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The Impact of Artificial Intelligence on Supply Chain Resilience: An Empirical Study

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Abstract. The rapid development and widespread application of artificial intelligence (AI) across various industries have garnered significant attention. This paper investigates the impact of AI on supply chain resilience using data from A - share listed companies in China from 2012 to 2022. The findings indicate that AI has a significant positive impact on supply chain resilience, which remains robust after multiple robustness tests and endogeneity treatments. Heterogeneous analysis shows that the enhancing effect of AI on supply chain resilience is more pronounced in state - owned enterprises, enterprises audited by the Big Four, and enterprises in the eastern region. Mechanism analysis reveals that AI enhances supply chain resilience by promoting R&D innovation, optimizing resource allocation efficiency, and improving financing speed. These results suggest that AI application can effectively enhance the risk - resistance and recovery capabilities of supply chains, with significant implications for promoting enterprise digital transformation and improving supply chain management levels.

Keywords: Artificial Intelligence; Supply Chain Resilience; R&D Innovation; Resource Allocation Efficiency; Financing Speed.

1. Introduction

In recent years, artificial intelligence (AI) has witnessed rapid global development and expanding application scenarios. The global AI market is projected to grow from $184.15 billion in 2024 to $2.53 trillion in 2033, at a compound annual growth rate of 33.83%. This growth is driven by advancements in machine learning and deep learning, increasing automation needs, and the exponential growth of data. Against this backdrop, China has been vigorously promoting the integration of AI technology with other fields. On March 5, 2025, Premier Li Qiang of the State Council proposed in the government work report at the third session of the 14th National People's Congress to continue promoting the "AI+" initiative, combining digital technology with manufacturing and market advantages, supporting the widespread application of large models, and developing new intelligent products like smart - connected new - energy vehicles, AI - enabled phones and computers, intelligent robots, and intelligent manufacturing equipment.

Following the introduction of national AI - supportive policies, many scholars and experts have extensively explored AI application scenarios. Guo Shidi (2025) [1] found that AI technology can enhance design accuracy and manufacturing efficiency in mechanical design and manufacturing. Shu Yan (2025) [2] pointed out that AI technology is showing great potential in paper - making enterprise management, improving operational efficiency and product quality. Dong Bangjun (2025) [3] discovered that deep - level intelligent interrogation can meet more functional needs, and AI interrogation technology is valuable in investigation and case - solving. Yang Ting (2019) et al. concluded that AI technology can change energy utilization modes in power systems and integrated energy systems, promote system intelligence, and advance the energy revolution to build a clean, low - carbon, safe, and efficient energy system [4]. Based on previous literature, this paper explores specific application scenarios and mechanisms of AI in China's manufacturing industry.

Theoretically, AI can effectively enhance supply chain resilience. Through machine learning and deep algorithms, AI can boost corporate innovation capabilities, introduce new technologies to optimize supply chain resource allocation, and thus improve supply chain resilience. AI can also analyze and assess financing risks via machine learning algorithms, enhancing financing efficiency [5]. This helps supply chains recover from disruptions and reduce customer losses, further improving resilience.

This paper selects A - share listed companies from 2012 to 2022 as samples to empirically test the impact and mechanism of AI on supply chain resilience. The results show that AI significantly positively affects supply chain resilience, and this result is robust after multiple stability tests and endogeneity treatments. Heterogeneity analysis indicates that the enhancing effect of AI on supply chain resilience is more evident in state - owned enterprises, big - four audited enterprises, and eastern - region enterprises. Mechanism analysis reveals that AI enhances supply chain resilience by promoting research and innovation, optimizing resource allocation efficiency, and increasing financing speed.

The contributions of this paper are: first, enriching the research perspective on supply chain resilience. Previous studies mainly focus on production manufacturing and corporate IT integration, while this paper focuses on AI, delving into its empowering effect on supply chain resilience. Second, uncovering the internal mechanisms of AI in enhancing supply chain resilience through R&D innovation, resource allocation efficiency, and financing speed improvement, providing a clear logical framework. It emphasizes AI's key role in advancing supply chain intelligence and industrial digital transformation, offering a new technical direction for supply chain management research. Third, enriching relevant research. Given the limited empirical research on AI's role in supply chain resilience enhancement, this paper conducts a systematic empirical analysis using data from listed companies' annual reports.

The structure of this paper is as follows: the second part is literature review, the third part is theoretical analysis, the fourth part is theoretical framework and research hypotheses, the fifth part is research design, the sixth part is empirical analysis, the seventh part is mechanism testing, and the eighth part is conclusions and recommendations.

2. Literature Review

With the acceleration of globalization and the significant increase in market uncertainty, supply chains face numerous severe challenges, such as the growing impact of natural disasters and pandemics. Against this backdrop, supply chain resilience has become a crucial capability for addressing these challenges. The initial definition of supply chain resilience was "the ability of a supply chain to return to its original state or a more desirable state after being disrupted" [6]. Ponomarov and Holcomb (2009) pointed out that supply chain resilience is the ability to anticipate potential disruptions, respond quickly, and recover, closely related to preparedness, response, and recovery capabilities [7]. Hohenstein et al. (2015) emphasized its importance, stating that it enables supply chains to maintain operations or transition to a better state during potential risks, improving customer service, market share, and financial performance [8]. With in-depth research, the definition has expanded and is widely accepted: supply chain resilience is the ability to maintain structure, function, and performance in the face of uncertainties, risks, and disruptions. This includes preventive measures before, response measures during, and recovery measures after disruptions [9]. To explore factors enhancing supply chain resilience, scholars have conducted systematic research from multiple dimensions such as supply chain digitalization, servitization of manufacturing, new - quality productivity empowerment, and corporate IT integration.

2.1. Literature on Supply Chain Resilience

Regarding factors affecting supply chain resilience, Zhang Shushan et al. (2024) studied its impact mechanism from the supply chain digitalization perspective, finding that it enhances resilience through information, product competitiveness, and internal control channels [10]. Fu Yuqi (2024) researched the impact of technical standardization, concluding that it significantly enhances supply chain resilience through supply chain collaboration [11].

Liu Tingli (2025) et al. found that the servitization of manufacturing significantly promotes supply chain resilience, mainly by mitigating the bullwhip effect and generating backward spillover effects. This effect is more pronounced in high-tech and AI - advanced enterprises, indicating that servitization enhances risk - resistance capabilities through technical spillovers [12]. Zhang Can (2024) et al. constructed a "knowledge - technology - data and calculation" framework, revealing that new - quality productivity enhances supply chain resilience through innovation, upgrades, and digital transformation [13]. Du Xiaorui (2023) proposed that emerging IT technologies significantly improve supply chain resilience and sustainability performance. These technologies enhance organizational and digital transformation capabilities, with supply chain resilience mediating the impact on sustainability performance [14].

