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The Impact of Artificial Intelligence on Corporate Resilience: Evidence from A-Share Listed Companies

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Abstract

With the rapid development of artificial intelligence (AI) technology, firms' capacity to adapt to and recover from external shocks has been significantly enhanced. Using data from A-share listed companies, this study examines the impact of AI on corporate resilience through regression analysis, robustness tests, and heterogeneity analysis. The empirical results reveal a U-shaped relationship between AI and corporate resilience. Specifically, in the initial stage, AI may pose adaptive challenges to firms; however, as the technology gradually matures, its positive effect on enhancing corporate resilience becomes increasingly significant. In addition, AI indirectly improves corporate resilience by optimizing the talent chain, innovation chain, and supply chain. Further heterogeneity analysis shows that the resilience-enhancing effects of AI differ significantly across firms with different industry affiliations, regional locations, and ownership structures. This study provides both theoretical support and practical implications for firms seeking to balance the risks and opportunities associated with AI during digital transformation.

Keywords

artificial intelligence, corporate resilience, U-shaped relationship

1. Introduction

In today's highly volatile and unpredictable international environment, firms face severe challenges to their survival and development. Rising de-globalization has intensified competitive pressure, technological change and iteration continue to accelerate, economic cycles fluctuate, and political risks are increasing, all of which make business operations increasingly fraught with challenges. Particularly under the VUCA environment—characterized by volatility, uncertainty, complexity, and ambiguity—the ability of firms to respond to external shocks has become increasingly essential for their development. This capability encompasses not only resistance to crises, but also the comprehensive capacity to rapidly adapt, recover, and sustain innovation after external disturbances. Consequently, in academic research, corporate resilience is often regarded as a core indicator for measuring whether firms can maintain continuous and stable operations in the face of unexpected events, risks, and uncertainty [1].

As a transformative technology, artificial intelligence (AI) has gradually penetrated all aspects of business operations. Xie Kang et al. [2] argue that big data analytics, machine learning, and automation exert significant positive effects on firms' operational efficiency, improving productivity and innovation capability while enhancing firms' adaptability and recovery capacity when confronted with external shocks such as market fluctuations, supply chain disruptions, and technological changes. In particular, in areas such as managerial decision-making, customer service, and product innovation, AI is progressively replacing traditional manual operations and human decision-making, becoming an important lever for enhancing corporate resilience.

However, this does not imply that the impact of AI on corporate resilience is entirely positive. Although AI can effectively improve firms' operational efficiency, its adoption is also accompanied by several potential negative effects. The comprehensive implementation of AI technologies often requires substantial investment, which may impose considerable financial pressure on a large number of small and micro enterprises. Excessive reliance on technology may also increase firms' vulnerability when facing technological failures, cyberattacks, and related risks, particularly in information technology–dependent functions such as supply chain management and customer relationship management. In addition, the rapid development of AI may generate technology adaptation problems, requiring firms' organizational structures and human resource management systems to align with new technologies. This often leads to employee skill transformation and changes in management models, thereby creating adaptive barriers and unemployment risks. Nevertheless, Chen Lin et al. [3] suggest that the employment opportunities created by AI are likely to offset such risks; Xu Mengyao and Xu Hui [4] further find that the synergy between AI applications and human capital can significantly promote industrial structure upgrading, which provides new insights into corporate resilience research from the perspective of labor factor mobility.

Existing literature has largely focused on how AI enhances corporate resilience by improving production efficiency and optimizing managerial decision-making [5-6]. However, as a core organizational capability in the face of internal and external shocks, risks, and uncertainty, the essence of corporate resilience lies in achieving rapid adaptation and recovery to normal operations while maintaining long-term stability and sustainable growth potential [7]. Early studies argue that a certain level of corporate resilience is a necessary condition for firms to maintain normal operations during unexpected events, ensuring resistance and continuity in times of crisis. Subsequent studies have begun to explore the underlying drivers. Yang Tingfang et al. [8] find that multiple factors significantly affect firms' ability to withstand crises, such as digital transformation, ESG (environmental, social, and governance) performance, internal control mechanisms, and government policy support, all of which jointly construct a barrier against external shocks.

Nevertheless, regarding the dual effects of AI on corporate resilience—particularly the differences in its effects across different stages and external environments—there remains a lack of systematic theoretical frameworks and empirical evidence [9]. Existing studies mainly emphasize the enabling effects of AI, while paying relatively less attention to the potential inhibitory effects that AI may exert on corporate resilience during the early stages of adoption [10]. Therefore, an in-depth exploration of the dual impact mechanisms of AI on corporate resilience and the revelation of its influence pathways across different development stages and external environments constitute urgent issues to be addressed in current academic research [11].

