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How Generative Artificial Intelligence Adoption Enhances Firm-Level Supply Chain Resilience: Empirical Evidence from Chinese A-Share Listed Firms

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ABSTRACT

Escalating global supply chain risks and rapid AI diffusion have elevated supply chain resilience (SCR) to a critical strategic imperative, yet whether and how generative artificial intelligence (GAI) adoption enhances firm-level SCR remains underexplored. Drawing on a panel dataset of Chinese A-share listed firms spanning 2017–2024, we quantify GAI adoption through systematic text analysis of annual reports, construct a composite SCR index via the entropy weight method, and estimate a two-way fixed effects model incorporating Bartik shift-share instrument and lagged province-by-industry mean instrumental variables to address endogeneity concerns. We find that GAI adoption significantly enhances firm-level SCR. Mechanism analysis reveals three positive transmission pathways: technological innovation, organizational investment intensification, and downstream customer structure optimization. It also uncovers a suppression effect operating through upstream supplier concentration, exposing an inherent trade-off between flexibility gains and coordination stability losses. Collectively, these findings indicate that GAI's SCR-enhancing effect is not automatic, but depends critically on the alignment between technological deployment and organizational adaptation, offering actionable implications for firms' GAI investment strategies in supply chain management.

KEYWORDS

Generative artificial intelligence; Supply chain resilience; Technological innovation; Supply chain concentration; Organizational reconfiguration

1. INTRODUCTION

In an era of heightened global uncertainty, SCR has evolved from a basic operational capability into a core strategic asset for firms and a critical foundation for national economic security [1, 2]. Resilient supply chains effectively buffer disruption impacts and accelerate post-shock recovery [3]. Yet escalating geopolitical tensions, trade frictions, extreme climate events, and global pandemics have rendered supply chain disruptions increasingly endemic [4]. The traditional efficiency-oriented supply chain paradigm has exposed systemic vulnerabilities amid deglobalization and global value chain restructuring, making the enhancement of supply chain survivability and resilience under prolonged crises a central challenge for both policymakers and firms [5].

Against this backdrop, GAI powered by large language models is fundamentally transforming supply chain management. Unlike traditional AI, which relies on historical data for prediction and automation, GAI possesses three distinctive capabilities: data generation and transformation, complex reasoning and scenario simulation, and autonomous learning and collaboration [6, 7]. These capacities enable GAI to enhance demand forecasting, supplier risk management, inventory optimization, and cross-chain coordination [8, 9]. However, GAI's impact is not uniformly positive — poor governance can generate trade-offs between operational sustainability and social legitimacy [10] — underscoring the need for systematic empirical investigation.

China offers a uniquely valuable research context for three reasons. First, it operates the world's most complete industrial system while facing acute pressure to enhance SCR amid geopolitical tensions and technological catch-up imperatives. Second, 2017 marked both the launch of China's national AI strategy and the proposal of the Transformer architecture, providing a natural and well-defined starting point for tracing GAI diffusion. Third, China hosts the world's largest GAI market — with 230 million users and over 4,500 enterprises as of June 2024 — yet deep organizational adoption remains limited: only 4% of firms have achieved end-to-end digital transformation, creating a pronounced technology–organization mismatch that warrants rigorous investigation.

This mismatch reflects a fundamental technology–organization fit dilemma. Prior research identifies three interrelated barriers to GAI adoption: the tension between automation and augmentation applications [11], the disconnect between strategic planning and grassroots implementation [12], and managers' homogenized expectations of digital tools [13]. GAI's greater cognitive complexity and heightened organizational reliance exacerbate these challenges, making its net effect on SCR theoretically ambiguous.

Against this backdrop, this study addresses two core research questions: Does GAI adoption significantly enhance firm-level SCR? And through what transmission mechanisms does this effect operate? Existing literature exhibits three notable gaps: large-scale causal evidence on the GAI–SCR relationship remains scarce, with prior studies constrained by narrow samples, short time horizons, and weak identification strategies [14, 15]; and the specific pathways through which GAI affects SCR remain poorly understood. Addressing these gaps will both advance theoretical understanding and yield actionable managerial insights.

Using a 2017–2024 panel of Chinese A-share listed firms (excluding financial and real estate sectors), we measure GAI adoption via systematic annual report text analysis and construct a composite SCR index through the entropy weight method. We employ a two-way fixed effects model with Bartik shift-share and province-by-industry mean instrumental variables to address endogeneity concerns.

This study makes two key contributions. First, it provides large-scale causal evidence on the GAI–SCR relationship by expanding the sample to cover all industries, extending the time horizon to 2024, and applying rigorous identification strategies. Second, it systematically documents the composite transmission mechanisms underlying GAI's SCR-enhancing effect — encompassing three positive pathways and one suppression effect — and thereby illuminates the micro-level logic through which GAI reshapes supply chain resilience.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature and develops the study's hypotheses; Section 3 describes the research design; Section 4 presents the main empirical results; Section 5 examines the transmission mechanisms; Section 6 concludes with policy implications and discusses limitations.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. Generative Artificial Intelligence and Supply Chain Resilience

SCR is defined as a firm's dynamic capability to maintain operational continuity, achieve rapid recovery, and adapt to environmental changes in the face of disruptions [1, 16, 17]. Extant studies have examined the antecedents of SCR from the perspectives of information technology, organizational capability, and network structure [18–20]. Traditional AI enhances SCR through real-time analytics, predictive modeling, and scenario simulation, enabling proactive risk identification and resource optimization [21–23].