2.2. Literature on Artificial Intelligence

AI, a field widely explored in recent decades, is a technology that can perform tasks requiring human intelligence, such as learning, reasoning, problem - solving, and language understanding. AI systems are trained on large datasets to perform specific tasks and optimize performance [15]. Asif, M. and Gouqing, Z. (2024) categorized AI into four dimensions: technical (machine learning, deep learning, neural networks), social (social media, education, healthcare applications), ethical (privacy, bias, liability), and application (autonomous vehicles, intelligent assistants, recommendation systems) [16].

As a key driver of technological revolution, AI is reshaping industries and driving R&D innovation. Scholars have highlighted AI's significant role in various sectors. Wu Fei (2025) found that AI integration with other industries creates value, fosters new productivity, and injects new dynamism into economic and social fields [17]. Farrelly, T., & Baker, N. (2023) discovered that generative AI bridges educational gaps and promotes equity and inclusion [18].

Farrelly, T., & Baker, N. (2023) also found that AI accelerates R&D by processing big data and identifying patterns. For instance, AI expedites drug discovery by analyzing gene sequences and simulating scenarios [19]. Zhao Mingchao (2025) concluded that AI, big data, and blockchain enhance business efficiency, investment decision - making, and market competitiveness, promoting fintech development and financing efficiency [20]. AI also optimizes resource allocation in industries, helping enterprises allocate R&D resources efficiently through predictive analysis and simulation, avoiding waste [21]. In healthcare, AI analyzes medical data for better resource utilization and operational efficiency [22].

2.3. Research Gaps and Innovations

In summary, existing research on enhancing supply chain resilience mainly focuses on production manufacturing and corporate IT integration, with limited exploration in other fields. Most studies concentrate on single technologies or industries, lacking in-depth analysis of cross-field technological integration. This paper innovatively focuses on the rapidly developing AI field, exploring its empowering effect on supply chain resilience. It also innovates in data by analyzing listed companies' annual reports to reveal AI's mechanisms.

AI, as a cutting-edge technology supported by the state, combined with big data and IoT, drives technological progress and enables intelligent supply chain management and industrial digital transformation. Supply chain resilience is crucial for national economic stability and sustainable development. AI reduces supply chain disruption risks and ensures smooth industrial operations. However, empirical research on AI's role in enhancing supply chain resilience, especially in multi-industry and multi-technology integration contexts, is still limited. This study addresses these gaps, offering new insights for theory and practice.

3. Theoretical Analysis

Artificial Intelligence (AI) enhances supply chain resilience and risk response capabilities through precise demand forecasting and intelligent decision support. First, AI's machine learning and deep learning algorithms enable analysis of massive datasets to achieve more accurate market demand predictions. Such precise forecasting helps enterprises adjust production plans in advance and optimize inventory levels [23], thereby improving supply chain preparedness for potential emergencies and enhancing resilience. Second, AI leverages big data and machine learning algorithms to accurately assess risks, providing intelligent decision support for enterprises through data analysis and simulation modeling, which further strengthens supply chain resilience.

Furthermore, AI drives R&D innovation by utilizing technologies like big data and IoT to collect and analyze real-time data across supply chain segments. Through deep learning algorithms, AI facilitates technological breakthroughs. As demonstrated by Yu et al. (2024): Traditional AI technologies promote innovation through dual pathways - participating in technology identification, market validation, and testing phases for technology-driven innovation, while embedding in user demand acquisition, evaluation, conversion, and personalized demand mining processes for demand-driven innovation [24]. The innovation-driving effect of AI has been validated both theoretically and practically. Taking China's A-share listed companies as an example, from 2012 to 2022, AI-related enterprises achieved an average annual growth rate of 35% in patent applications. Driven by AI technologies, these companies have expanded their R&D domains from traditional manufacturing and electronic equipment to emerging fields like software development and intelligent system integration. Concurrently, their average R&D investment reached 8% of operating revenue, significantly higher than the 5% ratio in non-AI enterprises. These statistics confirm AI's substantial role in empowering corporate innovation capabilities.

R&D innovation accelerates corporate digital transformation, which synergistically enhances supply chain resilience. Existing research has explored this synergistic relationship: Enterprises leverage regional digital ecosystems for technology spillovers, assimilate advanced technologies, and improve the application level of digital innovation technologies, thereby strengthening supply chain resilience [25]. This demonstrates that R&D innovation facilitates digital transformation and enhances technological application capabilities, ultimately improving supply chain resilience.

Enhanced financing efficiency significantly assists supply chains in responding to emergencies. Regarding the relationship between financing and supply chain resilience, Zhang Peini (2024) proposed: For modern enterprises, improving supply chain resilience enables rapid response to market changes, effective capture of market opportunities, and active resistance to market risks, all crucial for long-term stable development. Effective capital management optimizes supply chain fund allocation and reduces financial risks, thereby effectively enhancing supply chain resilience [26].

Optimized resource allocation improves supply chain resource utilization efficiency. Numerous scholars have investigated the relationship between resource utilization and supply chain resilience from various perspectives. Based on resource-based view and dynamic capabilities theory, Miao Zhuoqi et al. [27] analyzed how upstream supply chain social capital affects supply chain resilience, identifying the mediating role of supply chain external integration. Their findings indicate that both dimensions of supply chain social capital resources - structural capital and relational capital - positively influence corporate supply chain resilience.

4. Theoretical Framework Construction and Research Hypotheses

This study investigates how the development of artificial intelligence (AI) enhances supply chain resilience through three mechanisms: promoting R&D innovation, improving resource utilization efficiency, and accelerating financing efficiency. The measurement and evaluation indicators of supply chain resilience are categorized into three dimensions:

1. Structural indicators, including supply chain network structure, node connectivity, and partner diversity.

2. Process indicators, focusing on response speed during crises, information flow efficiency, and decision-making flexibility, which reflect the adaptive capacity of supply chains in emergencies.

3. Outcome indicators, evaluating post-disruption recovery capabilities and performance, such as recovery time, cost losses, and customer satisfaction [28].

