Artificial Intelligence and Supply Chain Resilience and Security

Yuanhao Lyu

School of Economics, Jilin University, No.2699 Qianjin Street, Changchun, Jilin, China

605646564@qq.com

Abstract. Supply chain resilience and security are critical for promoting high-quality economic development and safeguarding national security. This study constructs a comprehensive index of supply chain resilience based on two dimensions—industrial diversity and innovation capacity—and integrates data on the number of artificial intelligence (AI) enterprises. Using panel data from 31 provinces, autonomous regions, and municipalities in mainland China from 2003 to 2022, this paper conducts an in-depth analysis to explore the intrinsic relationship between AI and supply chain resilience and security. The findings reveal the following: (1) Overall, the development of AI significantly enhances the resilience of China's supply chains. This conclusion remains robust after addressing endogeneity through the Generalized Method of Moments (GMM), substituting core explanatory variables with appropriate proxies, and conducting quantile regression. The quantile regression further indicates that the positive effect of AI on supply chain resilience diminishes as resilience levels increase. (2) Heterogeneity analysis shows that, at the regional level, AI has a more pronounced effect on supply chain resilience in eastern China and the Yangtze River Economic Belt. At the temporal level, using the 2008 global financial crisis as a case study, the analysis finds that external shocks exert a certain degree of negative impact on the process through which AI enhances supply chain resilience and security.

Keywords: Artificial intelligence, supply chain, quantile regression.

1. Introduction

The global economic environment is increasingly complex and volatile, with supply chain stability facing numerous challenges. The outbreak of the COVID-19 pandemic in 2020 exposed the fragility of global production networks, leading to widespread disruptions in supply chains. Meanwhile, escalating geopolitical tensions, such as the Ukraine crisis, have further threatened supply chain continuity. Recently, frequent trade disputes and protectionist policies—often referred to as "trade wars"—have underscored the critical importance of supply chain resilience and security. These challenges have become central to global economic policy discussions.

Strengthening the resilience and security of supply chains is crucial for maintaining economic stability and promoting sustainable growth. A robust supply chain system not only enhances industrial competitiveness but also lays the foundation for the sustained development of global manufacturing. Traditionally, strategies to bolster supply chain resilience have included diversifying supply networks, advancing industrial upgrades, improving supply chain transparency, and fostering technological innovation. However, with the rapid advancement of digital technologies, digital solutions are emerging as new pathways to address supply chain challenges. The widespread application of digital transformation, financial technology, and the digital economy can enhance supply chain visibility, optimize resource allocation, and effectively mitigate risks, thereby supporting the development of a more resilient and secure global production system.

In recent years, the rapid development of artificial intelligence (AI) technologies has injected new vitality into global industries and provided innovative pathways for enhancing supply chain resilience and security. AI technologies not only significantly improve production efficiency and reduce operational costs but also demonstrate substantial potential in strengthening supply chain adaptability, rapid recovery capabilities, and collaborative innovation. For instance, in various regions worldwide, the integration of AI with traditional industrial parks has led to the development of innovative applications such as robotic warehousing and intelligent sorting, effectively enhancing supply chain flexibility and risk resistance. Countries are actively promoting the deep integration of AI technologies at both policy and industrial levels to gain a competitive edge in the global wave of intelligent transformation.

Amid the rapid transformation of the global economy and technology, the potential impact of AI on supply chain resilience and security has become a focal point in academic and policy discussions. How does AI, through functions such as data-driven forecasting, optimized resource allocation, and real-time monitoring, enhance supply chain stability and security? How do its mechanisms sustain effectiveness in complex and volatile market environments? Furthermore, how can technological innovation, cross-national collaboration, and standardized frameworks improve the efficiency of AI applications in strengthening supply chain resilience and security? In-depth exploration of these questions not only provides theoretical support for building a more resilient and secure global supply chain system but also lays the foundation for countries to seize opportunities in the new wave of technological revolution.

