasting and inventory optimization	Deeply bind to 1–2 mainstream platforms; fully leverage platform data resources	Establish basic data standards; ensure multi-platform data consistency
Large enterprises	Data silos, organization al inertia	Build data middle platforms; integrate ERP, WMS, CRM system data	Multi-platform layout + independent sites; reduce platform dependency risks	Establish enterprise-level data governance committees; formulate data asset management systems

Small and medium-sized enterprises (SMEs) should prioritize SaaS-based data tools, focusing on demand forecasting and inventory optimization as core scenarios, and deeply bind to 1–2 mainstream platforms to fully leverage platform data resources. Simultaneously, they should establish basic data standards to ensure multi-platform data consistency, preventing decision-making errors caused by data inconsistency.

Large enterprises should build data middle platforms to integrate ERP, WMS, CRM, and other system data, achieving full-chain data connectivity. They should adopt a strategy combining multi-platform layout with independent site development to reduce dependency risks on single platforms. Establishing enterprise-level data governance committees and formulating data asset management systems will elevate data governance to the strategic level.

Stratified Recommendations by Market Region

Target Market	Institutional Environment Characteristics	Data Element Application Focus	Compliance Requirements
European/ American markets	Strict GDPR, strong consumer data awareness	Focus on first-party data construction; reduce reliance on third-party cookies	Must pass GDPR compliance audits; establish data localization storage mechanisms
Emerging markets	Incomplete data regulations, weak infrastructure	Leverage platform data for rapid trial-and-error; flexibly adjust product selection strategies	Monitor data sovereignty policy changes; reserve compliance adjustment space

European and American market enterprises should focus on first-party data construction, reducing reliance on third-party cookies, and establishing proprietary user profiling systems. They must pass GDPR compliance audits and establish data localization storage mechanisms to mitigate compliance risks associated with cross-border data transmission.

Emerging market enterprises should fully leverage platform data for rapid trial-and-error and flexibly adjust product selection strategies. Simultaneously, they should closely monitor data sovereignty policy changes and reserve compliance adjustment space to prevent data supply disruptions caused by sudden policy shifts.

Stratified Recommendations by Platform Dependency

Dependency Type	Strategic Positioning	Data Capability Building Focus	Risk Hedging Measures
High platform dependency	Deep participant in platform ecosystem	Strengthen data capabilities with platforms; leverage platform APIs for real-time data	Build multi-platform operational capabilities; avoid single-platform policy risks
Low platform dependency	Branding, independent development	Build proprietary data middle platforms and user profiling systems	Increase DTC (direct-to-consumer) channel investment

High platform-dependency enterprises should strengthen data 对接 capabilities with platforms, fully leveraging platform APIs to obtain real-time sales, logistics, and user data. Simultaneously, they should build multi-platform operational capabilities to avoid systemic risks from single-platform policy changes (e.g., account suspensions, commission adjustments).

Low platform-dependency enterprises should prioritize building proprietary data middle platforms and user profiling systems, increasing DTC (direct-to-consumer) channel investment. Through independent sites, social media, and other channels, they should accumulate first-party data to construct brand moats.

Strategic Implementation Roadmap

Based on our research findings, we propose a three-stage implementation roadmap for data element application in cross-border e-commerce enterprises:

Stage 1 (Year 0–1): Data Foundation Consolidation Period. The focus is on completing data connectivity for core systems such as ERP and WMS, establishing unified data standards and quality control processes, and achieving visualization of basic supply chain data. During this stage, enterprises should prioritize solving the problems of "whether data exists" and "whether data is accurate."

Stage 2 (Year 1–3): Data Capability Deepening Period. The focus is on introducing advanced analytical models for demand forecasting and dynamic pricing, deepening data with mainstream cross-border e-commerce platforms, and establishing data-driven supplier collaboration mechanisms. During this stage, enterprises should prioritize solving the problem of "how to use data," translating data insights into business actions.

Stage 3 (Year 3–5): Data Ecosystem Construction Period. The focus is on building enterprise-level data middle platforms, achieving real-time integration of internal and external data, forming data-driven autonomous supply chain decision-making capabilities, and reducing dependency on single platforms. During this stage, enterprises should prioritize solving the problem of "how data creates differentiated competitive advantages," transforming data capabilities into strategic assets.

Policy Recommendations

First, improve the market-oriented allocation mechanism for data elements. Accelerate the issuance of data element circulation and trading rules for the cross-border e-commerce sector, establish data rights confirmation, pricing, and trading mechanisms, and reduce the cost of data element acquisition. Explore the establishment of cross-border e-commerce data trading platforms to provide enterprises with data assetization services.

Second, strengthen digital infrastructure construction for cross-border e-commerce. Support the digital upgrading of cross-border e-commerce platforms, logistics platforms, and payment platforms, and promote the application of blockchain, Internet of Things, and other technologies in cross-border trade to enhance full-chain digitalization levels.

Third, optimize the data governance environment for cross-border e-commerce. Improve cross-border data flow rules, promote the construction of data mutual recognition mechanisms with major trading partners, and strengthen data security protection enforcement to create a secure and trustworthy environment for enterprise data application.

Fourth, implement differentiated policy support. Addressing the insufficient data application capabilities of SMEs, provide inclusive support such as data technology training, SaaS service subsidies, and cloud resource vouchers. Addressing weak links in data governance, formulate industry data standards and best practice guidelines. In regions with weaker institutional environments, increase digital infrastructure investment to narrow the "digital divide" across regions.

Research Limitations and Future Directions

This study has the following limitations: First, the sample is limited to A-share listed companies in the cross-border e-commerce sector in China, and the external validity of our conclusions awaits further examination. Future research could extend to active cross-border e-commerce regions such as the United States (Amazon, Shopify ecosystems), Europe (GDPR compliance environments), and Southeast Asia (Shopee, Lazada platforms), comparing the relationships between data element application and supply chain resilience under different data governance regimes (e.g., the EU's strict GDPR regulation vs. the US market-driven model vs. China's platform-dominated model). Second, case analyses primarily rely on publicly available materials and lack first-hand data from within enterprises. Future research could obtain richer qualitative evidence through in-depth interviews and participant observation. Third, the relationship between data element application and supply chain resilience may involve more complex non-linear relationships that our linear model specification may not fully capture. Future research could explore more refined analytical frameworks such as threshold effects and non-linear moderation. Fourth, this study primarily focuses on the "quantity" of data element application, with insufficient attention to the "quality" of data element application (e.g., data analytics capabilities, data-driven decision-making culture). Future research could construct more comprehensive evaluation systems for data element application capabilities.

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