Emerging technologies derived from R&D innovation inevitably enhance the structural complexity and node connectivity diversity of supply chains, thereby improving resilience from the structural dimension. Resource allocation efficiency determines crisis response speed and decision flexibility, strengthening resilience through process indicators. Improved financing efficiency reinforces post-disruption recovery capabilities and reduces customer losses, enhancing resilience through outcome indicators. Based on existing research and practical evidence, this study proposes the theoretical framework shown in Figure 1 and formulates the following hypothesis:

H1: The development of artificial intelligence has a significant positive effect on supply chain resilience.

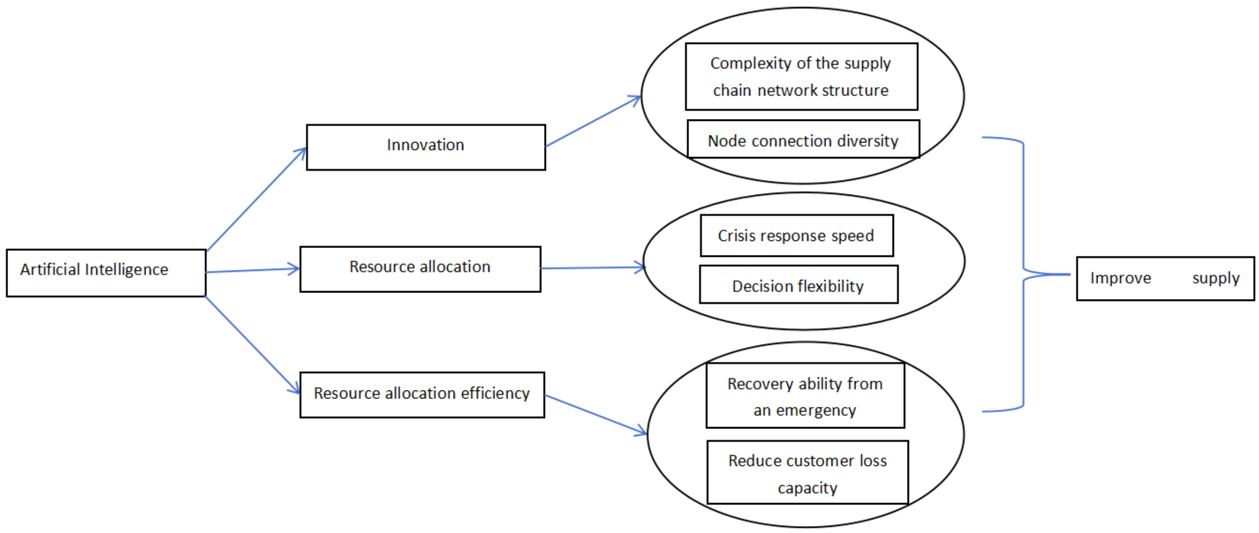

Figure 1. The study framework of Fig

5. Research Design

This chapter introduces the theoretical framework, data sources, variable definitions, model construction, and statistical methods, providing an empirical basis for examining AI's impact on supply chain resilience.

5.1. Variable Definition

Variable design and measurement are crucial for studying AI's impact on supply chain resilience.

Dependent Variable: The dependent variable is supplying chain resilience. Based on Li Dakun's definition [28], it is measured by supply chain recovery ability and resistance ability. Following Zhao Chenyu et al. (2021) [29], supply chain recovery ability is proxied by the deviation of production fluctuation from demand fluctuation, calculated as:

$$Matching_{it} = \frac{Var(Production_{it})}{Var(Demand_{it})} \tag{1}$$

Where, matching it represents the deviation of supply and demand. If Matchingit is greater than 1, it indicates significant fluctuations in supply and demand, implying low supply chain recovery ability.

$$Production_{it} = Demand_{it} + Inventory_{it} - Inventory_{it-1} \tag{2}$$

Productionit denotes the firm's production volume. Demandit signifies the firm's demand volume, measured by sales costs. Inventoryit represents the year - end net value of the firm's inventory.

The metric for supply chain resistance ability is asset occupation 1, calculated as the natural logarithm of the ratio of accounts receivable and prepayments to main business revenue.

The explanatory variable is AI. This paper constructs an index system for AI using five sub - indicators: AI software investment, AI hardware investment, Lnwords (the frequency of AI - related words in listed companies' annual reports, log - transformed +1), Lnwords_MDA (the frequency of AI - related words in the management discussion and analysis section of listed companies' annual reports, log - transformed +1), and Lnpatents (the number of AI - related patents of listed companies, log - transformed +1). The AI index ai is obtained through the entropy method.

The intermediate mechanism variables are: firstly, R&D innovation, measured by the number of patents issued, reflecting the technological progress from R&D innovation. Secondly, resource utilization efficiency, measured using the DEA model. Thirdly, financing efficiency, measured by the management expense ratio.

Control variables: in order to more accurately analyze the influence of artificial intelligence on supply chain toughness, the study introduces company scale, asset-liability ratio, total assets net profit margin, return on net assets, total assets turnover, accounts receivable proportion, fixed assets proportion, management holdings, large shareholders capital take up control variables to control other factors may affect the supply chain toughness.

5.2. Model and Data

This paper uses the Fixed Effects Model (FE) to control for time - invariant individual heterogeneity, mitigate endogeneity from individual differences, and ensure estimation robustness. The specific model is as follows:

$$Recov_{i,t} = \alpha + \beta ai_{i,t} + \gamma' Control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \quad (3)$$

Where Recovit is supply chain resilience, measured by recovery ability. ai is obtained via the entropy method from five indicators. Contorlit includes control variables like Size, Lev, ROA, ROE, ATO, REC, FIXED, Mshare, and Occupy. Year and Industry indicate year and industry fixed effects. To control for potential cross - sectional correlation, this paper clusters standard errors at the firm level in all regressions.

Table 1. Variable definitions and construction

variable symbol	Variable name	Note of variable construction
Recov	Supply chain recovery	See the above for the measurement methods
ai	artificial intelligence	See the above for the measurement methods
Size	Company size (total assets)	Total enterprise assets at the end of the year
Lev	asset-liability ratio	Total liabilities / total assets
ROA	Net profit margin of total assets	Net income / Total assets
ROE	Return on Equity	Net profit / owners' equity
ATO	turnover of total capital	Operating income / average total assets
REC	The proportion of accounts receivable	Net accounts receivable / Total assets
FIXED	The proportion of fixed assets	Net fixed assets / total assets
Mshare	The ratio of management shareholding	Proportion of the shares held by management of the total share capital of the Company
Occupy	Capital occupation of major shareholders	The amount of funds occupied by the major shareholders / the total assets of the company

The data used in this case is from listed companies during 2012 - 2022, sourced from CSMAR and Wind. Before empirical analysis, data preprocessing was done as follows:

(1) ST, *ST, and PT companies were excluded.

