Research on the Impact of Artificial Intelligence Applications on Corporate Supply Chain Resilience: Based on the Paths of Resilience Formation

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Abstract. Based on data from A-share listed firms in Sichuan Province (2015–2025), this study constructs a supply chain resilience index covering resistance, recovery, and development capabilities. Empirical results show that AI application significantly enhances enterprise supply chain resilience, with robustness confirmed through various tests and instrumental variable methods. Mechanism analysis reveals three mediating paths: internal resource integration, external resource integration, and market competitiveness. Heterogeneity analysis indicates that the positive effect of AI is stronger in non-state-owned enterprises, technology-intensive firms, and those with higher digital transformation levels. These findings provide strategic insights for building secure and stable supply chains under overlapping risks and offer policy implications for differentiated industrial policies and the development of digital-intelligent supply chains.

Keywords: Artificial Intelligence; Supply Chain Resilience; Resource Integration Capability; Market Competitiveness; Digital Transformation

1 Introduction

Currently, the global industrial and supply chain landscape is undergoing profound reshaping, posing severe challenges to the stability of corporate supply chains. Simultaneously, artificial intelligence (AI), with its adaptive learning, pattern recognition, and intelligent decision-making capabilities, is profoundly reshaping corporate production methods and management logic, demonstrating immense potential in risk monitoring, intelligent scheduling, logistics optimization, and collaborative innovation. How to systematically utilize AI to enhance the supply chain's capabilities in pre-emptive defense, in-process response, and post-event development has become crucial for corporate survival and national security.

Based on the resource-based view and dynamic capability theory, enterprises can enhance information processing efficiency and decision-making quality, as well as strengthen supply chain resilience, by integrating internal and external resources through digital technology.

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2 Literature Review

The emergence and evolution of Artificial Intelligence (AI) stand as one of the greatest scientific achievements of the 20th century and one of the leading disciplines that will shape future development in the new century. Research outcomes in AI-related fields have been extensively applied across various domains, including national life, industrial production, and national defense construction. In the modern business environment, enterprises utilize AI as an empowering partner to achieve a leap in productivity[2][3].

Supply chain resilience primarily refers to the ability of a supply chain to recover to a normal state or even achieve a more optimal state after being impacted by market risks[4][5]. Corporate supply chain resilience is a microcosmic manifestation of supply chain resilience. Supply chain resilience manifests as the buffering capacity of the supply chain system when subjected to shocks and its recovery ability to return to an equilibrium state[6].

The application of AI plays a pivotal role in shaping supply chain resilience[7]. On the one hand, AI enhances the transparency and risk controllability of supply chain operations. On the other hand, AI's descriptive and predictive digital analysis capabilities assist enterprises in perceiving and predicting various potential risks within the supply chain, facilitating effective risk prevention measures and thereby strengthening supply chain resilience[8]. Modgil et al. explored the application of artificial intelligence in supply chain management, particularly in addressing supply chain resilience in response to extreme events, through qualitative research methods and semi-structured interviews[9].

At the micro-level of enterprises, the impact of AI exhibits significant situational dependence and heterogeneity[10][11]. The application of AI in enterprises can enhance the stability of supply chain relationships, with the mechanism lying in improving market matching, risk management, and integration coordination[9][12]. At the same time, AI reduces the risk of supply chain disruptions by lowering agency costs and enhancing the level of intelligent business[13]. The application of AI in core enterprises has a significant bilateral spillover effect, which can enhance the resilience of upstream and downstream partners and even the entire supply chain network through the diffusion of knowledge, technology, and management practices[14][15]. This spillover effect is more pronounced in chains with moderate technological gaps and strong knowledge absorption capabilities, and it has a more significant promoting effect on high-tech enterprises, large-scale enterprises, specialized, refined, unique, and innovative enterprises, high-talent-density enterprises, and private enterprises[16].