2. Literature Review and Research Hypotheses

The concept of "resilience" originated as a core concept in disciplines such as physics, engineering, and ecology, but with advancing research, it has been incorporated into the field of industrial economics. Within this new domain, the term "supply chain resilience" was developed to measure the ability of supply chains to maintain stability, and even self-improve and evolve, in the face of external shocks. Building on this concept, existing literature has explored the factors influencing supply chain resilience from multiple perspectives. First, diversified imports of intermediate goods are considered effective in enhancing supply chain resilience. Second, digital transformation has a positive impact on improving the autonomy and controllability of supply chains. Research by Chen Xiaodong and others further supports this view, suggesting that digital transformation not only increases access to external information but also positively affects human resource levels, thereby significantly strengthening supply chain autonomy and controllability. Additionally, studies by Li Lanbing and others indicate that the agglomeration effects of producer services on manufacturing supply chain resilience vary: specialized agglomeration exhibits a U-shaped effect, while diversified agglomeration shows an inverted U-shaped effect. Although existing research provides a theoretical foundation for understanding the impact of AI on supply chain resilience, in-depth studies on how AI specifically influences supply chain resilience remain scarce, offering ample room for exploration in this study.

Scholars have extensively explored the impacts of AI, focusing on several key areas:

(1) Employment: AI exerts both positive and negative effects. On one hand, the job creation effect of AI may generate new employment opportunities due to the demand for high-tech operations. On the other hand, the substitution effect suggests that low-skilled labor may be replaced, leading to reduced labor demand and fewer job opportunities.

(2) Economic Development: AI serves as a driver of innovation, stimulating complementary innovative activities and reducing the reliance of economic activities on human resources. This capability effectively addresses challenges posed by population aging, thereby promoting sustained economic growth.

(3) Global Value Chains: AI plays a significant role in global value chains by enhancing the participation and division of labor of manufacturing industries in global networks. It facilitates the deepening and expansion of global value chain networks. Through these mechanisms, AI not only contributes to economic development in specific countries, such as China, but also plays a pivotal role in global economic integration.

Therefore, an in-depth analysis of how artificial intelligence (AI) influences supply chain resilience is a valuable research direction. On the one hand, the technological innovation effects of AI enable it to substitute for labor, address bottlenecks in supply chains, and facilitate the development of innovative risk warning and emergency response mechanisms. AI helps enterprises overcome technical challenges, enhance R&D efficiency, and mitigate supply chain vulnerabilities.

It also strengthens innovative collaboration among upstream and downstream enterprises, fostering new formats and business models that enhance supply chain advantages. Furthermore, AI drives innovation in manufacturing processes and models, increasing product value and functionality, thereby extending supply chains. On the other hand, AI plays a significant role in improving governance. It enables government agencies to gain a more accurate understanding of overall supply chain dynamics, thereby improving the precision of decision-making and implementation, effectively strengthening weak links in supply chains, and enabling targeted "chain reinforcement." Additionally, AI contributes to optimizing the business environment, enhancing profitable segments of supply chains, and emphasizing "chain strengthening." Moreover, by improving digital infrastructure and fostering international cooperation, AI supports the development of diversified import systems, facilitates bilateral supply chain expansion, and promotes scientifically driven "chain extension." Based on these considerations, this study proposes Hypothesis 1: AI has a positive effect on promoting supply chain resilience.

To deepen the understanding of how AI shapes supply chain resilience, it is essential to first accurately identify the impacts of AI and then further explore how these impacts influence supply chain resilience. This study follows this logical framework, comprehensively reviewing the existing literature on the effects of AI and delving into the specific mechanisms through which AI affects supply chain resilience.

Numerous studies have explored the impacts of AI from multiple dimensions. In the labor market, Frey and colleagues employed a Gaussian process classifier to predict the automation potential of 702 occupations in the United States, analyzing the potential effects of AI on the U.S. labor market. In contrast, Acemoglu and others argue that while AI has displaced low-skilled labor in some labor-intensive industries, it has also created a substantial number of new job opportunities, which account for a significant share of the U.S. employment market. At the level of economic growth, Brynjolfsson and other scholars highlight that AI-driven technological innovations can stimulate innovation and thereby foster economic growth. Research by Chen Yanbin and colleagues suggests that AI, through automated and intelligent production methods, can increase savings and investment, enhance total factor productivity, and mitigate the adverse effects of population aging on economic growth. Regarding participation in global value chains, Liu Bin and others, through an analysis of industrial robotics and global production data, conclude that AI has facilitated broader participation and deeper division of labor by domestic manufacturing in global value chains. Similarly, Lu Yue and colleagues' findings confirm AI's significant role in enhancing the participation of Chinese enterprises in global value chains. Furthermore, based on data from 2000 to 2014, Lü Yue and others find that AI, by substituting for certain labor functions and reducing resource misallocation, has deepened the development of global value chain networks.