(2) The insurance and finance industries were excluded.

(3) Missing - value observations were excluded.

Additionally, winsorization was performed. Finally, 27,740 firm - year observations were obtained.

6. Empirical Analysis

This chapter empirically analyses AI's impact on supply chain resilience and explores its mechanisms, using benchmark regression models and robustness tests to confirm AI's significant role in enhancing resilience.

6.1. Descriptive Statistics

The study uses Stata for descriptive statistics on the sample. The statistical information for the selected dependent variable, independent variable, and control variables is shown in the table below.

Table 2. Variable definitions and construction

	(1)	(2)	(3)	(4)	(5)
variable	sample capacity	mean value	standard deviation	minimum	maximum
Recov	27,740	6,792	337,873	-2.797e+06	2.336e+06
ai	27,740	0.037	0.056	5.75e-06	0.582
Size	27,740	22.290	1.281	19.590	26.440
Lev	27,740	0.424	0.204	0.035	0.925
ROA	27,739	0.037	0.068	-0.375	0.255
ROE	27,710	0.057	0.140	-0.962	0.415
ATO	27,738	0.630	0.425	0.057	2.902
REC	27,662	0.126	0.104	2.52e-05	0.506
FIXED	27,740	0.203	0.154	0.002	0.728
Mshare	26,990	0.141	0.195	0	0.706
Occupy	27,725	0.015	0.023	7.29e-05	0.189

The sample sizes for all variables are roughly the same. With a sufficiently large sample size, the impact of partial data missing on some variables can be ignored. From the table, the minimum values of ROA and ROE are negative, indicating some companies may be loss - making. The distributions of Size, Lev, FIXED, Recov2, and ai are relatively concentrated, while those of ROE, ATO, and Mshare are relatively wide. The distribution of Occupy is narrow, showing consistency in the proportion of major - shareholder fund occupation in the sample. The minimum value of supply chain recovery ability is 0, and the maximum is 0.635, indicating significant differences in supply chain recovery levels among sample firms. The minimum value of AI measurement is 5.75e - 06, and the maximum is 0.582, showing evident differences in AI application among companies during the sample period.

6.2. Benchmark Regression Analysis

To verify AI's impact on supply chain resilience, this paper constructs a fixed - effects model for empirical analysis, gradually adding control variables. The regression results are shown in the table below. Column (1) shows the estimation without control variables and fixed effects. Column (2) presents the estimation with industry and year fixed effects, where the estimated coefficient is significantly positive at the 1% level. Column (3) is the estimation with control variables but without fixed effects. Column (4) shows the estimation with both control variables and fixed effects, where the estimated coefficient is also significantly positive at the 1% level. The regression results indicate that AI significantly positively affects supply chain resilience, regardless of industry and year fixed effects. This impact remains significant even when other variables are controlled for. Controlling industry and year fixed effects notably enhances the model's explanatory power, indicating the importance of industry and time factors for supply chain resilience. As more variables, especially industry and year fixed effects, are added, the model's explanatory power gradually increases. This means that AI application in sample companies can significantly enhance supply chain recovery ability and risk - resistance, with a remarkable effect. The results confirm that AI significantly improves supply chain resilience, validating the hypothesis.

Table 3. Benchmark regression results

	(1)	(2)	(3)	(4)
VARIABLES	*Recov2*	*Recov2*	*Recov2*	*Recov2*
ai	0.034***	0.066***	0.059***	0.088***
	(4.482)	(7.647)	(7.527)	(11.166)
Size			-0.007***	-0.010***
			(-12.723)	(-18.754)
Lev			0.081***	0.067***
			(27.501)	(26.023)
ROA			0.247***	0.272***
			(14.767)	(16.660)
ROE			0.054***	0.042***
			(6.714)	(5.483)
ATO			-0.018***	-0.016***
			(-11.549)	(-11.633)
REC			-0.043***	-0.013***
			(-8.583)	(-2.987)
FIXED			-0.030***	-0.016***
			(-5.460)	(-4.240)
Mshare			-0.008***	-0.005***
			(-4.169)	(-2.961)
Occupy			0.013	-0.030
			(0.493)	(-1.255)
Constant	0.346***	0.334***	0.486***	0.516***
	(512.147)	(54.520)	(39.364)	(46.177)
Observations	27,740	27,740	26,884	26,884
R-squared	0.002	0.147	0.285	0.403
Industry FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6.3. Robustness Test

6.3.1. Replacing the Core Explanatory Variable.

The model was re - estimated by replacing the measure of AI. Based on the benchmark regression, we substituted the AI index ai with Lnwords_MDA (the log - transformed frequency of AI - related words in the management discussion and analysis section of listed companies' annual reports, plus 1), Lnwords (the log - transformed frequency of AI - related words in listed companies' annual reports, plus 1), and Lnpatents (the log - transformed number of AI - related patents of listed companies, plus 1), respectively. The results, as shown in the table below, indicate that the estimated coefficients remain significantly positive at the 1% level, consistent with the benchmark regression results, confirming the stability of the original regression model.

Table 4. Results of the robustness test for explanatory variables

	(1)	(2)	(3)
VARIABLES	Recov2	Recov2	Recov2
Lnwords_MDA	0.003***		
	(8.353)		
Lnwords		0.002***	
		(6.766)	
Lnpatents			0.007***
			(9.290)
Size	-0.009***	-0.009***	-0.009***
	(-17.380)	(-17.269)	(-18.921)
Lev	0.067***	0.067***	0.067***
	(25.563)	(25.433)	(25.927)
ROA	0.273***	0.273***	0.270***
	(16.668)	(16.600)	(16.503)
ROE	0.042***	0.042***	0.042***
	(5.466)	(5.487)	(5.528)
ATO	-0.016***	-0.016***	-0.016***
	(-11.501)	(-11.513)	(-11.515)
REC	-0.013***	-0.013***	-0.011**
	(-3.054)	(-2.993)	(-2.529)
FIXED	-0.017***	-0.017***	-0.017***
	(-4.588)	(-4.574)	(-4.449)
Mshare	-0.004***	-0.004***	-0.004***
	(-2.622)	(-2.598)	(-2.639)
Occupy	-0.029	-0.030	-0.029
	(-1.202)	(-1.225)	(-1.194)
Constant	0.503***	0.502***	0.513***
	(44.820)	(44.603)	(47.155)
Observations	26,884		
R-squared	0.398	26,884	26,884
Industry FE	YES		0.402
Year FE	YES		YES

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6.3.2. Replacing the Dependent Variable.