3 Theoretical Analysis and Research Hypothesis

3.1 Analysis of the Impact of the Degree of Artificial Intelligence Application on Supply Chain Resilience

The process of shaping supply chain resilience emphasizes capacity building at three levels: the pre-emptive defense capability to address potential crises, the rapid response capability in the event of a chain disruption, and the transformation and development capability after crisis management, namely resistance, recovery, and adaptation or growth[17]. Among them, resistance refers to the ability of the supply chain to maintain basic functions during an impact; recovery refers to the ability to quickly return to normal operating conditions after a disruption; and adaptation or growth emphasizes the evolutionary capability to achieve capability leapfrogging or even surpassing the original level through learning and reconstruction after experiencing an impact.

In terms of resilience, AI, through technologies such as natural language processing and machine learning, can capture and analyze heterogeneous information from multiple sources in real time, including news sentiment, meteorological data, geopolitical dynamics, and supplier financial status, to build an early risk warning system[1]. Secondly, in terms of recovery, when emergencies occur, traditional supply chains often rely on human experience for emergency decision-making, which leads to delayed responses and inefficiencies[18]. Finally, in terms of growth, AI is not only used to solve existing problems but also to mine hidden patterns through deep learning, assisting enterprises in developing alternative raw materials, designing modular product architectures, and constructing decentralized supply networks[19]. Based on the above analysis, this paper proposes the following hypothesis:

H1: The application of artificial intelligence has a significant positive impact on the resistance, resilience, and development of enterprise supply chain resilience.

AI does not directly act on resilience itself, but indirectly achieves this goal by reshaping the core capability system of enterprises. Specifically, AI empowers enterprises' internal resource integration capabilities, external resource integration capabilities, and market competitiveness, thereby driving the comprehensive improvement of supply chain resilience[20][21].

H2: Artificial intelligence applications enhance the resilience of enterprise supply chains by strengthening the ability to integrate internal resources.

H3: Artificial intelligence applications enhance the resilience of enterprise supply chains by strengthening the ability to integrate external resources.

H4: Artificial intelligence applications enhance the resilience of enterprise supply chains by strengthening market competitiveness.

4 Research Design

4.1 Model Specification

The shaping process of supply chain resilience emphasizes capacity building at three levels: the pre-emptive defense capability to address potential crises, the rapid response capability in case of chain disruptions, and the transformative development capability post-crisis management[1]. To accurately identify the causal effect of artificial intelligence (AI) on corporate supply chain resilience and control for unobservable individual heterogeneity and time trends, this paper constructs a two-way fixed effects panel data model as the benchmark regression model. The specific setup is as follows:

$$Resili_i t = \alpha 0 + \alpha 1 \times AI_i t + \Sigma(\beta k \times Control_k, it) + \delta_i + \theta_t + \varepsilon_i t \quad (1)$$

$Resili_i t$ is the dependent variable, representing the comprehensive index of supply chain resilience of the enterprise in year it; $AI_i t$ is the core explanatory variable, indicating the degree of artificial intelligence application by the enterprise in year $Control_k,it$ presents the control variable i; δ_i is the firm fixed effect, used to control for individual characteristics that do not change over time; θ_t is the year fixed effect, used to control for common time trends; and $\varepsilon_i t$ is the random disturbance term.

4.2 Variable Definition and Measurement

Dependent Variable: Enterprise Supply Chain Resilience (Resili). Drawing on the research approaches of Song Hua et al. (2024)[17], Tao Feng et al. (2023)[6], Wang Yuhao (2024)[22], Ge Xinting (2024)[18], and Wei Long (2025)[23], this study constructs an enterprise supply chain resilience index system from three dimensions: supply chain resistance, recovery, and development capabilities. The entropy weight method is employed to weight the indicators for comprehensive evaluation. For details, please refer to Table 1.