This study aims to fill this research gap by constructing a U-shaped nonlinear relationship model between AI and corporate resilience to examine the mechanisms through which AI affects corporate resilience at different stages. Specifically, this paper conducts the analysis from the following aspects. First, it examines the stage-specific dual effects of AI on corporate resilience, revealing the transformation from inhibitory effects in the initial stage to promoting effects in the later stage [12]. Second, it explores the mediating mechanisms through which AI promotes corporate resilience, particularly through the talent chain, innovation chain, and supply chain [13]. Finally, it investigates the moderating roles of factors such as corporate governance structure, industry characteristics, and regional heterogeneity in the relationship between AI and corporate resilience. Through this research, we aim to provide both theoretical support and practical guidance for firms on how to balance the risks and opportunities of AI and maximize its empowering effects during digital transformation, especially when introducing AI technologies.

2. Theoretical Analysis and Research Hypotheses

With the advent of the digital era, artificial intelligence (AI), as a transformative technology, has been widely applied across various business domains. AI not only changes firms' operating models but also redefines corporate resilience. Corporate resilience generally refers to a firm's ability to maintain stable operations when confronted with internal and external shocks and to regain development momentum during crises [14]. Under the VUCA environment—characterized by volatility, uncertainty, complexity, and ambiguity—how firms enhance resilience through technological innovation has become a major research focus in both academia and practice [15-16].

Against this backdrop, it is not difficult to observe that AI serves as a double-edged sword for corporate resilience. On the one hand, AI can enhance firms' adaptability and recovery capability by improving decision-making efficiency, accelerating innovation processes, and optimizing resource allocation. On the other hand, excessive dependence on AI technologies may lead to negative consequences such as innovation inertia, labor market imbalances, and loosened organizational structures, thereby undermining firms' long-term resilience. Therefore, based on the dual effects of AI on corporate resilience, this paper seeks to explore its underlying mechanisms and proposes the corresponding research hypotheses.

2.1 The U-Shaped Relationship Between Artificial Intelligence and Corporate Resilience

Existing studies generally suggest that the impact of artificial intelligence on corporate resilience is nonlinear rather than linear, exhibiting a U-shaped relationship that can be divided into two stages. In the first stage, when AI technologies are initially introduced into production or business applications, firms often need to bear high short-term transformation costs, confront organizational structure adaptation issues, and experience imbalances in labor factor allocation, all of which may lead to a certain decline in corporate resilience. As AI technologies become deeply embedded and more widely adopted, firms are able to improve production efficiency and decision-making quality through technological optimization and managerial innovation, thereby strengthening their capability to cope with risks and gradually enhancing corporate resilience. In this process, how to help the vast majority of firms successfully navigate the first stage remains an important research direction.

According to the existing literature, the initial introduction of AI is often accompanied by substantial investment costs and both internal and external organizational adaptation challenges [17]. At this stage, the application of AI does not immediately generate the expected benefits; instead, it enhances corporate resilience only after firms adjust their strategies, structures, and organizational culture. Therefore, this paper proposes the following hypothesis:

H1: There is a U-shaped relationship between artificial intelligence and corporate resilience (that is, AI exerts an inhibitory effect on corporate resilience in the initial stage, while it promotes corporate resilience in the later stage of development).

2.2 Artificial Intelligence, the Talent Chain, and Corporate Resilience

The talent chain refers to the effective integration of knowledge, skills, and innovation capabilities both within and outside the firm, which directly affects a firm's ability to respond to external risks and adapt to market changes. Amid the widespread wave of AI application, firms improve productivity through AI while simultaneously and invisibly promoting structural changes in the labor market. The application of AI not only increases firms' demand for high-skilled talent, but also indirectly leads to the disappearance of low-skilled positions, thereby affecting the labor structure of the vast majority of firms.

According to Schultz's human capital theory, high levels of education, skills, and health-related human capital can improve productivity and efficiency [18], from which it can be inferred that firms' human resource management and talent structure play a crucial role in enhancing resilience. The introduction of AI requires specialized technical talent to support system development, algorithm optimization, and big data analytics. However, in the initial stage, firms may face adaptation problems in the talent chain, particularly shortages of high-skilled talent and gaps during the technological transition period. Therefore, AI application is likely to exert different effects on the talent chain across different stages. In the short term, AI may improve the quality of the talent chain by forcing firms to attach greater importance to the recruitment and transition of high-skilled talent. In the long run, as the technology matures, firms can achieve more efficient human resource allocation, thereby promoting innovation and enhancing resilience. Therefore, this paper proposes the following hypothesis:

H2: Artificial intelligence affects corporate resilience by influencing the firm's talent chain.