The model was re - estimated by replacing the supply chain recovery indicator recov2. The resistance indicators resist1, resist2 and the recovery indicator recov were used as proxies for supply chain resilience. As shown in the table below, the regression coefficients in columns (1), (2), and (3) are all significantly positive at the 1% level, indicating robust and reliable results. This means the measurement method of the dependent variable does not affect the main conclusion of this study.

Table 5. Change the robustness test results for the explained variables

	(1)	(2)	(3)
VARIABLES	resist1	resist2	Recov
ai	0.775***	0.156***	553,054.962***
	(4.594)	(3.427)	(9.351)
Size	0.007	0.005*	-75,904.315***
	(0.742)	(1.900)	(-18.622)
Lev	-0.099*	-0.088***	544,191.638***
	(-1.886)	(-5.558)	(26.178)
ROA	-1.495***	-0.268**	2189244.177***
	(-6.598)	(-2.018)	(16.539)
ROE	0.186*	-0.098	339,139.679***
	(1.862)	(-1.086)	(5.540)
ATO	-0.946***	-0.261***	-129,951.190***
	(-31.999)	(-24.911)	(-11.547)
REC	5.735***	1.828***	-106,264.545***
	(54.020)	(39.538)	(-3.137)
FIXED	-0.551***	-0.077***	-129,827.060***
	(-7.864)	(-3.051)	(-4.300)
Mshare	0.033	0.026***	-40,956.444***
	(0.897)	(2.695)	(-3.062)
Occupy	0.589	0.252	-240,740.990
	(1.566)	(1.092)	(-1.233)
Constant	-1.807***	0.121**	1340435.561***
	(-6.148)	(2.339)	(15.028)
Observations	26,867	26,884	26,884
R-squared	0.648	0.446	0.407
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6.3.3. Excluding Disturbance Factors.

When studying listed companies from 2012 to 2022 to ensure robust conclusions and avoid impacts of major events and their lags, data from special years should be excluded. Since the COVID - 19 lockdown in 2020 - 2022 greatly affected corporate supply chain nodes and disrupted supply chain resilience, we removed the 2020 - 2022 data of sample companies and performed benchmark regression. The results, shown in the table below, indicate that the AI regression coefficient remains significantly positive at the 1% level, with or without industry and year fixed effects. Thus, the conclusion is still robust.

Table 6. Results of the robustness test excluding interference factors

	(1)	(2)	(3)	(4)
VARIABLES	Recov2	Recov2	Recov2	Recov2
ai	0.034***	0.066***	0.054***	0.085***
	(4.354)	(7.465)	(6.722)	(10.387)
Size			-0.008***	-0.009***
			(-11.583)	(-16.056)
Lev			0.084***	0.067***
			(25.166)	(22.323)
ROA			0.216***	0.251***
			(10.488)	(12.294)
ROE			0.063***	0.044***
			(6.119)	(4.420)
ATO			-0.020***	-0.018***
			(-12.365)	(-11.562)
REC			-0.046***	-0.011**
			(-8.461)	(-2.457)
FIXED			-0.033***	-0.015***
			(-5.635)	(-3.752)
Mshare			-0.008***	-0.005***
			(-4.029)	(-3.021)
Occupy			0.017	-0.024
			(0.610)	(-0.918)
Constant	0.345***	0.334***	0.491***	0.514***
	(461.404)	(51.431)	(35.620)	(40.262)
Observations	20,217	20,217	19,551	19,551
R-squared	0.002	0.181	0.285	0.414
Industry FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6.3.4. Propensity Score Matching (PSM).

Propensity score matching can resolve sample selection bias. This study used a 1:1 nearest - neighbor matching method. First, the AI index ai was dichotomized at the median (1 for above, 0 for below), creating a binary variable. Benchmark regression was then performed. As shown in the table below, the AI coefficient remains significantly positive at the 1% level regardless of industry and year fixed effects. Thus, the conclusion holds.

Table 7. Results of the PSM

	(1)	(2)	(3)	(4)
VARIABLES	Recov2	Recov2	Recov2	Recov2
ai	0.040***	0.072***	0.058***	0.090***
	(5.161)	(8.155)	(7.412)	(11.320)
Size			-0.008***	-0.010***
			(-12.640)	(-18.339)
Lev			0.081***	0.067***
			(25.941)	(24.711)
ROA			0.246***	0.273***
			(14.133)	(16.081)
ROE			0.056***	0.043***
			(6.636)	(5.382)
ATO			-0.018***	-0.016***
			(-10.925)	(-10.935)
REC			-0.044***	-0.012***
			(-8.524)	(-2.739)
FIXED			-0.033***	-0.018***
			(-5.745)	(-4.429)
Mshare			-0.008***	-0.005***
			(-4.098)	(-2.704)
Occupy			0.012	-0.037
			(0.447)	(-1.407)
Constant	0.345***	0.328***	0.490***	0.516***
	(489.800)	(47.747)	(38.540)	(44.173)
Observations	24,662	24,662	24,662	24,662
R-squared	0.003	0.147	0.287	0.405
Industry FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6.4. Endogeneity Analysis

In recent years, AI has rapidly developed in China and is easily influenced by other economic factors. There might be an endogeneity issue due to a potential bidirectional causal relationship between AI and other factors. This could bias the benchmark regression results. To address this, the study employs instrumental variable method for regression analysis. The 2SLS method is used, with industry - based and province - based averages as instrumental variables for the AI index. The regression results are shown in the table below. Columns (1) and (2) present results using industry - based instrumental variables, while columns (3) and (4) use province - based ones. Columns (1) and (3) show a significantly positive impact of AI on supply chain resilience based on industry and province, respectively. Columns (2) and (4) indicate that the explanatory variable coefficient is significantly positive at the 5% level. These findings confirm that AI significantly enhances supply chain resilience, even when considering endogeneity. Thus, the study's conclusions remain valid.