As a new generation of AI, GAI powered by large language models exhibits three core capabilities that distinguish it from traditional discriminative AI: data generation and transformation, complex reasoning and multi-dimensional scenario simulation, and autonomous learning and collaboration [6–8]. By generating novel insights and supporting context-aware decisions, GAI fundamentally reconfigures firms' information processing and decision-making systems.

Theoretically, this enabling effect can be explained through two complementary lenses. Organizational information processing theory posits that firms must expand their information processing capacity to navigate uncertainty [21, 24]; GAI addresses this imperative by integrating heterogeneous data sources and generating real-time simulations. Dynamic capabilities theory further argues that competitive advantage stems from firms' ability to sense, seize, and reconfigure resources [25, 26] — capacities that GAI strengthens through forward-looking planning and rapid iterative optimization.

Empirically, GAI transforms reactive risk response into proactive intervention by integrating multi-source data to generate structured risk alerts [8,14], thereby strengthening supply chain resistance. It shortens recovery cycles by simultaneously evaluating multiple response strategies [6,9], improving operational stability. It also reduces information asymmetry and coordination costs among supply chain partners [7, 27], enhancing supply–demand matching and self-renewal capacity. Consistent with preliminary empirical evidence [14], we propose:

H1. GAI adoption at the firm level is positively associated with SCR.

2.2. The Technological Innovation-Driven Mechanism

Technological innovation capability — developed through sustained R&D investment and knowledge accumulation — constitutes a core source of sustainable competitive advantage [28]. In the supply chain context, it enhances SCR by improving product and process adaptability to demand fluctuations and supply disruptions [29, 30].

GAI opens new avenues for innovation by lowering the costs of R&D information acquisition and processing [31], facilitating cross-domain knowledge recombination [32, 33], and accelerating innovation cycles through scenario simulation and iterative feedback [34]. The resulting innovation capabilities endow supply chains with the flexibility, visibility, and agility that are critical for withstanding disruptions [14, 35]. Accordingly, we propose:

H2a. GAI adoption at the firm level is positively associated with technological innovation capability.

H2b. Technological innovation capability is positively associated with SCR.

H2c. Technological innovation capability partially mediates the relationship between GAI adoption and SCR.

2.3. The Supply Chain Structure Reconfiguration Mechanism

Resource dependence theory suggests that firms reduce environmental uncertainty by diversifying their resource dependence structures [36, 37]. Digital technologies alleviate information asymmetry and expand firms' accessible supplier pools [38, 39], and GAI further enables efficient supplier identification and risk assessment, driving a structural shift from concentrated to diversified supplier bases [8].

The impact of supplier concentration on SCR, however, is inherently dual. High concentration amplifies disruption risk exposure when core suppliers fail [3, 20, 40], yet it also fosters deep trust, information sharing, and relationship-specific investments that accelerate post-disruption recovery

[41, 42]. In the GAI context, the technology primarily reduces supplier search and switching costs rather than deepening collaborative intensity, thereby eroding the relational assets that underpin the resilience benefits of concentration. This reasoning aligns with supply chain complexity theory — which links a greater number of supply chain nodes to elevated disruption and cascading failure risks [43] — and with evidence that digital technologies reconfigure the relationship between supply network structure and firm outcomes [44]. Thus:

H3a. GAI adoption at the firm level is negatively associated with upstream supplier concentration.

H3b. Upstream supplier concentration is positively associated with SCR.

H3c. Upstream supplier concentration exerts a suppression effect on the GAI-SCR relationship.

On the demand side, GAI enhances firms' data analytics and personalized marketing capabilities [9, 45], enabling precise identification of latent demand and expansion of SME customer bases, thereby reducing dependence on a small number of large core customers. High customer concentration amplifies demand-side disruption risks and constrains strategic flexibility [20, 40, 46], whereas diversified customer portfolios achieve a form of "demand hedging" that bolsters SCR. Accordingly:

H4a. GAI adoption at the firm level is negatively associated with downstream customer concentration.

H4b. Downstream customer concentration is negatively associated with SCR.

H4c. Downstream customer concentration partially mediates the GAI–SCR relationship; specifically, GAI adoption enhances SCR by reducing customer concentration, thereby lowering firms' demand-side dependence on a small number of large customers.

2.4. The Organizational Investment Strengthening Mechanism

Transaction cost theory posits that firm boundaries reflect the trade-off between market and hierarchical governance costs [47–49]. Digital technologies — particularly AI — systematically reconfigure firms' organizational structures and resource allocation patterns, altering both internal and external transaction costs [50, 51].

GAI adoption compels firms to increase investments in digital marketing systems, IT infrastructure, data governance, and workforce reskilling, leading to higher selling, administrative, and financial expenses [11, 50, 52–55]. These expenditures are not mere efficiency losses; rather, they represent strategic organizational investments and capability reconfiguration consistent with the "productivity J-curve," whereby digital technology adoption entails upfront intangible asset accumulation before productivity gains materialize [50].

At the supply chain level, these investments enhance firms' information sharing, coordination, and risk recovery capabilities — all of which are foundational to SCR [1, 56, 57]. More specifically, increased selling expenses strengthen demand stabilization [52, 53], higher administrative expenses reflect investments in coordination and digital infrastructure [11, 50], and improved financial resource allocation provides a buffer against liquidity risks [57, 58]. Thus:

H5a. GAI adoption at the firm level is positively associated with comprehensive organizational investment.

H5b. Comprehensive organizational investment is positively associated with SCR.

H5c. Comprehensive organizational investment partially mediates the relationship between GAI adoption and SCR.