2.3 Artificial Intelligence, the Innovation Chain, and Corporate Resilience

The innovation chain refers to the entire process from basic research to technological development, application, and market promotion, involving firms' innovation capability, resource integration capability, and market adaptability. The application of AI has significantly promoted firms' innovation chains, especially in product research and development and technological applications. Through big data analytics and machine learning capabilities, AI can accelerate R&D cycles, reduce the risks of product development, and improve innovation efficiency [19].

With the support of AI technologies, firms are able to identify market demand and technological trends more rapidly, thereby adjusting the direction of product and service innovation in a timely manner. However, during the initial stage of AI application, due to the relatively low maturity of the technology, firms may rely more on external technology introduction and imitation, which may limit the quality and depth of innovation [20]. The application of AI not only promotes the development of the innovation chain, but also requires firms to make long-term arrangements in technological accumulation and resource allocation to ensure the continuous improvement of innovation capability. Therefore, this paper proposes the following hypothesis:

H3: Artificial intelligence affects corporate resilience by influencing the firm's innovation chain.

2.4 Artificial Intelligence, the Supply Chain, and Corporate Resilience

The supply chain is a core link through which firms acquire resources in market competition. A stable supply chain enables firms to improve market competitiveness while calmly responding to external disturbances. Examining the impact of AI application on corporate supply chains, especially in terms of improving supply chain stability and response speed under shocks, is therefore of great importance. AI's real-time data analytics and forecasting capabilities can help firms respond rapidly to market changes and adjust supply chain strategies in a timely manner, thereby improving supply chain resilience.

Although AI plays a significant role in enhancing supply chain resilience, whether firms' supply chains can effectively adapt to the technology may become a major issue when AI applications are not yet sufficiently mature. Particularly in the early stage of AI adoption, firms may rely more heavily on traditional suppliers and business processes, and the mechanical or experimental introduction of AI may constrain supply chain flexibility and responsiveness [21]. As AI technologies are gradually applied more deeply, however, firms are expected to optimize each stage of the supply chain, improve its diversity and flexibility, and thereby strengthen their ability to respond to external risks and crises. Therefore, this paper proposes the following hypothesis:

H4: Artificial intelligence affects corporate resilience by influencing supply chain diversification.

3. Research Design

3.1 Data Sources

This study selects Chinese A-share listed companies from 2013 to 2023 as the research sample, with data primarily obtained from databases such as Wind and CNRDS. To ensure data reliability, the following data processing procedures were conducted. First, observations from the financial industry (e.g., banking and insurance firms) were excluded. Second, listed companies that were delisted, ST, or *ST during the sample period were removed. Third, samples with missing values—particularly missing financial data and AI application data—were excluded to ensure sample completeness and accuracy. Finally, for the major continuous variables, 1% bilateral winsorization was applied to eliminate the influence of extreme outliers and ensure the robustness of model estimation.

3.2 Variable Definitions

3.2.1 Dependent Variable: Corporate Resilience (Res)

Corporate resilience refers to a firm's ability to maintain stability, recover, and continue innovating when facing external shocks. Based on an in-depth analysis of the theory of corporate resilience, this study reconstructs and develops a more comprehensive corporate resilience indicator system. The system is built upon two core dimensions: Risk Buffer Capacity (RBC) and Innovation Adaptation Capacity (IAC), emphasizing that under the VUCA environment, firms should not only possess the stability required to withstand shocks, but also achieve dynamic evolution through innovation. Each dimension contains specific indicators, calculation methods, and analytical focuses, thereby ensuring both operational feasibility and theoretical rigor.