Table 8. The endogeneity test results

	(1)	(2)	(3)	(4)
VARIABLES	*ai*	*Recov2*	*ai*	*Recov2*
iv	0.964***		0.277***	
	(15.514)		(5.267)	
Size	0.011***	-0.009***	0.011***	-0.010***
	(11.810)	(-15.356)	(11.505)	(-6.494)
Lev	-0.018***	0.067***	-0.015***	0.068***
	(-5.389)	(25.174)	(-4.684)	(21.269)
ROA	-0.039**	0.272***	-0.031**	0.273***
	(-2.545)	(16.484)	(-1.986)	(15.763)
ROE	0.012*	0.042***	0.010	0.041***
	(1.795)	(5.476)	(1.488)	(5.310)
ATO	0.005***	-0.016***	0.005***	-0.016***
	(3.385)	(-11.560)	(3.189)	(-10.126)
REC	0.016**	-0.012***	0.014*	-0.013***
	(2.098)	(-2.917)	(1.785)	(-2.736)
FIXED	-0.036***	-0.017***	-0.034***	-0.016**
	(-6.459)	(-4.253)	(-5.987)	(-2.316)
Mshare	0.011***	-0.005***	0.010***	-0.005**
	(3.684)	(-2.730)	(3.247)	(-2.181)
Occupy	0.006	-0.030	0.014	-0.030
	(0.372)	(-1.256)	(0.793)	(-1.271)
ai		0.070**		0.098
		(2.341)		(0.721)
Constant	-0.223***	0.512***	-0.219***	0.518***
	(-11.206)	(39.399)	(-10.996)	(17.209)
Observations	26,884	26,884	26,884	26,884
R-squared	0.441	0.394	0.431	0.394
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6.5. Heterogeneity Analysis

Heterogeneity analysis is an empirical method to study result differences across groups or conditions, aiming to reveal hidden complexities and diversities in data. It involves in - depth analysis of differences in data or research subjects, focusing on how individual characteristics or conditions heterogeneously affect the relationship between independent and dependent variables. In this study, we conduct group - wise regression by dividing samples into different groups, performing regression analysis separately, and comparing the regression coefficients of core variables for significant differences.

6.5.1. Enterprise Nature.

Enterprise nature refers to the basic attributes of an enterprise in terms of law, economy, organization, etc., reflecting the ownership structure, business objectives, management models, and other characteristics of an enterprise. In China, enterprises are basically divided into two categories: state-owned enterprises and private enterprises. State-owned enterprises are those in which the state owns all or most of the equity, are usually directly managed by the government or supervised through state-owned assets management departments, and cover key areas such as energy, transportation, finance, and communications, undertaking major national economic tasks and social responsibilities.

Private enterprises, on the other hand, are owned by individuals or private enterprises, aim to maximize profits, and operate independently, widely distributed in manufacturing, services, technology, trade, and other fields. State-owned enterprises have significant advantages over private enterprises in terms of resources and policy support: they can obtain government resources and policy support, and have lower financing costs. Guo Yingjiang (2021) [30] believes that state-owned enterprises have natural systemic advantages compared to private enterprises, and that state-owned enterprises and local financing platforms have implicit guarantees and credit endorsements from local governments, with their financing thresholds becoming increasingly lower. Shu Changjiang et al. (2020) [31] believe that many small and medium-sized non-state-owned enterprises with strong profitability face difficulties in financing, and that the high leverage of large state-owned enterprises, which does not generate corresponding cash flow, exacerbates the financing difficulties of small and medium-sized private enterprises, thus creating a "crowding-out effect" on them. If artificial intelligence has a positive impact on financing efficiency, which in turn affects supply chain resilience, then we should expect this result to be more pronounced in state-owned enterprises, as they have lower financing costs and a greater propensity to finance.

Therefore, this paper divides the sample into two groups according to enterprise nature, with private enterprises coded as 0 and state-owned enterprises as 1. Then the benchmark regression is carried out, and the results are shown in the following table: column (1) is for private enterprises and column (2) for state-owned enterprises. Both column (1) and column (2) show positive significance at the 1% level, and the regression coefficient in column (2) is significantly larger than that in column (1). The positive impact of AI on supply chain resilience is greater in SOEs, likely due to their resource and policy advantages in utilizing AI technology to enhance supply chain resilience. Thus, it can be concluded that AI has a greater positive impact on supply chain resilience in SOEs, confirming the hypothesis.

Table 9. Analysis of the heterogeneity between state-owned enterprises and private enterprises

	(1)	(2)
VARIABLES	*Recov2*	*Recov2*
ai	0.074***	0.094***
	(4.374)	(11.433)
Size	-0.008***	-0.011***
	(-7.295)	(-19.300)
Lev	0.066***	0.067***
	(11.168)	(25.191)
ROA	0.330***	0.264***
	(9.217)	(13.594)
ROE	0.031**	0.043***
	(2.295)	(4.587)
ATO	-0.015***	-0.016***
	(-7.053)	(-10.327)
REC	-0.018**	-0.012***
	(-2.030)	(-2.775)
FIXED	-0.014*	-0.016***
	(-1.775)	(-4.952)
Mshare	0.012	-0.005***
	(0.805)	(-2.946)
Occupy	-0.110**	0.016
	(-2.384)	(0.621)
Constant	0.474***	0.539***
	(21.569)	(42.473)
Observations	8,370	18,514
R-squared	0.417	0.417
Industry FE	YES	YES
Year FE	YES	YES

Robust t-statistics in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

6.5.2. Audit Quality.

When exploring the impact of AI on supply chain resilience (SCR) across enterprises, we focus on audit quality besides enterprise nature. Enterprise nature determines market position and resource access, while audit quality shows internal management and risk control. High-quality auditing can spot potential risks, allocate audit resources to high-risk areas, and enhance risk management. It also creates value by detecting issues and suggesting improvements, optimizing resource allocation, boosting investment efficiency, reducing agency costs, and resolving conflicts between management and shareholders. Moreover, it strengthens risk resistance by identifying risks and enhancing management. The higher the audit quality, the more efficient the resource allocation and the stronger the risk resistance. Zhang Wei (2025) [32] indicates auditing offers reliable decision-making basis for risk response strategies, aiding SCR recovery post - disruption. Wang Wensheng (2024) [33] states auditing supervises and assesses public resource use, preventing waste and misuse, and promoting rational fund use. If AI improves resource allocation efficiency and affects SCR, its impact should be more evident in enterprises with high audit quality due to their superior resource allocation and risk resistance.

To analyze audit quality's heterogeneous impact on AI's effect in enhancing SCR, this paper measures audit quality by whether an enterprise hires a Big Four auditor, dividing samples into two groups: those that do (coded 1) and those that don't (coded 0). The benchmark regression results are shown in the table below, with column (1) for Big Four - audited enterprises and column (2) for others. Both columns show positive significance at the 1% level, but with significant differences in significance levels. The greater the difference between the mean of column (2) and the overall mean, the higher the likelihood of rejecting the null hypothesis, confirming the hypothesis.