Table 1. Measurement of supply chain resilience variables

first-level dimension	secondary indicator	measurement method	indicator attribute
Resistance Capacity (ResisCap)	Accounts receivable ratio	ln(Accounts receivable / Main business income)	-
	Relationship stability	The number of non-newly emerging suppliers/customers among the top five suppliers/customers / 5	+
Restoration Capacity (RecovCap)	Bullwhip Effect	Var(Production) / Var(Demand) Where is the production volume, Productionand is the demand volume	-
	inventory turnover ratio	Cost of goods sold / Average inventory balance	+
	Cash profit ratio	Net cash flow from operating activities / Total profit	+
	Sedimentary redundant resources	Management expenses / Operating income	-
	Return on net assets	Net profit / Average balance of shareholders' equity	+
Growth Capability (GrowthCap)	Number of patent applications	ln(1 + number of invention patent applications)	+
	Breadth of patent knowledge	1 - Σ[(N_imt / N_it)²] N_imtThe value represents the number of invention patent applications filed by a companyi under the technology classification as of year X, out of the total number of applications. N itThe closer this value is to 1, the more diversified the knowledge portfolio is.	+

All indicators are standardized using range normalization, and negative indicators are inverted. The entropy weight method is employed to calculate the weights of each indicator, and then ResisCap, RecovCap, and GrowthCap are synthesized separately. Subsequently, the entropy weight method is used again to synthesize the overall resilience index, Resili.

Core Explanatory Variable: Degree of Artificial Intelligence Application (AI). Due to the strong permeability and dependency inherent in the application level of artificial intelligence, it is difficult to be measured and calculated separately. By utilizing machine learning methods to generate an artificial intelligence dictionary and conducting in-depth mining of annual reports and patents of listed companies, indicators are constructed by capturing relevant feature words related to artificial intelligence. The selection of the feature word library is basically consistent with the results of Yao Jiaquan[25]. Given the typical "right-skewed" characteristics of such data, the feature word frequency is increased by 1 and then taken to the natural logarithm, resulting in the enterprise's artificial intelligence application level (AI).

Control Variable. The following control variables are selected in this paper:

Cash flow level (Cash): Net cash flow from operating activities / Total assets.

Customer concentration (Cc): The proportion of sales from the top five customers.

Supplier concentration (Sc): The proportion of procurement from the top five suppliers.

Board size: The natural logarithm of the number of board members.

Enterprise size (Size): The natural logarithm of total assets.

Asset-liability ratio (Lev): Total liabilities / Total assets.

Industrial structure (Str): The ratio of the added value of the tertiary industry to the added value of the secondary industry in the province.

Regional economic development level (GDP): The logarithm of the per capita GDP of the province in question.

Age: The natural logarithm of the number of years since establishment.

4.3 Data Sources and Descriptive Statistics

The financial-related data used in this paper are sourced from the CSMAR database and Wind database. Patent data are derived from public announcements by the China National Intellectual Property Administration (CNIPA). The original data on artificial intelligence-related word frequency are obtained from the annual reports of listed companies. Regional macroeconomic data are sourced from the China Statistical Yearbook and statistical bulletins of various provinces. Additionally, the following processing was applied to the original dataset in this paper: 1. Excluding companies in the finance and insurance industries; 2. Excluding companies in ST and *ST status; 3. Excluding observations with missing key variables; 4. To eliminate the impact of extreme values, all continuous variables were subjected to winsorization at the upper and lower 1% levels.

Table 2 The main descriptive statistical results are presented.Some leading enterprises have already achieved a high level of application. The adoption of digital technology among enterprises exhibits distinct differentiation characteristics.

Table 2. Descriptive Statistics

	N	Mean	SD	Min	p25	Median	p75	Max
Resili	28849	11.596	7.797	0.623	3.983	11.14	18.553	26.211
AI	28849	0.831	1.15	0	0	0	1.386	4.787
Cash	28849	0.051	0.065	-0.169	0.012	0.048	0.088	0.302
Cc	28849	32.512	21.815	1.61	15.37	27.12	45.49	96.53
Sc	28849	33.554	18.767	2.32	19.44	29.34	43.92	94.22
Boardsize	28849	2.109	0.195	1.609	1.946	2.197	2.197	2.708
Size	28849	22.264	1.261	19.688	21.353	22.055	22.96	26.465
Lev	28849	0.41	0.195	0.031	0.254	0.403	0.554	0.886
Str	28849	1.581	1.057	0.5	1.096	1.27	1.4	5.69
GDP	28849	11.331	0.466	9.085	11.04	11.379	11.666	12.207
Age	28849	2.082	0.84	0	1.386	2.197	2.773	3.434