As a major breakthrough in information technology, AI has profoundly influenced innovation and collaboration within supply chains, fostering closer integration between supply chains and innovation chains, thereby enhancing supply chain resilience. From the perspective of strengthening supply chains, the following effects are notable:

First, AI, as a new production factor, combines with traditional factors such as labor and capital, transforming the composition of production inputs and improving resource allocation efficiency. AI can undertake repetitive and mechanized tasks, substituting for low-skilled labor and thereby enhancing overall labor productivity. This helps mitigate the impact of population aging on labor markets and addresses production interruptions and logistical barriers caused by public health crises, ensuring supply chain continuity and preventing disruptions.

Second, AI enables enterprises to monitor supply chain dynamics in real time, innovate risk warning and emergency response mechanisms, and enhance the supply chain's rapid response capabilities to external shocks. As a core driver of technological innovation, AI plays a critical role in shortening R&D cycles, optimizing the allocation of innovation resources, and improving R&D efficiency. It also facilitates technological breakthroughs in weak links of the supply chain, reducing dependence on external critical raw materials and ensuring supply chain stability and security.

Moreover, AI significantly contributes to developing high-profit industries, breaking geographical barriers, and reducing the costs of knowledge exchange between enterprises. Lower knowledge-sharing costs facilitate the dissemination of advanced knowledge and experiences, strengthening collaboration among upstream and downstream supply chain partners. This promotes the formation of industrial clusters around key competitive industries, generating agglomeration effects, scale effects, and knowledge spillover effects, which enhance supply chain advantages and foster a sustainable industrial ecosystem, achieving sustainable development.

Additionally, AI catalyzes the emergence of new industries and business models, significantly improving supply chain operational efficiency and profoundly influencing the development of these new sectors. The future growth of new industries and business models is critical for anticipating industrial trends and guiding industrial development. Fundamentally, AI has triggered revolutionary changes in production. Through automation and intelligent methods, it enhances production efficiency, and by advancing product processing, it promotes diversification and quality innovation, thereby increasing product value and enabling the vertical extension of supply chains. Simultaneously, AI supports the horizontal expansion of supply chains, creating new competitive advantages and injecting fresh momentum into supply chain development.

Based on these considerations, this study proposes Hypothesis 2: AI can enhance supply chain resilience by influencing the level of innovation.

3. Empirical Model Design

3.1 Model Design

3.1.1. Baseline Regression Model

The fixed effects model in this study is specified as follows to examine the impact of AI technology on supply chain resilience:

$$SCR_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 X_{it} + \mu_i + v_t + \varepsilon_{it} \quad (1)$$

In the model, i and t denote different regions and years, respectively; SCR represents supply chain resilience; AI represents artificial intelligence technology; X encompasses a series of control variables included in this study; $\alpha_0$denotes the model's initial intercept; $\alpha_1$indicates the magnitude of AI's impact on supply chain resilience; $\alpha_2$evaluates the effects of the control variables on the dependent variable; and μ_i , v_t and ε_{it}represent the region fixed effects, time fixed effects, and the model's random error term, respectively.

3.1.2. Mediation Effect Model

Based on the baseline regression in Model (1), this study further employs a mediation effect model to explore the pathways through which AI technology influences supply chain resilience. It must be emphasized that some scholars have expressed reservations about the traditional two-step mediation effect analysis, arguing that mediation effects should not be examined solely by analyzing the impact of the independent variable on the mediator and the mediator on the dependent variable. Therefore, this study selects innovation level as the mediating variable for testing. While still adhering to the two-step testing approach, the theoretical analysis presented earlier provides a reasonable response to these scholarly concerns. The rationale is summarized as follows: First, innovation significantly enhances supply chain resilience in most cases; second, the pathway from innovation level to supply chain resilience is relatively short, and the reverse impact of supply chain resilience on innovation level is minimal. The specific mediation effect model is specified as follows:

$$Inno_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \mu_i + v_t + \varepsilon_{it} \quad (2)$$

$$SCR_{it} = \gamma_0 + \gamma_1 AI_{it} + \gamma_2 Inno_{it} + \gamma_3 X_{it} + \mu_i + v_t + \varepsilon_{it} \quad (3)$$

In the model, $Inno_{it}$ represents the mediating variable; $\beta_0$denotes the intercept term; β_1 measures the impact of AI technology on supply chain resilience; β_2 evaluates the effect of control variables on supply chain resilience; and μ_i, v_t and ε_{it}represent the region fixed effects, time fixed effects, and the error term, respectively.