Table 10. Analysis of the heterogeneity in audit quality

	(1)	(2)
VARIABLES	*Recov2*	*Recov2*
ai	0.092***	0.090***
	(3.419)	(11.090)
Size	-0.009***	-0.010***
	(-5.489)	(-16.462)
Lev	0.036**	0.068***
	(1.993)	(25.698)
ROA	0.291***	0.270***
	(3.585)	(16.332)
ROE	0.076**	0.041***
	(2.042)	(5.305)
ATO	-0.029***	-0.016***
	(-4.564)	(-11.045)
REC	-0.019	-0.012***
	(-0.772)	(-2.750)
FIXED	-0.047***	-0.015***
	(-2.895)	(-3.803)
Mshare	-0.024*	-0.004**
	(-1.966)	(-2.575)
Occupy	-0.032	-0.030
	(-0.257)	(-1.265)
Constant	0.568***	0.514***
	(14.347)	(40.753)
Observations	1,517	25,367
R-squared	0.484	0.403
Industry FE	YES	YES
Year FE	YES	YES

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

6.5.3. Regional Differences.

There are significant differences in economic development, technological innovation, and infrastructure construction across regions. Developed regions usually have stronger economic foundations and better infrastructure, enabling them to better cope with supply chain disruptions. Policy support, market openness, and administrative efficiency vary by region, as does technological innovation, all of which impact supply chain stability and recovery capacity. For instance, the establishment of free trade pilot zones can enhance industrial chain resilience through institutional innovation and policy support. Yang Lv (2025) [34] et al. found that the development of new - quality productive forces in city clusters such as the Pearl River Delta, Beijing-Tianjin-Hebei, Yangtze River Delta, and Shandong Peninsula maintains a national leading position; Cheng Yufeng (2024) [35] indicated that the technological innovation development level of universities in the eastern region is the highest, with a pronounced "east - medium - west" stepped distribution. Thus, the productivity and technological innovation development level is highest in the eastern region, followed by the central region, and lowest in the western region. If AI can drive technological progress and impact supply chain resilience, its effect is expected to be most evident in eastern region enterprises, less so in the central region, and least in the western region, as emerging technologies like AI are applied more widely in production, exerting a greater impact on supply chain resilience.

According to geographical divisions, enterprises in different provinces are categorized into eastern, central, and western regions. This paper conducts group - based regression analysis by region, with results shown in the table below. Column (1) presents regression results for eastern region enterprises, column (2) for the central region, and column (3) for the western region. The table shows that the regression coefficients for all three groups are positive and significant, with the largest coefficient for the eastern region, followed by the central region, and the smallest for the western region, confirming the hypothesis.

Table 11. Analysis of regional heterogeneity in the eastern, central and western regions

	(1)	(2)	(3)
VARIABLES	*Recov2*	*Recov2*	*Recov2*
ai	0.091***	0.084***	0.074**
	(10.320)	(4.029)	(2.567)
Size	-0.010***	-0.011***	-0.007***
	(-16.144)	(-11.673)	(-5.033)
Lev	0.067***	0.071***	0.064***
	(21.842)	(13.040)	(8.231)
ROA	0.261***	0.226***	0.406***
	(13.761)	(7.059)	(7.186)
ROE	0.048***	0.037**	0.013
	(5.435)	(2.340)	(0.551)
ATO	-0.016***	-0.013***	-0.025***
	(-9.056)	(-4.822)	(-6.117)
REC	-0.014***	-0.017	0.004
	(-2.840)	(-1.493)	(0.302)
FIXED	-0.015***	-0.018***	-0.019
	(-3.298)	(-2.971)	(-1.439)
Mshare	-0.005**	-0.002	-0.016**
	(-2.502)	(-0.563)	(-2.486)
Occupy	-0.039	-0.015	0.022
	(-1.198)	(-0.458)	(0.490)
Constant	0.521***	0.554***	0.467***
	(34.812)	(27.851)	(16.332)
Observations	19,251	4,432	3,201
R-squared	0.418	0.398	0.451
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Region	East	Center	West

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

7. Mechanism Analysis

AI significantly enhances R & D innovation, resource allocation efficiency, and financing speed, positively impacting supply chain resilience. Increased R & D innovation leads to new technologies, adding nodes and complexity to the supply chain, thus enhancing resilience structurally. AI optimizes resource allocation through data analysis and IoT, improving crisis response and decision-making flexibility, which enhances resilience process-wise. Moreover, AI assesses financing risks via machine learning, reduces information asymmetry, and boosts financing speed, enabling quicker recovery post - disruption and minimizing customer losses, thereby strengthening resilience in terms of results. AI plays a crucial role in all these aspects. Research on the mechanism of AI's impact on supply chain resilience through these three intermediate variables is essential. As Tang Longji and Pan Yonggang pointed out in "Digital Supply Chain: Transformation and Upgrading Route and Value Reconstruction Practice", the application of AI in supply chains can significantly enhance supply chain intelligence and resource allocation efficiency, strongly supporting supply chain transformation [36]. Additionally, Miguel Cossio and Kevin Lawrence mentioned in "The Future of Supply Chain Risk Management" that AI technology can effectively improve supply chain crisis response and recovery capabilities, enhancing resilience [37].

The first is the mechanism test based on AI and R & D innovation. The specific model is as follows:

$$patent_{i,t} = \alpha + \beta ai_{i,t} + \gamma' Control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \tag{4}$$

In the above model, patenti,t is the intermediate mechanism variable R & D innovation, measured by the number of independent utility model applications in the current year. Other variables are consistent with those in the previous model. The theoretical analysis shows that AI promotes R & D innovation, which is crucial for enhancing supply chain resilience. The regression results in column (1) of the table show that AI has a significantly positive effect on R & D innovation, indicating that AI boosts R & D innovation levels and, in turn, supply chain resilience.