5 Empirical Result Analysis

5.1 Benchmark Regression

Using model (1) regression, Table 3 the benchmark regression estimation results of the impact of artificial intelligence (AI) on enterprise supply chain resilience are presented. Column (1) only includes the core explanatory variable AI without any control variables; column (2) adds all control variables to column (1); columns (3) to (5) regress with the three sub-dimensions of supply chain resilience - ResisCap (resistance capability), RecovCap (recovery capability), and GrowthCap (growth capability) - as the dependent variables, respectively. All regressions control for firm-specific fixed effects and year fixed effects.

The benchmark regression results are largely consistent with the conclusions of theoretical analysis, confirming Hypothesis H1 (that the application of artificial intelligence has a significant positive impact on the resilience of corporate supply chains).

Table 3. Regression Analysis

variable	(1)	(2)	(3)	(4)	(5)
	Resili	Resili	ResisCap	RecovCap	GrowthCap
AI	0.326^{***}	0.238^{***}	0.219^{***}	0.000	0.017
	(4.560)	(3.405)	(3.230)	(0.682)	(0.825)
Cash		2.183^{***}	0.419	1.650^{***}	0.146

		(3.402)	(0.677)	(274.921)	(0.826)
Cc		0.003	0.004	0.000***	-0.001
		(0.650)	(0.978)	(2.864)	(-1.007)
Sc		0.002	0.003	0.000***	-0.001
		(0.573)	(0.849)	(2.996)	(-0.926)
Boardsize		0.011	0.159	-0.001	-0.174
		(0.027)	(0.408)	(-0.417)	(-1.388)
Size		0.169	0.020	0.017***	0.138***
		(1.186)	(0.146)	(16.344)	(3.003)
Lev		0.664	0.718	-0.077***	0.022
		(1.308)	(1.477)	(-16.227)	(0.162)
Str		-0.516**	-0.496**	-0.002	-0.023
		(-2.335)	(-2.439)	(-1.313)	(-0.338)
GDP		0.128	0.260	-0.001	-0.143
		(0.223)	(0.490)	(-0.134)	(-0.738)
Age		2.323***	2.484***	0.019***	-0.182***
		(11.915)	(13.212)	(8.040)	(-3.222)
_cons	11.324***	1.586	-0.830	0.449***	2.031
	(190.449)	(0.221)	(-0.124)	(8.643)	(0.843)
id	YES	YES	YES	YES	YES
year	YES	YES	YES	YES	YES
N	28,849	28,849	28,849	28,849	28,849
r2	0.654	0.659	0.641	0.918	0.749

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2 Robustness Test

To ensure the reliability of the benchmark regression results, this paper conducted various forms of robustness checks and Table 4 presented the corresponding estimation results.

After a series of robustness tests, including the exclusion of special samples, the replacement of variable measures, and the addition of higher-dimensional fixed effects, the positive promoting effect of artificial intelligence applications on supply chain resilience remains significantly valid, indicating that the core conclusions of this paper exhibit good robustness.