The theoretical framework of this paper is summarized in Figure 1.

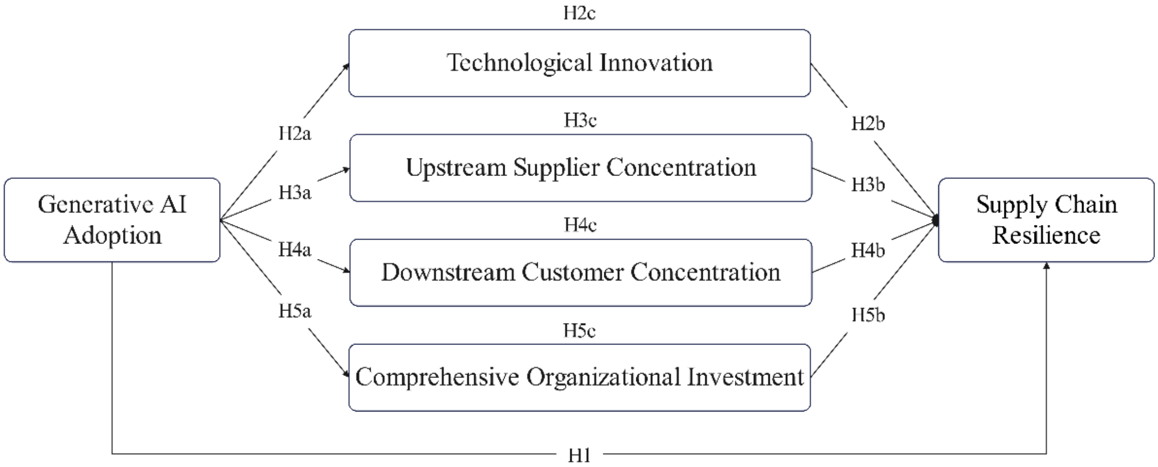

Figure 1. Theoretical framework

3. RESEARCH DESIGN

3.1. Sample Selection and Data Sources

This study employs Chinese A-share listed firms on the Shanghai and Shenzhen Stock Exchanges over the period 2017–2024 as the research sample. The choice of 2017 as the starting point is motivated by two considerations. First, Google's research team formally introduced the Transformer architecture in 2017, establishing the core technical foundation for subsequent GAI large language models (e.g., GPT and BERT) and marking the formal inception of the GAI technological paradigm. Second, in the same year, the State Council issued the New Generation Artificial Intelligence Development Plan, and the Ministry of Industry and Information Technology subsequently released the Three-Year Action Plan for Promoting the Development of the New Generation Artificial Intelligence Industry (2018–2020). These policy initiatives elevated AI to a national strategic priority for the first time and explicitly called for its deep integration with the real economy. The year 2017 thus serves as a natural starting point for tracing GAI's evolution from technological breakthrough to industrial diffusion.

Annual report texts are obtained from the Sina Finance website. Firm-level financial data and basic corporate information are sourced from the CSMAR database, and patent data are drawn from the CNRDS database.

To ensure sample quality, the following screening criteria are applied: (1) Firms in the financial and real estate sectors are excluded based on official industry classification standards: the 2012 CSRC industry classification is applied for 2017–2022, and the China Listed Companies Association industry classification is applied for 2023–2024; (2) Firm-year observations classified as ST, *ST, or suspended from trading during the sample period are eliminated; (3) Observations from industries with only one listed firm in a given year are dropped to avoid invalid industry fixed effects estimation; (4) Firms with fewer than two consecutive years of observations, as well as those with extensive missing values on core variables, are excluded; (5) Observations with missing values on any remaining key variables are removed; (6) All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme values. After applying these screening procedures, the final sample comprises an unbalanced panel of 27,382 firm-year observations covering 4,453 listed firms.

3.2. Variable Definition and Measurement

3.2.1. Dependent Variable: Supply Chain Resilience

SCR is defined as a firm's comprehensive capability to maintain stable supply chain operations, achieve rapid recovery, and continuously adapt to environmental changes when confronted with external shocks. Given its inherently multidimensional nature, we follow Su et al. [59] and develop a firm-level SCR evaluation index spanning five dimensions: resistance capability, recovery capability, operational capability, supply–demand matching capability, and renewal capability. Corresponding financial and operational indicators are selected to measure each dimension, as detailed in Table 1. The entropy weight method is then applied to assign weights to each indicator and compute a composite SCR index.

Table 1. Supply chain resilience evaluation index system

Dimension	Indicator Measurement	Direction
Resistance Capability	Ln (Accounts Receivable / Main Business Revenue)	-
Recovery Capability	Residual from a linear regression of firm performance (measured as EBIT per employee) on firm size, leverage, firm age, board size, and revenue growth rate	+
Operational Capability	Accounts Payable Turnover = Operating Cost / [(Ending Accounts Payable + Beginning Accounts Payable) / 2]	+
	Accounts Receivable Turnover = Operating Revenue / [(Ending Accounts Receivable + Beginning Accounts Receivable) / 2]	+
Supply-Demand Matching Capability	Ln (|Current Net Inventory − Lagged Net Inventory|)	-
Renewal Capability	Ln (Number of Granted Invention Patents + 1)	+

3.2.2. Explanatory Variable: Generative AI Adoption

Following Guo et al. [14], we adopt a text-based measurement approach to quantify firm-level GAI adoption, using the frequency of GAI-related keyword disclosures in listed firms' annual reports.