Table 12. Mechanistic testing

	(1)	(2)	(3)
VARIABLES	*patent*	*Overinvest*	*Mfee*
ai	525.430***	-0.076*	0.097***
	(3.119)	(-1.761)	(6.545)
Size	33.832***	0.025***	-0.014***
	(8.579)	(9.275)	(-17.524)
Lev	-17.499	0.062***	-0.032***
	(-1.493)	(3.404)	(-5.882)
ROA	-119.680**	-0.065	-0.161***
	(-2.479)	(-1.381)	(-7.239)
ROE	64.934**	0.150***	-0.014
	(2.538)	(4.775)	(-1.461)
ATO	20.787***	-0.007	-0.056***
	(3.427)	(-1.206)	(-26.836)
REC	-65.337**	-0.032	-0.066***
	(-1.995)	(-1.224)	(-8.317)
FIXED	-16.326	0.606***	-0.015**
	(-1.317)	(23.139)	(-2.186)
Mshare	-7.573	0.011	-0.012***
	(-1.216)	(1.507)	(-3.338)
Occupy	114.198	0.012	0.119***
	(0.816)	(0.252)	(3.733)
Constant	-733.884***	-0.638***	0.482***
	(-8.676)	(-8.939)	(20.327)
Observations	26,884	24,633	26,884
R-squared	0.188	0.051	0.439
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Second, we test the mechanism linking AI to resource allocation efficiency. AI also enhances supply chain resilience by optimizing resource allocation. While we previously discussed how AI strengthens supply chain structural resilience through innovation, we now focus on its process - based impact. AI boosts resource allocation efficiency via real - time monitoring and dynamic adjustment. Using IoT and sensor technology, AI tracks and adjusts resource use in real time, improving efficiency and supply chain resilience. This study adopts Richardson's (2006) method, first estimating firms' optimal annual investment and then calculating over - investment to measure investment efficiency.

$$\begin{aligned} Invest_{nit} &= \beta_0 Growth_{nit-1} + \beta_2 Lev_{nit-1} + \beta_3 Roa_{nit-1} + \beta_4 Age_{nit-1} + \beta_5 Size_{nit-1} \\ &+ \beta_6 Invest_{nit-1} + \sum Indu + \sum Year + \varepsilon_{nit} \end{aligned} \tag{5}$$

Among them, fixed asset investment $Invest_{nit}$ is measured as the ratio of the original value of fixed assets to the total assets at the beginning of the period; $Growth_{nit-1}$ represents the growth rate of enterprise operating revenue; The asset-liability ratio Lev_{nit-1} is calculated as total liabilities divided by total assets; Roa_{nit-1} denotes return on total assets; Age_{nit-1} indicates firm age; $Size_{nit-1}$ measures firm size using the natural logarithm of total assets; $Invest_{nit-1}$ represents the prior-year fixed asset investment, calculated using the same method. Indu and Year denote industry and year dummy variables, respectively. When the residual from Equation (5) is greater than 0, $Overinvest_{nit}$takes the same value as the residual, measuring the degree of corporate overinvestment. If the residual is less than 0, indicating underinvestment, $Overinvest_{nit}$ is set to 0 [38]. The model shows a larger variable means lower resource allocation efficiency. Based on this, the specific regression model is as follows:

$$Overinvest_{i,t} = \alpha + \beta ai_{i,t} + \gamma' Control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \tag{6}$$

In the above model, $Overinvest_{i,t}$ is the intermediate mechanism variable resource allocation efficiency, measured by $Overinvest_{nit}$, with other variables consistent with previous definitions. Regression results in column (2) of the table show that the coefficient of AI on Overinvestnit is significantly negative at the 10% level. This indicates a substantial negative impact of AI on over - investment, implying a significant positive impact on resource allocation efficiency and, in turn, enhanced supply chain resilience.

Third, we test the mechanism linking AI to financing efficiency. AI assesses corporate credit risk via machine learning algorithms analyzing financial statements, operating data, and credit records. This automated approval method shortens financing cycles and boosts efficiency, enhancing supply chain resilience [39]. Citing Li Zhonghao (2023), executive pay positively impacts investment efficiency by reducing inefficiency [40]. We use the management expense ratio (management expenses/main business revenue × 100%) to measure financing speed. The regression model is as follows:

$$Mfee_{i,t} = \alpha + \beta ai_{i,t} + \gamma' Control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \tag{7}$$

In the above model, $Mfee_{i,t}$ is the intermediate mechanism variable financing speed, measured by the management expense ratio, with other variables as previously defined. As shown in column (3) of the table, the regression coefficient is significantly positive at the 1% level. This indicates that AI positively impacts financing speed, thereby enhancing supply chain resilience.

8. Conclusions and Recommendations

8.1. Research Conclusions

This study explores how AI affects supply chain resilience (SCR) through theoretical and empirical analyses. Results show that AI significantly enhances SCR. After controlling for firm size, debt - to - asset ratio, and profitability, the positive effect of AI remains robust. AI's regression coefficient is significantly positive at the 1% level, indicating its effectiveness in boosting supply chain recovery and risk - resistance capabilities.

Further analysis reveals that AI enhances SCR through three key mechanisms. First, it boosts firms' R & D innovation, strengthening supply chain structural resilience through technological progress and network optimization. Second, by monitoring resource use and adjusting allocations in real - time, AI reduces over - investment and improves resource allocation efficiency, enhancing SCR from a process - based perspective. Third, AI optimizes credit risk assessment, improves financing efficiency, and strengthens supply chain recovery post - disruption, enhancing SCR from a result - based perspective.

The study also conducts robustness tests and addresses endogeneity issues, confirming the stability of the results. Heterogeneous impact analyses show that AI's impact on SCR varies significantly by enterprise nature, audit quality, and region. Specifically, the positive impact of AI is more pronounced in state - owned enterprises, firms with higher audit quality, and eastern - region enterprises, due to their respective advantages in resource access, policy support, audit - aided resource allocation, risk management, and regional development levels.

8.2. Policy Recommendations

ased on the findings, the following policy recommendations are proposed to promote the application of AI in enhancing SCR and driving high - quality supply chain development.

First, increase investment in AI technology. Firms should actively adopt AI to optimize supply chain management, using machine learning, deep learning, and big data analysis to improve demand forecasting and risk assessment.

Second, accelerate digital transformation. Firms should leverage AI for R & D innovation, boosting supply chain intelligence through cooperation with universities and research institutes.

Third, optimize resource allocation. AI can help firms improve resource utilization efficiency via real - time monitoring and dynamic adjustment, reducing over - investment and waste.

Fourth, enhance financing efficiency. AI can optimize financing processes by analyzing financial data and credit records, lowering costs, and improving post - disruption recovery capabilities.

Fifth, state - owned enterprises should leverage their resource and policy advantages to increase AI investment and collaborate with academic and research institutions. Firms with high audit quality should integrate AI with high - quality auditing to strengthen supply chain risk management.

Research Prospects: Future research should expand the sample scope, analyze industry differences, and incorporate case studies to better understand AI's role in enhancing SCR. Current research uses data from A - share listed companies. Future work could include global firms and non - listed companies, especially SMEs, to explore AI's impact in diverse economic and policy contexts.

In summary, as AI technology advances, its role in enhancing SCR will become more significant. Firms should embrace AI to optimize supply chain management and build resilience against market uncertainties.

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