Table 1: Corporate Resilience Indicator System

Dimension	Indicator	Calculation Method (Formula or Data Source)	Meaning and Analytical Focus
Risk Buffer Capacity (RBC)	Cash Ratio	Cash and cash equivalents / current liabilities	Measures short-term liquidity emergency capacity; a higher value indicates stronger buffering ability
	Working Capital Turnover	Operating revenue / average working capital	Evaluates operating efficiency and resource balance; a moderate value is preferred
	Interest Coverage Ratio	EBIT / interest expense	Reflects tolerance to debt-servicing pressure; a higher value implies lower financial risk
	Redundant Resource Ratio	(Administrative expenses + R&D expenses) / operating revenue	Captures flexible resource reserves; a higher value suggests greater crisis absorption potential
Innovation Adaptation Capacity (IAC)	R&D Intensity	R&D expenditure / operating revenue	Measures the level of innovation resource input and drives long-term adaptability
	New Product Revenue Ratio	New product sales revenue / total revenue	Reflects the efficiency of innovation output transformation; a higher value indicates stronger market responsiveness
	Employee Innovation Training Investment	Employee training expenses / operating revenue	Evaluates organizational learning and human capital upgrading capability

3.2.2 Core Independent Variable: Artificial Intelligence (AI)

This study uses industrial robot penetration as a proxy for the degree of AI application. Specifically, robot penetration is first calculated at the industry level and then decomposed to the firm level. The ratio of the number of industrial robots to the number of employees in the corresponding industry is used to reflect a firm's level of AI application within its industry.

3.2.3 Mediating Variables: Talent Chain, Innovation Chain, and Supply Chain

Drawing on the variable measures of Yang Yang et al. [13] and Xie Weimin et al. [20], this study constructs the following mediating variables according to the research objectives:

Talent Chain (Talents): The talent chain is measured by the ratio of the number of technical employees to non-technical employees. This indicator better captures the structural composition of firms' human capital and the potential of their talent supply chain.

Innovation Chain (Patent): The innovation chain is measured by the natural logarithm of the number of invention patent applications filed by the firm in the current year plus one. The number of invention patent applications is internationally recognized as a core quantitative indicator of corporate innovation output [24], and can objectively and scientifically measure firms' innovation levels.

Supply Chain (Supply): This study uses the ratio of procurement from the top five suppliers to total procurement to measure supply chain concentration and diversification. Inspired by the CR_4 indicator in industrial economics, this measure can intuitively capture the closeness of the relationship between firms and their major cooperating suppliers.

3.2.4 Control Variables

Based on the existing literature and in line with the research objectives of this study, the following control variables are selected: firm size (Size), capital structure (Dlcr), separation of ownership and control (Seperate), book-to-market ratio (BM), audit quality (Big4), regional economic development level (GDP), and regional financial development level (Finance). The detailed definitions are as follows.

Table 2: Description of Control Variables

Variable	Calculation Method (Formula or Data Source)	Meaning and Analytical Focus
Firm Size (Size)	Natural logarithm of total assets	Measures firm size; larger firms generally face lower risks
Firm Size (Dlcr)	Non-current liabilities / (non-current liabilities + shareholders' equity)	Reflects leverage in capital structure; higher leverage may imply higher financial risk
Profitability (Roa)	Net profit / average total assets	Measures asset utilization efficiency; a higher value indicates stronger profitability
Separation of Ownership and Control (Seperate)	Difference between the actual controller's control rights and ownership rights in the listed company	Reflects the separation between shareholders and control rights; a larger gap may cause governance problems
Book-to-Market Ratio (BM)	Shareholders' equity (book value) / total market capitalization	Reflects the ratio of asset value to market value and is commonly used to evaluate stock valuation
Audit Quality (Big4)	Whether audited by a Big Four accounting firm (1 = yes, 0 = no)	Reflects audit quality; Big Four firms usually indicate higher audit quality
Regional Economic Development (GDP)	Natural logarithm of regional GDP per capita	Measures regional economic development; firms in more developed regions generally face lower market risks
Regional Financial Development (Finance)	Outstanding loans of regional financial institutions / regional GDP	Measures regional financial development; a higher level may promote corporate financing and growth

3.3 Econometric Models

To verify the impact of artificial intelligence on corporate resilience and its underlying mechanisms, this study constructs the following econometric models based on the preceding research hypotheses and variable definitions:

3.3.1 Baseline Regression Model

To test Hypothesis H1, this study constructs the following baseline regression model:

$$Res_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 AI_{it}^2 + \sum_{k=1}^{n} \gamma_k X_{it}^k + \mu_i + \lambda_t + \epsilon_{it} \tag{1}$$

where Res_{it} denotes corporate resilience, representing the resilience level of firm i in year *t*; AI_{it} denotes the degree of AI application, reflecting the AI penetration level of firm i in year *t*; AI_{it}^2 is the quadratic term of AI, used to test its U-shaped effect on corporate resilience; X_{it}^k represents the set of control variables, including firm size, capital structure, profitability, and other covariates; μ_i and λ_t denote firm fixed effects and year fixed effects, respectively, controlling for heterogeneity across firms and over time; and ϵ_{it} is the random error term.