Specifically, we retrieve the full texts of A-share listed firms' annual reports for the sample period from the Sina Finance website and search each report for a predefined set of GAI-related keywords, including: "artificial intelligence," "machine learning," "natural language processing," "image understanding," "intelligent data analysis," "business intelligence," "intelligent robot," "deep learning," "biometrics," "investment decision support system," "face recognition," "semantic search," "speech recognition," "identity verification," and "autonomous driving." The total number of keyword occurrences is aggregated for each firm-year observation, and the final GAI adoption measure is constructed as the natural logarithm of (total keyword frequency + 1).

3.2.3. Mechanism Variables

Technological Innovation (TI): Following Yu et al. [60], technological innovation is measured as the ratio of R&D expenditure to total assets. Higher R&D intensity reflects more active innovation activities and stronger knowledge absorption and recombination capabilities, enabling firms to more effectively translate GAI's enabling potential into tangible technological improvements.

Upstream Supplier Concentration (SC): Following Tang [61], supplier concentration is measured as the proportion of total annual purchases sourced from the top five suppliers. This indicator captures a firm's degree of dependence on its core suppliers; higher values signal greater resource dependence and elevated supply chain vulnerability.

Downstream Customer Concentration (CC): Following Tang [61], customer concentration is measured as the proportion of total annual sales to the top five customers. This indicator reflects a firm's revenue dependence on its core customers; higher values indicate tighter constraints on strategic flexibility and greater SCR risks.

Comprehensive Organizational Investment (COI): Following Li and Zhang [62], COI is measured as the sum of selling expenses, administrative expenses, and financial expenses scaled by total assets. This composite indicator encompasses firms' aggregate expenditures on customer relationship maintenance, internal management coordination, and financial resource allocation, thereby capturing the actual intensity of strategic organizational reconfiguration undertaken during GAI adoption. As discussed in Section 2.4, in the context of digital transformation, COI reflects not only cost pressure but — more importantly — the organizational adaptation process through which firms convert technological potential into resilience capacity.

3.2.4. Control Variables

Drawing on Guo et al. [14] and Su et al. [59], we control for firm size, firm age, leverage ratio, revenue growth rate, quick ratio, operating cash flow, board size, and independent director ratio. Detailed definitions and measurements of all variables are presented in Table 2.

Table 2. Definition and measurement of main variables

Variable Type	Variable Name	Variable Symbol	Variable Definition
Dependent Variable	Supply Chain Resilience	SCR	Composite SCR index
Explanatory Variable	Generative Artificial Intelligence Adoption	GAI	Ln (firm GAI keyword frequency + 1)
Mechanism Variables	Technological Innovation	TI	R&D expenditure / total assets
	Upstream Supplier Concentration	SC	Top-5 supplier purchases / total annual purchases
	Downstream Customer Concentration	CC	Top-5 customer sales / total annual sales
	Comprehensive Organizational Investment	COI	(Selling expenses + administrative expenses + financial expenses) / total assets
Control Variables	Firm Size	Size	Ln (total assets)
	Firm Age	Age	Ln (observation year - founding year)
	Leverage Ratio	Lev	Total liabilities / total assets
	Revenue Growth Rate	Growth	Revenue increase in current year / revenue in prior year
	Quick Ratio	QR	(Current assets - inventories)/current liabilities
	Operating Cash Flow	Cash	Net cash flow from operating activities / total assets
	Board Size	Board	Ln (number of directors + 1)
	Independent Director Ratio	IDR	Number of independent directors / total number of directors

3.3. Model Specification

3.3.1. Baseline Regression Model

To empirically examine the impact of firm-level GAI adoption on SCR, we estimate the following baseline regression model:

$$SCR_{it} = \alpha + \beta GAI_{it} + \gamma Controls_{it} + year + ind + \varepsilon_{it} \tag{1}$$

Where i indexes firms and t indexes years; SCR_{it} denotes the SCR of firm i in year t; GAI_{it} measures the GAI adoption level of firm i in year t; $Controls_{it}$ is a vector of control variables defined in Table 2; year and ind represent year fixed effects and industry fixed effects, respectively; and ε_{it} is the idiosyncratic error term.

Our primary coefficient of interest is β, which captures the direction and magnitude of the causal effect of GAI adoption on SCR. To address potential heteroskedasticity and within-firm serial correlation, we cluster robust standard errors at the firm level in all regressions.

3.3.2. Mediation Effect Models

To identify the underlying mechanisms through which GAI affects SCR, we employ the classical stepwise regression approach proposed by Baron and Kenny [63] to estimate a series of mediation models.

Specifically, under this framework, Equation (1) estimates the total effect of GAI on SCR. We then estimate the following two equations to examine the mediating effects:

$$M_{it}=\alpha_1+\beta_1 GAI_{it}+\gamma_1 Controls_{it}+year+ind+\varepsilon_{it} \tag{2}$$

$$SCR_{it}=\alpha_2+\beta_2 GAI_{it}+\gamma_2 Controls_{it}+\delta M_{it}+year+ind+\varepsilon_{it} \tag{3}$$

Where M_{it} denotes the four mediating variables examined in this study: technological innovation (TI), upstream supplier concentration (SC), downstream customer concentration (CC), and comprehensive organizational investment (COI).