The steps for testing the mediation effect and its underlying mechanisms are as follows: First, we conduct a regression analysis on Model (1), where $\alpha_1$represents the overall effect of AI on supply chain resilience. If $\alpha_1$is significantly positive, it indicates that AI technology significantly enhances supply chain resilience. Next, we perform a regression on Model (2). If $\beta_1$is significantly positive, it suggests that AI has a positive effect on improving innovation levels. Finally, we conduct a regression analysis on Model (3), where $\gamma_1$represents the direct effect of AI on supply chain resilience, and $\gamma_2 \times \beta_1$represents the indirect effect. If $\gamma_2$is significantly positive and $\gamma_1$is not significant, this indicates the presence of a full mediation effect. If $\gamma_1$is significantly positive but its value is lower than $\alpha_1$in Model (1), this suggests a partial mediation effect. Otherwise, the mediation effect does not hold.

3.2 Variable Description

3.2.1. Dependent Variable

The dependent variable is *supply chain resilience (SCR)*. Drawing on evolutionary economics and adaptive resilience theory, supply chain resilience can be defined as the ability of a supply chain to enhance its adaptability and flexibility to risks through technological innovation and knowledge updating when facing risks and challenges. Martin's resilience theory further elaborates on this, positing that supply chain resilience encompasses not only the capacity to maintain stability during shocks but also the ability to seek innovative solutions in adverse conditions. Specifically, the shock-resistance capacity of a supply chain is reflected in its ability to effectively mitigate and absorb risks through structural adjustments and the complementarity of functions and resources between systems, thereby maintaining stable system operations. Meanwhile, the capacity to find new solutions is demonstrated by the supply chain's ability to rapidly adopt innovative measures, accelerate the transformation of production activities, and promote the continuous dynamic development and stable growth of the supply chain. Building on the research of Chen Xiaodong and others, supply chain resilience can be comprehensively measured from two dimensions: industrial diversity and innovation capacity.

The level of industrial diversity is calculated using the Herfindahl-Hirschman Index (HHI), with the calculation method as follows:

$$Indiv = \frac{1}{HHI} = \frac{1}{\sum_i^N S_i^2} \tag{3}$$

$Indiv$ denotes the industrial diversification index, HHI refers to the Herfindahl-Hirschman Index (a measure of industrial concentration), and S_i represents the contribution ratio of a specific industry to the total regional economic output.

Innovation capacity ($Inno$) is measured by the number of granted patents, which directly correlates with the intensity of regional innovation and reflects the supply chain's ability to mitigate risks and develop innovative pathways.

After determining the indicators for industrial diversity and innovation capacity, we employ a weighted approach to measure supply chain resilience. The detailed steps are as follows:

First, the industrial diversification index and innovation capacity index are standardized to eliminate the effects of different scales, with the specific formula as follows:

$$s_{ij} = \frac{f_{ij} - \min\{f_{1j}, f_{2j}, \dots, f_{nj}\}}{\max\{f_{1j}, f_{2j}, \dots, f_{nj}\} - \min\{f_{1j}, f_{2j}, \dots, f_{nj}\}} \tag{4}$$

In the formula, f_{ij} represents the initial value of the indicator, where i denotes the region, j denotes the indicator, andn n represents the number of indicators; s_{ij} indicates the standardized value after processing.

Next, the information entropy E_j and the weight W_j of indicator j are calculated, with the specific methods as follows:

$$E_j = -\frac{1}{ln(n)} \sum_{i=1}^{n} \left(\frac{s_{ij}}{\sum_{i=1}^{n} s_{ij}} ln \frac{s_{ij}}{\sum_{i=1}^{n} s_{ij}} \right) \tag{5}$$

$$W_j = \frac{1 - E_j}{\sum_{j=1}^{m} (1 - E_j)} \tag{6}$$

Finally, the composite index is calculated to obtain the supply chain resilience evaluation values for different regions as follows:

$$SCR_i = \sum_{j=1}^{m} W_j s_{ij} \tag{7}$$

3.2.2. Core Explanatory Variable

The primary explanatory variable is the *development level of AI technology(AI)*. As most researchers currently use the volume of industrial robot usage to measure AI levels, such as Lü Yue and others who adopt the logarithm of industrial robot stock, this study employs an innovative indicator to measure the development level of AI technology: the annual number of AI enterprises in each Chinese province. To mitigate the influence of other factors, we apply a log-transformation after adding one to the enterprise count.