Table 4. Robustness Test

variable	(1)	(2)	(3)	(4)	(5)
	Exclude samples	Replace AI	Replace Resili	Increase industry fixation	Increase urban fixation
	Resili	Resili	Resili_1	Resili	Resili
AI_1		1.448***			
		(17.119)			
AI	0.252***		0.534***	0.241***	0.231***
	(3.380)		(3.244)	(3.417)	(3.224)
Cash	2.223***	2.009***	25.697***	2.284***	2.259***
	(3.229)	(3.161)	(17.085)	(3.570)	(3.502)
Cc	0.004	0.003	0.013	0.004	0.003
	(0.808)	(0.714)	(1.145)	(0.808)	(0.543)
Sc	0.003	0.002	0.011	0.002	0.003
	(0.573)	(0.509)	(1.145)	(0.495)	(0.623)
Boardsize	0.085	0.125	0.236	0.034	0.065
	(0.203)	(0.315)	(0.251)	(0.084)	(0.161)
Size	0.175	0.099	0.750**	0.213	0.246
	(1.211)	(0.712)	(2.272)	(1.477)	(1.641)
Lev	0.645	0.616	0.232	0.564	0.608
	(1.220)	(1.234)	(0.194)	(1.126)	(1.205)
Str	-0.502**	-0.564***	-1.152**	-0.479**	-0.325
	(-2.218)	(-2.652)	(-2.285)	(-2.171)	(-1.224)
GDP	0.045	0.196	0.414	0.046	0.371
	(0.077)	(0.352)	(0.317)	(0.080)	(0.548)
Age	2.268***	2.422***	6.817***	2.295***	2.282***
	(11.482)	(12.586)	(14.605)	(11.756)	(11.560)
_cons	2.152	1.549	20.522	1.491	-3.181
	(0.293)	(0.222)	(1.253)	(0.206)	(-0.378)
id	YES	YES	YES	YES	YES
year	YES	YES	YES	YES	YES
Ind	NO	NO	NO	YES	YES
City	NO	NO	NO	NO	YES
N	26,034	28,849	28,849	28,832	28,832
r2	0.655	0.666	0.649	0.661	0.663

t statistics in parentheses

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

5.3 Heterogeneity Analysis

To further explore the differences in the impact of artificial intelligence on the resilience of enterprise supply chains across enterprises with different characteristics, this paper conducts a heterogeneity analysis from three dimensions: ownership nature of the enterprise, technology intensity, and level of digital transformation, Table 5 presenting the corresponding grouped regression results.

Firstly, based on the heterogeneity analysis of the ownership nature of enterprises, there are significant differences in resource acquisition, decision-making mechanisms, and willingness to adopt new technologies among enterprises with different ownership structures, which may lead to heterogeneity in the impact of artificial intelligence (AI) on supply chain resilience.

Secondly, a heterogeneous analysis based on the degree of technology intensity. The degree of technology intensity reflects the dependence of enterprises on technological innovation and the differences in their technological absorption capabilities, which may affect the efficiency of transforming artificial intelligence (AI) technology into supply chain resilience.

Thirdly, an analysis based on the heterogeneity of digital transformation levels. The degree of digital transformation determines a company's ability to utilize data elements and integrate emerging technologies, which may affect the actual effectiveness of artificial intelligence (AI) in enhancing supply chain resilience.

Table 5. Heterogeneity Analysis

variable	(1)	(2)	(3)	(4)	(5)	(6)
	non-state-o	state-ow	Non-technology-int	technolo-	Digitali-	Digitali-
	Resili	Resili	Resili	Resili	Resili	Resili
AI	0.265^{***}	0.035	0.081	0.251^{***}	0.284	0.247^{***}
	(3.167)	(0.276)	(0.778)	(2.631)	(0.875)	(3.245)
Cash	2.059^{***}	2.734^{**}	1.227	3.179^{***}	2.104^{**}	1.254
	(2.635)	(2.487)	(1.414)	(3.339)	(2.008)	(1.512)
Cc	-0.000	0.014	0.005	0.004	-0.001	0.003
	(-0.033)	(1.591)	(0.773)	(0.512)	(-0.147)	(0.518)
Sc	0.001	0.011	0.010^{*}	-0.006	0.010	-0.002
	(0.267)	(1.607)	(1.710)	(-0.902)	(1.522)	(-0.302)
Boards	0.188	-0.544	-0.501	0.127	0.234	-0.132
	(0.374)	(-0.853)	(-0.929)	(0.218)	(0.364)	(-0.258)
Size	0.062	0.411	-0.101	0.335	0.011	0.306
	(0.366)	(1.530)	(-0.516)	(1.486)	(0.048)	(1.510)
Lev	0.377	1.216	0.810	0.098	-0.889	0.887
	(0.625)	(1.271)	(1.112)	(0.134)	(-1.091)	(1.317)
Str	0.300	-1.421^{***}	-0.899^{***}	-0.032	-0.784^{**}	0.167
	(0.967)	(-4.202)	(-2.975)	(-0.103)	(-2.161)	(0.642)