4. EMPIRICAL ANALYSIS

4.1. Descriptive Statistics

Table 3 reports the descriptive statistics for all main variables. The mean value of SCR is 0.125, with a standard deviation of 0.091, ranging from 0.004 to 0.856. The mean value of GAI is 0.787, with a median of 0 and a standard deviation of 1.063, indicating a highly right-skewed distribution. This pattern suggests that GAI adoption among Chinese A-share listed firms remains concentrated in a relatively small subset of firms, with overall organizational-level penetration still in the early stages of diffusion. This distributional finding is consistent with the Accenture assessment cited in the introduction — that deep enterprise-level adoption remains limited — and corroborates the micro-level existence of an "organizational transformation deficit." It stands in sharp contrast to the macro-level figures on user base and industry scale presented earlier, together capturing the structural mismatch between high macro-level enthusiasm and lagging micro-level penetration that characterizes GAI development in the Chinese context.

The Pearson correlation matrix (Table 4) reveals a significant positive correlation between GAI and SCR ($r = 0.0354$, $p < 0.01$), providing preliminary statistical support for H1. The pairwise correlation between Size and Lev is 0.4791, and that between QR and Lev is −0.6681, suggesting potential collinearity among certain control variables. However, variance inflation factor (VIF) diagnostics yield a mean VIF of 1.45 and a maximum VIF of 2.19 — both well below the conventional threshold of 10 — confirming that multicollinearity does not pose a material threat to estimation validity.

Table 3. Descriptive statistics of main variables

Variable	N	Mean	SD	Min	Median	Max
SCR	27,382	0.125	0.091	0.004	0.105	0.856
GAI	27,382	0.787	1.063	0.000	0.000	4.159
TI	27,382	0.028	0.023	0.000	0.023	0.133
SC	27,382	0.340	0.187	0.059	0.298	0.890
CC	27,382	0.344	0.225	0.027	0.293	0.949
COI	27,382	0.079	0.065	0.007	0.060	0.377
Size	27,382	22.281	1.238	20.189	22.064	26.190
Age	27,382	2.982	0.311	2.079	2.996	3.611
Lev	27,382	0.395	0.194	0.056	0.387	0.880
Growth	27,382	0.126	0.303	-0.502	0.088	1.565
QR	27,382	2.282	2.454	0.268	1.437	15.087
Cash	27,382	0.051	0.065	-0.136	0.049	0.240
Board	27,382	2.208	0.171	1.792	2.303	2.639
IDR	27,382	0.380	0.053	0.333	0.364	0.571

4.2. Correlation Analysis

Table 4. Pearson correlation matrix of main variables

Variable	SCR	GAI	Size	Age	Lev
SCR	1				
GAI	0.0354***	1			
Size	0.1918***	-0.0135**	1		
Age	0.0240***	-0.0582***	0.2032***	1	
Lev	-0.0176***	-0.0602***	0.4791***	0.1686***	1
Growth	0.0510***	-0.0454***	0.0293***	-0.1247***	0.0288***
QR	0.0149**	0.0981***	-0.3348***	-0.1872***	-0.6681***
Cash	0.1527***	-0.1005***	0.1072***	0.0298***	-0.1478***
Board	0.0566***	-0.0598***	0.2611***	0.1052***	0.1230***
IDR	0.0070	0.0402***	-0.0143**	-0.0148**	-0.0068
Variable	Growth	QR	Cash	Board	IDR
Growth	1				
QR	-0.0426***	1			
Cash	0.0692***	0.0470***	1		
Board	0.0168***	-0.1155***	0.0354***	1	
IDR	-0.0214***	0.0147**	0.0050	-0.5903***	1

Note: *** and ** represent the significance level at 1% and 5%, respectively

4.3. Baseline Regression

Table 5 reports the baseline regression results. Columns (1) and (2) include only industry and year fixed effects without control variables, while columns (3) and (4) progressively incorporate firm-level controls. Our discussion centers on column (4), where the coefficient on GAI is positive and statistically significant at the 1% level (β = 0.0064). This indicates that, after controlling for industry and year fixed effects and a comprehensive set of firm characteristics, a one-standard-deviation increase in GAI adoption is associated with a 0.0064-unit increase in the composite SCR index — equivalent to 7.0% of its standard deviation — an economically meaningful magnitude.

Notably, as fixed effects and control variables are progressively added, the estimated GAI coefficient follows a distinct "rise-then-fall" pattern: it increases from 0.0030 in column (1) to 0.0084 in column (2), then declines to 0.0064 in column (4). This pattern is indicative of a bidirectional confounding structure induced by omitted variables. The marked coefficient increase upon introducing fixed effects suggests that unobservable industry and year factors exert a negative confounding influence on the GAI–SCR relationship; failing to account for these factors would lead to a substantial underestimation of GAI's true effect. Conversely, the subsequent decline from 0.0084 to 0.0064 after adding firm-level controls suggests that factors such as firm size and financial health are positively associated with GAI adoption and, in more parsimonious specifications, act as positive confounders. Incorporating these controls eliminates the spurious component and yields a more precise estimate of GAI's independent contribution to SCR.

Across all four specifications, the sign and statistical significance of GAI remain highly stable. The two-way fixed effects model in column (4) achieves an adjusted R^2 of 0.2406, indicating substantial explanatory power. Collectively, these results provide strong empirical support for H1.