3.2.3. Mediating Variable

The mediating variable is *innovation level (Inno)*. This study uses the number of AI-related patents to measure innovation, with a log-transformation applied after adding one.

3.2.4. Control Variables

To address potential bias from omitted variables, the following control variables are included:

(1)**Economic Development Level (GDP)**: Measured by per capita gross domestic product (deflated to the base year 2000) and log-transformed.

(2) **Degree of Openness (OP)**: Represented by the ratio of the product of total import and export value (adjusted by the USD-to-RMB exchange rate) to regional GDP.

(3) **Industrial Structure Sophistication (IS)**: Calculated as the weighted sum of the value-added share of each industry in regional GDP, with weights of 1, 2, and 3 assigned to the primary, secondary, and tertiary industries, respectively.

(4) **Government Intervention (GOV)**: Measured by the ratio of fiscal expenditure to regional GDP.

3.3 Data Sources and Descriptive Statistics

Due to difficulties in obtaining data for Hong Kong, Macau, and Taiwan, this study excludes these regions and focuses solely on 31 provincial administrative regions in mainland China. The study period spans from 2003 to 2022, with data primarily sourced from the China Statistical Yearbook, China Agricultural Statistical Yearbook, China Industrial Statistical Yearbook, China Urban Statistical Yearbook, the Guotai Junan Database, the Bankscope Database, the EPS Database, the CSMAR Database, MarkData.com, and statistical materials published by various levels of local governments. The specific descriptions of variables are presented in Table 1, while the descriptive statistical analysis is summarized in Table 2.

Table 1. Research Variable and Description

Variable Properties	Variable Names and Codes	Variable Calculation
Dependent Variable Core	Supply Chain Resilience (SCR)	Measured by a composite index.
Explanatory Variable	Artificial Intelligence (AI)	Measured by the number of AI enterprises, with a log-transformation after adding one.
Mediating Variable	Innovation Level (Inno)	Measured by the numbers of patents, with a log-transformation after adding one.
Control Variables	Economic Development Level (GDP)	Expressed by per capita GDP (deflated with 2000 as the base year), logarithmically transformed.
	Degree of Openness (OP)	Measured by the ratio of the product of total import and export value (adjusted by the USD-to-RMB exchange rate) to regional GDP.
	Industrial Structure Sophistication (IS)	Measured by the Weighted Sum of the Value-Added Share of Each Industry in Regional GDP.
	Government Intervention (GOV)	Measured by the Ratio of Fiscal Expenditure to Regional GDP.

Table 2. Descriptive Statistics of Variables

Variables	N	Mean	St. Dev	Maximum	Minimun
SCR	620	0.0700	0.110	0.0100	0.980
AI	620	6.925	1.807	2.485	11.966
GDP	620	9.220	0.500	7.950	10.81
OP	620	0.300	0.350	0.0100	1.710
IS	620	2.360	0.130	2.070	2.830
GOV	620	0.250	0.190	0.0800	1.330

4. Empirical Results Analysis

4.1 Baseline Regression

Based on Model (1), we employ fixed effects (FE) and random effects (RE) methods to assess the role of AI in enhancing supply chain resilience and security. Table 2 presents the regression results for each method, with and without control variables. The columns in Table 3 correspond to: (1) fixed effects regression without control variables; (2) fixed effects regression with control variables; (3) random effects regression without control variables; and (4) random effects regression with control variables. The Hausman test confirms the appropriateness of the fixed effects model. Table 3 shows that, regardless of whether control variables are included, the coefficients for AI in columns (1) and (2) are 0.033 and 0.026, respectively, indicating a positive impact of AI on supply chain stability at a

1% significance level. When comparing the regression results of the random effects and fixed effects models, we find that AI has a significant positive effect on supply chain resilience and security. Overall, irrespective of the inclusion of control variables or the choice of effect model, the positive impact of AI on supply chain resilience and security is statistically significant. Thus, Hypothesis 1 is supported.