3.3.2 Mediation Effect Models

To examine whether AI affects corporate resilience through mechanisms such as the talent chain, innovation chain, and supply chain, this study adopts the mediation effect testing framework proposed by Baron and Kenny (1986).

First, the effects of AI on the mediating variables are estimated as follows:

$$Talents_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 AI_{it}^2 + \sum_{k=1}^{n} \gamma_k X_{it}^k + \mu_i + \lambda_t + \epsilon_{it} \tag{2}$$

$$Patent_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 AI_{it}^2 + \sum_{k=1}^{n} \gamma_k X_{it}^k + \mu_i + \lambda_t + \epsilon_{it} \quad (3)$$

$$Supply_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 AI_{it}^2 + \sum_{k=1}^{n} \gamma_k X_{it}^k + \mu_i + \lambda_t + \epsilon_{it} \quad (4)$$

Next, the impacts of the mediating variables on corporate resilience are tested using the following model:

$$Res_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 AI_{it}^2 + \alpha_3 Talents_{it} + \alpha_4 Patent_{it} + \alpha_5 Supply_{it} + \sum_{k=1}^{n} \gamma_k X_{it}^k + \mu_i + \lambda_t + \epsilon_{it} \quad (5)$$

Through the above models, it is possible to examine whether AI indirectly affects corporate resilience through the talent chain, innovation chain, and supply chain.

3.3.3 Endogeneity and Robustness Tests

To mitigate potential endogeneity concerns between AI and corporate resilience, this study employs the instrumental variable (IV) approach and the Heckman two-stage procedure as robustness checks. In addition, following Lewbel (1997), this paper adopts the heteroskedasticity-based internal instrument construction method. The core idea of this method is that when the model error term exhibits heteroskedasticity, internal instruments can be constructed using higher-order moments, such as the cubic deviations of endogenous variables from their sample means, thereby achieving parameter identification in the absence of conventional external instrumental variables. Specifically, following Zhao Wentao and Wang Lan [25], this study applies the cubic transformation to the deviation between robot penetration and its sample mean, while also using the lagged term of AI as an instrumental variable to test whether the causal relationship between AI and corporate resilience is affected by endogeneity bias. The constructed instrumental variables satisfy the requirements of being correlated with the endogenous variable while remaining uncorrelated with the error term, thereby effectively alleviating endogeneity bias caused by measurement errors or omitted variables.

3.3.4 Threshold Effect Model

To further examine the nonlinear impact of AI application on corporate resilience, this study additionally employs a threshold effect model. It is assumed that the impact of AI exhibits a threshold effect, such that AI significantly affects corporate resilience only when its application level exceeds a certain critical value. The threshold model is specified as follows:

$$Res_{it} = \alpha_0 + \alpha_1 AI_{it} \cdot I(AI_{it} > \theta) + \sum_{k=1}^{n} \gamma_k X_{it}^k + \mu_i + \lambda_t + \epsilon_{it} \quad (6)$$

where $I(AI_{it} > \theta)$ is an indicator function that takes the value of 1 when AI_{it} exceeds the threshold value θ, and 0 otherwise.

4. Empirical Results and Analysis

4.1 Baseline Regression Analysis

First, the baseline regression model is used to test the impact of artificial intelligence on corporate resilience. To ensure the robustness of the regression results, different estimation methods are employed. By progressively controlling for different sets of variables, the relationship between AI and corporate resilience is systematically examined.

Across all models, the coefficient of artificial intelligence (*AI*) is positive and statistically significant at the 1% level, indicating that AI exerts a significant positive effect on corporate resilience. The coefficient of the quadratic term (AI^2) is negative and statistically significant in some specifications, suggesting that the impact of AI exhibits a nonlinear U-shaped pattern, whereby AI may impose certain inhibitory effects in the initial stage, while its impact on corporate resilience becomes increasingly pronounced as the technology gradually matures.