Table 5. Baseline regression results: the impact of GAI adoption on supply chain resilience

Variable	(1)	(2)	(3)	(4)
	SCR	SCR	SCR	SCR
GAI	0.0030***	0.0084***	0.0038**	0.0064***
	(0.0010)	(0.0011)	(0.0009)	(0.0010)
Size			0.0167***	0.0151***
			(0.0015)	(0.0013)
Age			0.0002	-0.0086**
			(0.0036)	(0.0034)
Lev			-0.0456***	-0.0257**
			(0.0086)	(0.0076)
Growth			0.0128***	0.0124***
			(0.0020)	(0.0019)
QR			0.0008	0.0019***
			(0.0005)	(0.0005)
Cash			0.1610***	0.1450***
			(0.0155)	(0.0137)
Board			0.0116	0.0142
			(0.0097)	(0.0087)
IDR			0.0352	0.0293
			(0.0316)	(0.0267)
Constants	0.1228***	0.1186***	-0.2835***	-0.2361***
	(0.0017)	(0.0013)	(0.0429)	(0.0377)
Industry FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES
N	27,382	27,382	27,382	27,382
Adjusted R^2	0.0012	0.1927	0.0680	0.2406

Note: *** and ** represent the significance level at 1% and 5%, respectively. Robust standard errors clustered to the enterprise level are in parentheses.

4.4. Robustness Checks

4.4.1. Instrumental Variable Estimation

To address endogeneity concerns arising from reverse causality, omitted variables, and measurement error, we employ two distinct instrumental variables and conduct two-stage least squares (2SLS) estimation.

The first instrument is a Bartik shift-share IV, constructed as the interaction between a firm's 2017 baseline GAI adoption level and the national annual GAI patent application growth rate. The second is a one-period lagged province-by-industry mean IV, calculated as the average GAI adoption of all other firms in the same province and two-digit industry, excluding the focal firm.

Both instruments satisfy the relevance and exogeneity conditions. First-stage regressions yield significantly positive coefficients on IV1 ($\beta = 0.4497$, $p < 0.01$) and IV2 ($\beta = 0.1729$, $p < 0.01$). The Kleibergen–Paap rk LM statistics reject under-identification at the 1% level, and all Kleibergen–Paap/Cragg–Donald Wald F-statistics far exceed the Stock–Yogo critical value of 16.38, ruling out weak instrument bias.

Second-stage results confirm the causal effect of GAI on SCR: coefficients are 0.0124 ($p < 0.01$) under IV1 and 0.0360 ($p < 0.01$) under IV2, both exceeding the OLS baseline estimate of 0.0064. This upward adjustment suggests that OLS suffers from attenuation bias attributable to measurement error. Notably, IV1 identifies the local average treatment effect (LATE) of individual firm adoption, whereas IV2 captures broader ecosystem-level synergies from regional-industry GAI diffusion, which accounts for its larger magnitude.

Table 6. 2SLS instrumental variable estimation results

Variable	First Stage	Second Stage	First Stage	Second Stage
	GAI	SCR	GAI	SCR
IV1	0.4497***			
	(0.0156)			
IV2			0.1729***	
			(0.0281)	
GAI		0.0124***		0.0360***
		(0.0032)		(0.0133)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Kleibergen-Paap rk LM	191.809***		39.284***	
Cragg-Donald Wald F	5,886.872		113.354	
Kleibergen-Paap rk Wald F	832.533		37.762	
N	16,493		20,208	

Note: *** represents the significance level at 1%. Controls variables include Size, Age, Lev, Growth, QR, Cash, Board and IDR. The same is below.

4.4.2. Additional Robustness Checks

To further address concerns regarding measurement error and model specification, we conduct three supplementary robustness checks, with results reported in Table 7.

First, we replace the core explanatory variable. The Management Discussion and Analysis (MD&A) section contains firms' most substantive disclosures on strategic priorities and technology applications and, relative to the full report text, carries less informational noise and greater signal precision. We accordingly re-measure GAI adoption as the natural logarithm of one plus the count of GAI-related keywords in the MD&A section. The re-estimated GAI coefficient of 0.0061 ($p < 0.01$) is virtually identical to the baseline, confirming that our measurement is robust to the choice of textual scope.

Second, we replace the construction method for the dependent variable by re-computing the composite SCR index using the coefficient of variation method (SCR_CV) in place of the entropy weight method, thereby ruling out any influence of the specific weighting scheme on our conclusions. The resulting GAI coefficient of 0.0033 ($p < 0.01$) remains consistent with the baseline in both sign and statistical significance. The somewhat attenuated magnitude likely reflects the greater weight that the coefficient of variation approach assigns to dimensions with higher dispersion. Crucially, the core statistical inferences are unchanged, confirming that our substantive conclusions are not materially sensitive to the choice of weighting method.

Third, we augment the baseline model with industry × year interactive fixed effects to absorb heterogeneous macroeconomic shocks and policy changes that vary across industries and years. The estimated GAI coefficient of 0.0062 ($p < 0.01$) is virtually unchanged from the baseline, indicating that time-varying unobservable industry-level factors do not materially confound the estimated causal effect.

Table 7. Additional robustness check results

Variable	Alternative explanatory variable	Alternative dependent variable	High-dimensional fixed effects
	SCR	SCR_CV	SCR
GAI_MD&A	0.0061***		
	(0.0010)		
GAI		0.0033***	0.0062***
		(0.0008)	(0.0010)
Constants	-0.2380***	-0.0859***	-0.2354***
	(0.0377)	(0.0339)	(0.0380)
Controls	YES	YES	YES
Industry FE	YES	YES	NO
Year FE	YES	YES	NO
Industry × Year FE	NO	NO	YES
N	27,382	27,382	27,345
Adjusted R^2	0.2401	0.2649	0.2417

Note: *** and ** represent the significance level at 1% and 5%, respectively.