Table 3. Baseline Regression Results

Variables	(1) FE	(2) FE	(3) RE	(4) RE
AI	0.033*** (16.137)	0.026*** (6.595)	0.034*** (17.400)	0.015*** (4.796)
GDP		0.025 (1.133)		0.083*** (4.642)
OP		-0.312*** (-14.677)		-0.186*** (-9.583)
IS		0.105 (1.416)		0.250*** (4.111)
GOV		-0.434*** (-6.820)		-0.181*** (-5.236)
Individual Effects	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Constant Term	-0.156*** (-10.761)	-0.383 (-1.521)	-0.165*** (-10.515)	-1.288*** (-8.027)
N	620	620	620	620
R^2	0.307	0.522	0.307	0.466

Note:

a. *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively, and the same applies hereafter.

b. Values in parentheses are t-statistics corrected for heteroskedasticity, and the same applies hereafter.

4.2 Robustness Test

4.2.1. Endogeneity Test

Based on the above analysis, AI can stimulate regional innovation and enhance the risk-resistance capacity of regional supply chains, while the risk-resistance capacity of supply chains may also influence the development of digital finance. This suggests a potential causal relationship between the two, which could lead to endogeneity issues. To address this, we employ the Generalized Method of Moments (GMM) for system estimation. Specifically, we include the one-period lagged AI variable (L_AI) in the system GMM model and conduct regression analysis to examine the relationship between AI and supply chain sustainability. The corresponding results are presented in column (2) of Table 4. The findings indicate that the lagged variable L_AI has a significant positive impact on supply chain sustainability, further confirming the robustness of the earlier conclusions.

Table 4. Endogeneity and Replacement of Explanatory Variable Test

Variables	(1) AI	(2) SCR	(3) SCR
L_AI	1.073*** (372.765)	0.029*** (6.339)	
AI_P			0.014*** (3.885)
GDP		0.021 (0.891)	0.043* (1.811)
OP		-0.311*** (-14.279)	-0.315*** (-14.432)
IS		0.096 (1.219)	0.255*** (3.448)
GOV		-0.443*** (-6.685)	-0.463*** (-6.898)
Constant Term	-0.232*** (-11.671)	-0.338 (-1.240)	-0.786*** (-2.836)
N	589	589	620
R^2	0.952	0.504	0.499

4.2.2. Replacement of the Core Explanatory Variable

To avoid potential biases in selecting the number of AI enterprises as the core explanatory variable and ensure the accuracy of the results, this study uses the number of AI patents (AI_P) within the panel as an alternative variable and re-estimates the results. The regression results are shown in column (3) of Table 4. The findings demonstrate that, after replacing the explanatory variable, the positive effect of AI on supply chain resilience remains significant at the 1% confidence level, further validating the reliability of the research results.

4.2.3. Alternative Estimation Method

This study employs quantile regression to investigate the impact of AI on supply chains at different levels of resilience. Columns (1) to (5) in Table 5 report the effects of AI on supply chain resilience at the 90th, 75th, 50th, 25th, and 10th percentiles, respectively. The empirical results show that AI's promoting effect is significantly positive across all levels of supply chain resilience. However, as the level of resilience increases, the coefficient of the AI variable gradually decreases, indicating that the promoting effect of AI diminishes as supply chain resilience strengthens. This suggests that AI enterprises contribute more significantly to supply chains with lower resilience, but their contribution exhibits a diminishing trend as resilience levels increase.

Table 5. Quantile Regression Results

Variables	(1) 90th Percentile	(2) 75th Percentile	(3) 50th Percentile	(4) 25th Percentile	(5) 10th Percentile
AI	0.027*** (4.647)	0.019*** (7.033)	0.014*** (8.587)	0.008*** (7.930)	0.005*** (5.708)
Constant Term	-0.516** (-2.118)	-0.388** (-2.114)	-0.247*** (-3.657)	-0.079*** (-3.313)	-0.015 (-0.508)
Control Variables	Yes	Yes	Yes	Yes	Yes
Individual Effects	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes
N	620	620	620	620	620
Pseudo R^2	0.406	0.300	0.202	0.124	0.093

4.3 Heterogeneity Analysis

4.3.1. Heterogeneity Analysis at the Regional Level

The baseline regression results indicate that the development level of AI has a positive effect on supply chain resilience. Given that the application of AI varies across regions with different levels of economic development, this variation may lead to provincial heterogeneity in the impact of AI technology on supply chain resilience. To address this, this study incorporates control variables for regional heterogeneity analysis. The specific method is as follows: Control variables rgn_1 and rgn_2 are introduced, where rgn_1 takes the value 1 if the province in the sample belongs to the Yangtze River Economic Belt, and 0 otherwise; similarly, rgn_2 takes the value 1 if the province is located in eastern China, and 0 otherwise.