Table 3: Baseline Regression Results

Variable	(1)	(2)	(3)	(4)
AI	0.0062***	0.0065***	0.0051***	0.0054***
AI²	-0.0011*	-0.0010*	-0.0018**	-0.0042***
Size	0.0143***	0.0140***	0.0138***	0.0139***
Dlcr	-0.0212**	-0.0198**	-0.0194*	-0.0178*
Ra	0.0562***	0.0559***	0.0556***	0.0558***
Seperate	0.0142*	0.0139*	0.0140*	0.0138*
BM	0.0025	0.0023	0.0021	0.0022
Big4	0.0234*	0.0232*	0.0230*	0.0228*
GDP	0.059**	0.047**	0.048**	0.049**
Finance	0.0012	0.0011	0.0011	0.0010
Constant	1.3154***	1.1105***	1.1187***	1.1178***
R²	0.8914	0.8927	0.8935	0.8945
F	342.4237***	311.2485***	290.2384***	273.1869***
Observatins	3,276	3,276	3,276	3,276

4.2 Mediation Effect Analysis

To further explore the mechanisms through which AI affects corporate resilience, this study follows the approach of Liu Ping and Wu Aokai [26] and conducts mediation effect analysis to examine whether AI influences corporate resilience through mediating variables such as the talent chain, innovation chain, and supply chain.

Table 4: Results of Mediation Effect Analysis

Variable	(1)	(2)	(3)	(4)
AI	0.0048***	0.0045***	0.0053***	0.0054***
AI²	-0.0011*	-0.0011*	-0.0011*	-0.0013**
Talents	0.0056***	0.0054***	0.0052***	0.0053***
Patent	0.0041**	0.0039**	0.0038**	0.0039**
Supply	0.0039***	0.0038***	0.0037***	0.0041***
Constant	1.3082***	1.3047***	1.3121***	1.3112***
R²	0.8762	0.8784	0.8791	0.8802
F	298.1855***	265.4920***	246.4857***	229.6392***
Observatins	3,276	3,276	3,276	3,276

The regression results show that AI has significant positive effects on the talent chain (Talents), innovation chain (Patent), and supply chain (Supply), and that the transmission paths are consistent with expectations. The mediation effect tests confirm that the influence of AI on corporate resilience is realized not only through a direct effect, but also indirectly through improvements in the talent chain, innovation chain, and supply chain.

4.3 Robustness Tests

To ensure the reliability of the regression results, robustness tests are conducted using the instrumental variable (IV) approach and the lagged AI variable.

After the robustness checks, the regression coefficient of lagged AI remains statistically significant, confirming the robustness of the baseline results. These findings indicate that the application of AI not only exerts a significant effect on corporate resilience in the current period, but also generates a long-term effect in future periods.

Taken together, the baseline regression analysis, mediation effect analysis, and robustness tests indicate that AI exerts a significant positive effect on corporate resilience, and that this effect is indirectly realized through mechanisms such as the talent chain, innovation chain, and supply chain. In addition, the impact of AI also exhibits certain stage-specific and heterogeneous characteristics, as firms across different industries and regions demonstrate varying resilience enhancement effects under AI application.

Table 5: Regression Results of Robustness Tests

Variable	(1)	(2)	(3)	(4)
AI (Lagged)	0.0023***	0.0021***	0.0020***	0.0022***
AI^2	-0.0001*	-0.0001*	-0.0001*	-0.0001*
Size	0.0134***	0.0130***	0.0132***	0.0133***
Dlcr	-0.0193*	-0.0187*	-0.0184*	-0.0180*
Ra	0.0528***	0.0523***	0.0517***	0.0521***
Seperate	0.0121*	0.0119*	0.0122*	0.0120*
Constant	0.3125***	0.3079***	0.3153***	0.3139***
R^2	0.8892	0.8904	0.8912	0.8924
F	324.5468***	291.4432***	267.3498***	245.3902***
Observatins	3,276	3,276	3,276	3,276

5. Heterogeneity Analysis

To further examine the heterogeneous effects of AI on corporate resilience, this study considers factors such as industry characteristics, regional characteristics, and ownership structure, and analyzes the differences in resilience enhancement among different types of firms when applying AI.

5.1 Heterogeneity Analysis by Industry Characteristics

Firms across different industries differ significantly in terms of technology application and market demand, especially between the manufacturing and non-manufacturing sectors. Manufacturing firms generally require greater levels of production automation and intelligent applications; therefore, the resilience-enhancing effect of AI may be more significant for these firms [27]. In contrast, non-manufacturing firms rely less on production-related AI applications and more on management and service functions, so the resilience-enhancing effect of AI may be less pronounced.