5. MECHANISM TESTS

5.1. Technological Innovation Pathway

Table 8 reports the stepwise regression results for the technological innovation mediation test. Column (1) confirms the total effect of GAI on SCR ($\beta = 0.0064$, $p < 0.01$). Column (2) shows that GAI significantly promotes technological innovation ($\beta = 0.0045$, $p < 0.01$), supporting H2a. In column (3), TI remains positively associated with SCR ($\beta = 0.6809$, $p < 0.01$) while the direct effect of GAI attenuates to 0.0033 ($p < 0.01$), confirming partial mediation and supporting H2b and H2c. The Sobel test statistic is 9.267 ($p < 0.01$), and the bias-corrected bootstrap 95% confidence interval for the indirect effect [0.0028, 0.0034] excludes zero. The mediated effect accounts for 48.37% of the total effect, establishing technological innovation as the dominant transmission channel.

This finding is consistent with organizational information processing theory and dynamic capabilities theory: GAI expands firms' cognitive resource pools and accelerates knowledge recombination, systematically strengthening supply chains' adaptive and recovery capabilities. Among all three mechanisms examined, the technological innovation pathway accounts for the largest mediated share, providing a clear empirical foundation for understanding GAI's value creation logic.

Table 8. Mediation test results—technological innovation pathway

Variable	(1)	(2)	(3)
	SCR	TI	SCR
GAI	0.0064***	0.0045***	0.0033***
	(0.0010)	(0.0003)	(0.0010)
TI			0.6809***
			(0.0533)
Constants	-0.2361***	0.0575***	-0.2753***
	(0.0377)	(0.0072)	(0.0373)
Controls	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
N	27,382	27,382	27,382
Adjusted R^2	0.2406	0.3716	0.2596

Note: *** represents the significance level at 1%.

5.2. Supply Chain Concentration Pathway

Table 9 reports estimation results for both the upstream supplier concentration (SC) and downstream customer concentration (CC) pathways. Although both involve supply chain concentration adjustments, their underlying mechanisms diverge fundamentally: the upstream pathway operates as a suppression effect, while the downstream pathway constitutes partial mediation.

Upstream pathway: suppression effect. GAI significantly reduces supplier concentration ($\beta = -0.0146$, $p < 0.01$), supporting H3a, while SC exerts a positive independent effect on SCR ($\beta = 0.0400$, $p < 0.01$), supporting H3b. After incorporating SC, the GAI coefficient increases from 0.0064 to 0.0070, satisfying the suppression effect criterion of Wen and Ye [64]. The Sobel test statistic is −4.476 ($p < 0.01$), with a bootstrap 95% CI of [−0.0007, −0.0005] excluding zero, confirming a significantly negative indirect effect and supporting H3c. Economically, while GAI-driven supplier diversification enhances procurement flexibility, it simultaneously erodes the coordination stability and relationship-specific assets accumulated under concentrated partnerships, offsetting approximately 9.18% of GAI's net positive effect on SCR.

Downstream pathway: partial mediation. GAI significantly reduces customer concentration ($\beta = -0.0144$, $p < 0.01$), supporting H4a, while CC negatively affects SCR ($\beta = -0.0255$, $p < 0.01$), supporting H4b. After incorporating CC, the direct effect of GAI attenuates to 0.0060. The Sobel test statistic is 3.513 ($p < 0.01$), with a bootstrap 95% CI of [0.0003, 0.0005] excluding zero. The mediated effect accounts for 5.77% of the total effect, confirming partial mediation and supporting H4c.

Combining both pathways, the net effect transmitted through supply chain concentration adjustment is approximately −3.41% (5.77% − 9.18%), indicating a slight net suppression of GAI's SCR-enhancing impact. This asymmetry — where upstream coordination losses outweigh downstream demand-hedging gains — reveals a structural paradox in GAI-driven supply chain reconfiguration and underscores the need for managers to balance supplier diversification against the preservation of strategic collaborative relationships.

Table 9. Mediation test results—supply chain concentration pathway

Variable	(1)	(2)	(3)	(4)	(5)
	SCR	SC	SCR	CC	SCR
GAI	0.0064***	-0.0146***	0.0070***	-0.0144***	0.0060***
	(0.0010)	(0.0024)	(0.0010)	(0.0030)	(0.0010)
SC			0.0400***		
			(0.0062)		
CC					-0.0255***
					(0.0050)
Constants	-0.2361***	1.1870***	-0.2836***	1.2933***	-0.2032***
	(0.0377)	(0.0611)	(0.0386)	(0.0788)	(0.0381)
Controls	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	27,382	27,382	27,382	27,382	27,382
Adjusted R^2	0.2406	0.2187	0.2459	0.2543	0.2435

Note: *** represents the significance level at 1%.

5.3. Comprehensive Organizational Investment Pathway

Table 10 reports the stepwise regression results for the COI mediation test. Column (1) confirms the total effect of GAI on SCR ($\beta = 0.0064$, $p < 0.01$). Column (2) shows that GAI significantly increases COI ($\beta = 0.0068$, $p < 0.01$), supporting H5a. In column (3), COI exerts a positive effect on SCR ($\beta = 0.0915$, $p < 0.01$), supporting H5b, while the direct effect of GAI attenuates to 0.0057. The Sobel test statistic is 4.481 ($p < 0.01$), with a bootstrap 95% CI of [0.0005, 0.0008] excluding zero, confirming partial mediation with the mediated effect accounting for 9.76% of the total effect, supporting H5c.

The positive COI–SCR relationship warrants interpretation. Rather than implying that higher operational expenditures are intrinsically value-enhancing, this finding reflects a process of strategic organizational reconfiguration: GAI adoption compels firms to restructure their marketing systems, internal coordination mechanisms, and financial resource allocation, with these expenditures representing necessary investments for converting technological potential into dynamic capabilities. This is consistent with the "productivity J-curve" hypothesis [50], whereby upfront organizational adaptation costs precede efficiency gains that subsequently materialize as enhanced customer responsiveness, internal coordination, and financial buffering capacity.