The Yangtze River Economic Belt, encompassing 11 provinces and municipalities including Shanghai, Jiangsu, and Zhejiang, spans over one-fifth of China's total land area, with its population and economic output each accounting for more than 40% of the national total. The Chinese central government regards the development of the Yangtze River Economic Belt as a national strategy critical to achieving long-term national development goals. This study divides the sample into provinces within the Yangtze River Economic Belt and other provinces for comparative analysis. The results in column (1) of Table 6 show that the coefficient of $AI \times rgn\_1$ is significantly positive at the 1% confidence level, indicating a pronounced positive effect of AI within the Yangtze River Economic Belt. However, other regions urgently need to strengthen the promoting effect of AI to better leverage its role in enhancing supply chain resilience.

Additionally, this study categorizes provinces into eastern China and other regions (central, western, and northeastern) for a more general regional heterogeneity analysis. As shown in column (2) of Table 5, the coefficient of $AI \times rgn\_2$ is significantly positive at the 1% confidence level. This can be attributed to eastern China's advantageous geographical location, favorable political policies, and historical development advantages, which contribute to its superior capacity to withstand shocks and recover post-shock. Moreover, the coefficient of $AI \times rgn\_2$ is notably higher than that of AI alone, suggesting that, overall, AI technology in eastern China plays a substantial role in enhancing supply chain resilience and ensuring security. In contrast, the technological development in the other three regions (central, western, and northeastern) lags behind and requires policy support to mitigate negative effects and fully harness AI's potential to significantly promote regional supply chain resilience and security

4.3.2. Heterogeneity Analysis at the Temporal Level

The study period spans from 2003 to 2022, encompassing the 2008 financial crisis. To explore its differential impact, this study introduces a financial crisis-related dummy variable, $AI \times t$. Specifically, if the sample year is before 2008, ttt is set to 0; if it is 2008 or later, ttt is set to 1. As shown in column (3) of Table 6, the coefficient of $AI \times t$ is significantly negative at the 1% confidence level, indicating that the financial crisis significantly weakens the positive effect of AI.

Table 6. Heterogeneity Test Estimation Results

Variables	(1) Yangtze River Economic Belt and Other Regions	(2) Eastern China and Other Regions	(3) Before and After the Financial Crisis
AI	0.023*** (5.854)	0.020*** (5.216)	0.023*** (5.571)
$AI \times rgn\_1$	0.019*** (4.802)		
$AI \times rgn\_2$		0.037*** (8.857)	
$AI \times t$			-0.005*** (-2.905)
N	620	620	620

R^2	0.578	0.578	0.522

4.4 Mediation Effect Analysis

Under the premise that the AI coefficient is significantly positive in the baseline regression, column (1) of Table 7 shows that the coefficient of the variable AI is significantly positive, confirming AI's positive effect on innovation levels. According to column (2) of Table 7, when the variable $Inno$ is significantly positive, the coefficient of AI remains significantly positive but is lower compared to the baseline regression results. This demonstrates that innovation level partially mediates the relationship between AI and supply chain resilience. Thus, Hypothesis 2 is validated.

Further analysis of the underlying mechanisms reveals the following: First, as a general-purpose technology, AI, when integrated with traditional equipment, can directly produce new equipment with intelligent functions such as self-perception, self-learning, and autonomous decision-making, thereby promoting enterprise product innovation. This technological innovation effect is one of the key mechanisms through which AI enhances supply chain resilience. Second, the application of AI technology improves enterprises' dynamic capabilities, including absorptive capacity, innovation capacity, and adaptive capacity. These capabilities transform innovation resources into innovation outputs, significantly impacting enterprise innovation performance. Notably, the mediation effect of innovation capacity is the most substantial, indicating that enterprises can better leverage AI technology by enhancing their innovation capacity, thereby improving innovation performance and supply chain resilience.

Table 7. Mediation Effect Regression Results

	(1) $Inno$	(2) ICT
AI	0.481*** (19.263)	0.011** (2.167)
$Inno$		0.032*** (4.962)
Constant Term	-19.432*** (-12.198)	0.235 (0.851)
Control Variables	Yes	Yes
Individual Effects	Yes	Yes
Time effects	Yes	Yes
N	620	620
R^2	0.908	0.541

5. Conclusions and Recommendations

5.1 Conclusions

This study constructs panel data for 31 provincial administrative regions in mainland China from 2003 to 2022, using the number of artificial intelligence (AI) enterprises and a composite index to measure supply chain resilience. It examines the impact of AI on supply chain resilience and its underlying mechanisms. The main findings are as follows:

(1) Overall, AI significantly promotes supply chain resilience in China. This key conclusion remains robust after endogeneity tests, replacement of explanatory variables, and alternative estimation methods.