Table 6: Regression Results of Heterogeneity Analysis by Industry Characteristics

Variable	(1) Manufacturing	(2) Non-Manufacturing
AI	0.0056***	0.0022**
AI^2	-0.0002**	-0.0001
Size	0.0141***	0.0129***
Dlcr	-0.0234**	-0.0187*
Ra	0.0572***	0.0532***
Seperate	0.0153*	0.0124*
Constant	0.3075***	0.3194***
R^2	0.8854	0.8742
F	312.8238***	265.7467***
Observatins	1,638	1,638

The regression results show that the positive effect of AI on corporate resilience is significantly stronger in the manufacturing sector than in the non-manufacturing sector. In addition, the quadratic term is also significantly negative in manufacturing firms, indicating that the impact of AI on corporate resilience follows a U-shaped relationship within the manufacturing sector. Although the effect of AI is relatively smaller in non-manufacturing firms, it still remains positive, suggesting that AI also contributes to resilience enhancement in non-manufacturing firms, albeit with weaker intensity.

5.2 Heterogeneity Analysis by Regional Characteristics

Given China's vast territory, regional development disparities are substantial. The eastern region is generally more economically developed and enjoys relatively better digital infrastructure and policy support. Therefore, AI application may exert a stronger resilience-enhancing effect on firms located in eastern China. By contrast, firms in the central and western regions may face more infrastructure and technology adoption challenges, so the effect of AI may be less pronounced.

The regression results indicate that the resilience-enhancing effect of AI is strongest in the eastern region, where a significant U-shaped relationship is also observed, suggesting that AI entered firms in eastern China earlier and can more effectively enhance corporate resilience.

Although firms in the central and western regions also benefit from AI application, the magnitude of the effect is relatively weaker. In particular, the effect of AI on corporate resilience is more limited in the western region, which may be related to factors such as local infrastructure conditions and technology acceptance.

Table 7: Regression Results of Heterogeneity Analysis by Regional Characteristics

Variable	(1) Eastern Region	(2) Central Region	(3) Western Region
AI	0.0064***	0.0023**	0.0021*
AI^2	-0.0002***	-0.0001	-0.0001
Size	0.0153***	0.0132***	0.0128***
Dlcr	-0.0253***	-0.0197**	-0.0201**
Ra	0.0595***	0.0526***	0.0514***
Seperate	0.0161*	0.0130*	0.0128*
Constant	0.3104***	0.3187***	0.3146***
R^2	0.8945	0.8768	0.8710
F	328.4216***	274.3521***	260.4571***
Observatins	1,092	1,092	1,092

5.3 Heterogeneity Analysis by Ownership Structure

Ownership structure is an important factor affecting firms' operating models and decision-making processes. State-owned enterprises (SOEs) generally receive stronger policy support, but their decision-making efficiency and innovation capability may be constrained by institutional arrangements. By contrast, non-state-owned enterprises (non-SOEs) are more flexible and usually respond faster to technological application and innovation. Therefore, the resilience-enhancing effects of AI may differ across ownership types.

Table 8: Regression Results of Heterogeneity Analysis by Ownership Structure

Variable	(1) SOEs	(2) Non-SOEs
AI	0.0039**	0.0055***
AI^2	-0.0001	-0.0002***
Size	0.0138***	0.0152***
Dlcr	-0.0191**	-0.0223**
Ra	0.0527***	0.0584***
Seperate	0.0141*	0.0163*
Constant	0.3201***	0.3037***
R^2	0.8771	0.8894
F	272.5642***	310.3475***
Observatins	1,638	1,638

Among non-SOEs, the positive effect of AI on corporate resilience is more significant, and the quadratic term is also statistically significant, indicating that its impact follows a U-shaped relationship.

Compared with non-SOEs, the resilience-enhancing effect of AI is relatively limited in SOEs, which may be associated with their decision-making patterns and the lag in technology adoption.

Overall, the heterogeneity analysis across industry, region, and ownership characteristics shows that the impact of AI on corporate resilience differs significantly. Specifically, manufacturing firms, firms in eastern China, and non-SOEs benefit more significantly from the resilience-enhancing effect of AI. This implies that firms should take industry characteristics, regional differences, and ownership structure into account when formulating digital transformation strategies, so as to utilize AI more effectively to improve resilience.

6. Conclusions

Through theoretical analysis and empirical examination, this study investigates the dual impact of artificial intelligence on corporate resilience. The empirical findings confirm the potential of AI in enhancing corporate resilience while also revealing the challenges brought by AI adoption. Based on the baseline regression analysis, robustness tests, and heterogeneity analysis, this study draws the following major conclusions.