GDP	-0.613	0.201	-0.266	0.669	0.356	-0.201
	(-0.737)	(0.234)	(-0.346)	(0.773)	(0.428)	(-0.246)
Age	2.336***	1.924***	2.150***	2.299***	2.453***	2.067***
	(10.117)	(3.736)	(7.533)	(8.289)	(7.764)	(7.498)
_cons	12.579	-5.497	12.098	-7.156	1.719	2.616
	(1.217)	(-0.496)	(1.240)	(-0.649)	(0.165)	(0.254)
id	YES	YES	YES	YES	YES	YES
year	YES	YES	YES	YES	YES	YES
N	19,949	8900	13,985	14,864	11,178	17,671
r2	0.640	0.695	0.677	0.649	0.669	0.710

t statistics in parentheses

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

6 Mechanism Test

To further reveal the mechanism by which artificial intelligence affects the resilience of enterprise supply chains, this paper conducts mechanism tests from three paths: internal resource integration capability, external resource integration capability, and market competitiveness. Drawing on the mediation effect testing method proposed by Wen Zhonglin et al., a stepwise regression model is constructed[24]. table 6 The corresponding mechanism test results are presented.

Firstly, the mediating role of internal resource integration capability. Internal resource integration capability refers to the ability of enterprises to coordinate and optimize the allocation of internal resources such as production, inventory, logistics, and funds. To verify this mechanism, this paper uses total factor productivity (TFP_LP) as a proxy variable for internal resource integration capability. A higher TFP_LP indicates higher efficiency in internal resource allocation and stronger integration capability. Column (1) reports the regression results of artificial intelligence (AI) on internal resource integration capability. Therefore, internal resource integration capability is an important transmission path for AI to empower supply chain resilience, and hypothesis H2 is preliminarily verified.

Secondly, the mediating role of external resource integration capability. External resource integration capability refers to the ability of enterprises to acquire, coordinate, and utilize resources from external partners such as suppliers, customers, and logistics service providers. To verify this mechanism, this paper uses supply chain collaborative innovation (Collab) as a proxy variable for external resource integration capability. A higher value of this indicator indicates a higher degree of collaboration between enterprises and upstream and downstream partners in the supply chain, as well as a stronger ability to integrate external resources. Column (3) reports the regression results of artificial intelligence (AI) on external resource integration capability. This result indicates that external resource integration capability plays a partial mediating effect between AI and supply chain resilience, that is, AI enhances the external resource integration capability, thereby improving the supply chain resilience of enterprises. Hypothesis H3 is verified.

Thirdly, the mediating role of market competitiveness. Market competitiveness refers to the comprehensive strength of a firm relative to its competitors in terms of product pricing, customer response, and market share acquisition. To verify this mechanism, this paper uses market competitive position (MktComp) as a proxy variable for market competitiveness, where a higher index indicates stronger market power and more prominent competitive ability of the firm. Column (5) reports the regression results of artificial intelligence (AI) on market competitiveness. This result indicates that market competitiveness also plays a partial mediating effect between AI and supply chain resilience, that is, AI enhances supply chain resilience by strengthening market competitiveness, thus verifying hypothesis H4.