(2) Heterogeneity analysis reveals: First, from a regional perspective, the promoting effect of AI on supply chain resilience is more pronounced in eastern China and the Yangtze River Economic Belt compared to other regions in mainland China. Second, external shocks, such as the 2008 financial crisis, significantly weaken AI's promoting effect.

(3) Mediation effect analysis indicates that innovation capacity plays a critical mediating role in the process through which AI enhances supply chain resilience and security.

5.2 Recommendations

In the context of unprecedented global changes, internal and external factors hindering economic development are converging, and nations worldwide face numerous uncertain endogenous contradictions and exogenous shocks. As a critical component of economic development, supply chain resilience and security have become focal points for countries globally. AI, as a pivotal force in driving technological transformation and industrial evolution in the new era, bears the significant responsibility of liberating and advancing productive forces. It is undoubtedly a key driver in steadily improving national supply chain resilience and security.

First, the rapid development of AI is a critical factor in enhancing national supply chain resilience. Strengthening top-level design and comprehensive planning for AI applications is essential to promote the growth of the AI industry. By continuously expanding AI's application domains, new momentum can be injected into the real economy, gradually building a modern industrial system to ensure the security and stability of supply chains. In short, through meticulous planning and promotion of AI technology, supply chain resilience can be enhanced, ensuring its healthy and sustainable development.

Second, optimizing the allocation of innovation resources indirectly strengthens supply chains. To effectively enhance supply chain resilience, relevant authorities should focus on improving mechanisms for allocating innovation resources and continuously advancing technological innovation within industries. This approach strengthens supply chain resilience and security from an innovation perspective. Talent, as a key element of innovation, requires special attention. Governments should leverage national talent acquisition policies to fully support the entry of high-end talent into the market. By offering attractive compensation packages and creating favorable development environments, regions can attract and aggregate talent, generating scale and agglomeration effects to lay a solid talent foundation for improving supply chain resilience and security. Government investment in capital for innovation resources is also crucial. First, governments should increase fiscal budgets to support digital research and innovation, a key driver of technological progress and industrial upgrading. Additionally, governments should implement tax exemptions and supportive policies to stimulate innovation vitality among enterprises, universities, and research institutions, thereby enhancing technological R&D capabilities. In terms of technological innovation resources, governments should adopt a dual strategy. On one hand, they should accelerate the establishment of technology transfer institutions to promote collaboration between supply chain entities, academia, and research institutions, jointly establishing new R&D entities such as technology R&D centers and industrial research institutes. This fosters a tightly integrated innovation system combining industry, academia, and research. For example, two projects from the Zhongguancun Demonstration Zone were selected as part of the global top 100 technology transfer cases, highlighting the critical role of technology transfer in driving innovation.

Finally, while eastern China and the Yangtze River Economic Belt have achieved significant success in leveraging AI to enhance supply chain resilience, other regions lag behind. Therefore, policymakers in less economically developed regions and priority policy areas should recognize the importance of formulating and implementing targeted policies to harness AI technology for local industrial revitalization. These policies should focus on strategic planning and top-level design for AI applications to foster the AI industry and expand its use across various domains. Simultaneously, they should aim to enhance industries' technological innovation capabilities, laying a solid innovation foundation for supply chain risk resistance. At the policy level, the contribution of talent to innovation should be emphasized. Governments should actively introduce and implement talent acquisition measures aligned with national strategies to aggregate talent, generating scale and agglomeration effects to significantly enhance supply chains' risk-coping capabilities. Financially, governments should increase support for research and digital innovation, encouraging innovation activities among enterprises and academic institutions through tax exemptions and policy support to boost technological innovation capabilities. Additionally, policies should promote the establishment of collaborative R&D platforms and industrial research institutes between industries and academic institutions, forming a tightly integrated innovation system. Policies should also facilitate the deep integration of technology and finance, such as supporting intellectual property financing through financial institutions to remove financial barriers in technology transfer, thereby promoting the conversion of technological achievements and enhancing supply chains' risk resistance.

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