This mechanism complements Wang et al.'s [65] finding that digital empowerment enhances SCR by reducing inter-firm transaction costs. Whereas that channel operates at the external coordination level, COI captures a distinct internal adaptation pathway. Together, they suggest that GAI enhances SCR through a dual route: reducing external transaction costs while simultaneously requiring strategic internal investments that ultimately build adaptive capacity.

Table 10. Mediation test results—comprehensive organizational investment pathway

Variable	(1)	(2)	(3)
	SCR	COI	SCR
GAI	0.0064***	0.0068***	0.0057***
	(0.0010)	(0.0007)	(0.0010)
COI			0.0915***
			(0.0183)
Constants	-0.2361***	0.2886***	-0.2623***
	(0.0377)	(0.0198)	(0.0378)
Controls	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
N	27,382	27,382	27,382
Adjusted R^2	0.2406	0.3902	0.2432

Note: *** represents the significance level at 1%.

6. CONCLUSIONS AND POLICY IMPLICATIONS

6.1. Conclusions

Drawing on organizational information processing theory and dynamic capabilities theory, this study systematically examines the causal impact of GAI adoption on firm-level SCR using a 2017–2024 panel dataset of Chinese A-share listed firms. Two core findings emerge.

First, GAI adoption exerts a significant and robust positive effect on SCR. The baseline two-way fixed effects estimate indicates that a one-standard-deviation increase in GAI adoption is associated with a 0.0064-unit increase in the composite SCR index, equivalent to 7.0% of SCR's standard deviation. This conclusion holds consistently across a comprehensive set of identification strategies, including Bartik shift-share and province-by-industry mean instrumental variable estimation, as well as alternative variable specifications and model robustness checks.

Second, GAI enhances SCR through a distinctive "three-positive, one-negative" composite transmission structure. Technological innovation constitutes the dominant channel, accounting for 48.37% of the total effect. Comprehensive organizational investment (9.76%) and downstream customer structure optimization (5.77%) represent additional positive pathways. At the same time, upstream supplier concentration reduction generates a suppression effect that offsets 9.18% of the total effect, revealing an inherent structural trade-off between the flexibility gains from supplier diversification and the coordination stability losses arising from eroded relationship-specific assets. Collectively, these findings demonstrate that GAI's impact on SCR is not a unidirectional optimization process but a dynamic equilibrium among multiple competing forces — simultaneously building new capabilities while partially eroding traditional sources of resilience.

6.2. Policy Implications

These findings offer actionable guidance for policymakers and corporate managers seeking to leverage GAI to strengthen supply chain resilience.

Prioritize GAI-enabled technological innovation as the core strategic lever. Given that technological innovation accounts for nearly half of GAI's total SCR-enhancing effect, promoting GAI adoption alone is insufficient. Policymakers should expand R&D super-deduction schemes to cover GAI-related research expenditures and support the development of industry-shared GAI R&D platforms.

Advancing supply chain data standardization and cross-firm coordination mechanisms will further unlock GAI's information integration strengths and activate the full GAI→technological innovation→SCR causal chain.

Mitigate the risk of GAI-induced supply chain fragmentation. The documented suppression effect highlights a critical structural risk: while GAI facilitates supplier diversification, indiscriminate diversification may undermine the coordination stability derived from long-term strategic partnerships. Policymakers should avoid one-size-fits-all supplier diversification mandates. Instead, firms should be guided toward a dual-layer supply chain architecture that maintains a stable core of strategic suppliers for critical resources while deploying GAI to manage a flexible peripheral supplier base — striking an appropriate balance between dynamic responsiveness and operational stability.

Synchronize GAI deployment with organizational capability building. The COI pathway confirms that GAI's SCR benefits are not automatic but contingent on parallel organizational adaptation. Firms should incorporate SCR enhancement as a core performance metric for evaluating GAI investment returns, and technology deployment plans should be accompanied by organizational reconfiguration roadmaps covering customer relationship management, internal process integration, and digital talent development — enabling firms to successfully navigate the "productivity J-curve" and translate technological potential into tangible resilience gains.

6.3. Limitations and Future Research

While this study makes meaningful contributions to the literature on GAI and supply chain resilience, three limitations point to directions for future research.

First, the accuracy of GAI measurement can be further improved. This study captures firm-level GAI adoption through keyword frequencies extracted from annual reports, yet a systematic gap may exist between textual disclosure and the actual depth of GAI integration into daily operations. Future research could cross-validate this measure using alternative sources such as GAI-related patent filings, AI-specific job postings, and procurement records for AI technologies.

Second, the SCR construct warrants broader operationalization. The indicators used here are derived from publicly available financial data, which offer limited coverage of non-financial dimensions such as supplier relationship quality, supply chain visibility, and emergency response capabilities. Future studies could complement these financial proxies with supply chain disruption event data or firm-level survey instruments to construct a more comprehensive and behaviorally grounded resilience index.

Third, longer time horizons and stronger causal identification are needed. Our sample period (2017–2024) largely covers GAI's early diffusion stage, and the full effects of the large-scale adoption wave triggered by ChatGPT's launch in late 2022 remain unfolding. Future research could extend the time horizon to trace GAI's dynamic effects over longer periods and exploit quasi-natural experimental settings to further consolidate causal credibility.

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