Table 6. Mechanism Test

variable	(1)	(2)	(3)	(4)	(5)	(6)
	Internal integration		External integration		market competition	
	TFP_LP	Resili	Collab	Resili	MktComp	Resili
AI	0.014***	0.231***	0.060***	0.211***	0.001***	0.233***
	(2.790)	(3.311)	(12.143)	(3.019)	(2.669)	(3.340)
TFP_LP		0.504***				
		(3.187)				
Collab				0.444***		
				(2.892)		
MktComp						3.773***
						(2.637)
Cash	1.029***	1.664**	-0.075*	2.216***	0.034***	2.054***
	(18.564)	(2.556)	(-1.858)	(3.455)	(6.956)	(3.200)
Cc	0.000	0.003	-0.000	0.003	0.000	0.003
	(0.931)	(0.602)	(-0.595)	(0.670)	(0.932)	(0.623)
Sc	0.002***	0.001	-0.000	0.002	-0.000	0.003
	(5.096)	(0.299)	(-0.721)	(0.595)	(-1.426)	(0.612)
Boardsize	-0.006	0.014	0.103***	-0.035	0.003	0.000
	(-0.196)	(0.034)	(3.732)	(-0.088)	(1.009)	(0.000)
Size	0.594***	-0.131	0.152***	0.101	0.001	0.165
	(44.967)	(-0.768)	(15.548)	(0.698)	(0.685)	(1.165)
Lev	0.163***	0.582	-0.062*	0.691	-0.010***	0.701
	(3.567)	(1.147)	(-1.768)	(1.360)	(-2.673)	(1.380)
Str	-0.030*	-0.501**	-0.003	-0.515**	0.003**	-0.529**
	(-1.925)	(-2.268)	(-0.189)	(-2.344)	(1.998)	(-2.394)
GDP	-0.087**	0.172	0.042	0.110	-0.005	0.148

	(-2.012)	(0.299)	(0.984)	(0.192)	(-1.134)	(0.259)
Age	-0.081***	2.364***	0.009	2.319***	0.005***	2.302***
	(-6.176)	(12.111)	(0.746)	(11.890)	(3.807)	(11.813)
_cons	-3.536***	3.368	-0.341	1.738	0.140**	1.058
	(-6.309)	(0.466)	(-0.664)	(0.243)	(2.242)	(0.148)
id	YES	YES	YES	YES	YES	YES
year	YES	YES	YES	YES	YES	YES
N	28,849	28,849	28,849	28,849	28,849	28,849
r2	0.940	0.660	0.779	0.660	0.784	0.660

t statistics in parentheses

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

7 Conclusions and Prospects

This paper takes A-share listed companies in Sichuan Province from 2015 to 2025 as a sample, constructs an evaluation system for enterprise supply chain resilience from three dimensions: resistance, recovery, and development, and examines the impact and mechanism of artificial intelligence (AI) application. The main conclusions are as follows: First, AI significantly enhances the resilience of enterprise supply chains, but the current effect is mainly concentrated in resistance, with insufficient manifestation in recovery and development capabilities, indicating that deep empowerment requires time accumulation. Second, internal resource integration, external resource integration, and market competitiveness are three transmission paths for AI-empowered resilience, all of which exert partial mediating effects. Third, the enhancement effect of AI is more significant in non-state-owned enterprises, technology-intensive enterprises, and enterprises with a higher degree of digital transformation. Enterprise ownership, technological foundation, and digitalization level are important conditional boundaries.

Based on the aforementioned conclusions, this paper derives the following insights: Firstly, strengthen the strategic layout of AI in enterprises and promote the deep integration of AI and supply chain management. Secondly, we should improve the differentiated policy support system and create a favorable institutional environment. Thirdly, we should emphasize the differentiated effects of policy implementation and adopt categorized strategies.

This paper preliminarily reveals the core effects, mechanisms, and boundary conditions of artificial intelligence (AI) empowering enterprise supply chain resilience, providing theoretical basis and empirical evidence for understanding the profound transformation of supply chain management in the digital era. Future research can further deepen in areas such as refining measurement methods, deeply exploring mechanisms, expanding sample scope, and investigating dynamic effects, in order to more comprehensively reveal the complex relationship between AI and supply chain resilience, and provide more solid academic support for promoting enterprise digital transformation and supply chain resilience construction.

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