First, the positive impact of AI on corporate resilience is significant in the long run, particularly in improving decision-making efficiency, resource allocation, innovation capability, and supply chain management. AI's capabilities in big data analytics, machine learning, and automated decision-making effectively optimize managerial decision-making, enabling firms to adapt to and recover from external shocks more rapidly. The results suggest that AI not only improves firms' operational efficiency in the short term, but also strengthens their ability to cope with risks and crises in the long term. The empirical evidence further confirms a significant U-shaped relationship between artificial intelligence and corporate resilience: although AI may create certain adaptive challenges in the early stage of technology adoption, firms' resilience improves significantly as the technology gradually matures.

Second, the effect of AI on corporate resilience is not merely direct, but is also indirectly realized through mediating mechanisms such as the talent chain, innovation chain, and supply chain, thereby enhancing firms' adaptability and recovery capability. The application of AI encourages firms to recruit high-skilled talent, accelerates technological innovation, and improves supply chain flexibility and diversification. These mechanisms jointly strengthen firms' capacity to withstand and recover from crises, indicating that AI is not merely a technological tool, but rather an important strategic asset for firms in coping with risks in complex environments.

However, this study also finds significant heterogeneity in the impact of AI on corporate resilience. Specifically, the resilience-enhancing effect of AI is more pronounced among manufacturing firms, firms located in eastern China, and non-SOEs. The heterogeneity tests suggest that these differences are closely related to industry characteristics, regional economic development levels, and ownership structure. Manufacturing firms generally have stronger demand for automation and intelligent technologies, enabling AI to more directly improve production efficiency and innovation capability. Firms in eastern China, benefiting from more advanced digital infrastructure and policy support, are better able to implement AI technologies and thus enhance resilience. By contrast, the effects of AI are relatively limited in central and western regions and among some SOEs, likely due to constraints such as infrastructure conditions, technology acceptance, and corporate governance systems.\

The findings further indicate that although AI adoption may bring short-term challenges such as technology adaptation and workforce transformation, in the long run, AI provides firms with stronger capabilities to cope with external risks through improved production efficiency, optimized decision-making, and innovation promotion. Therefore, firms should pay close attention to the stage-specific characteristics of AI adoption, rationally plan technological transformation, overcome initial difficulties, and fully utilize the resilience-enhancing effects brought by technological maturity.

Overall, the emergence of AI technology undoubtedly provides a new pathway for improving corporate resilience, especially when firms are confronted with complex environments and unexpected events. However, the impact of AI is not purely unidirectional, and some firms need to cautiously consider its potential risks during the adoption process. Future research may further explore the interaction between AI and internal factors such as corporate culture and management models, thereby constructing a more comprehensive theoretical framework to help firms better leverage AI to enhance resilience during digital transformation.

References

[1] Hillmann, J., & Guenther, E. (2020). Organizational resilience: A valuable construct for management research? *International Journal of Management Reviews, 23*(1), 7–44. https://doi.org/10.1111/ijmr.12239

[2] Xie, K., Lu, P., & Sheng, J. Y. (2024). Artificial intelligence, product innovation, and adaptive transformation in manufacturing. *Journal of Beijing Jiaotong University (Social Sciences Edition), 23*(1), 84–95.

[3] Chen, L., Gao, Y. P., & Yu, L. H. (2024). How does artificial intelligence change firms' demand for labor? Evidence from big data on online recruitment platforms. *Management World, 40*(6), 74–93.

[4] Xu, M. Y., & Zheng, H. (2024). Artificial intelligence, human capital, and industrial structure upgrading: Evidence from independent and synergistic effects. *Operation and Management, 11*, 228–234.

[5] Luo, J., Zhang, J. J., & Li, K. (2023). How does digital technological innovation drive total factor productivity in manufacturing firms? Evidence from listed firms' patent data. *Journal of Finance and Economics, 2*, 95–109, 124.

[6] Huang, X. H., Yu, L. M., & Yuan, Y. M. (2023). Industrial robots and firm innovation: A human capital perspective. *Studies in Science of Science, 41*(2), 356–368.

[7] Van der Vegt, G. S., Essens, P., Wahlström, M., & George, G. (2015). Managing risk and resilience. *Academy of Management Journal, 58*(4), 971–980.

[8] Yang, T. F., Chen, Y. Q., & Zhou, J. L. (2025). The impact of corporate digital transformation on organizational resilience: Evidence from Chinese listed companies. *Journal of Industrial Technological Economics, 44*(1), 55–66.

[9] Mo, Y. L., & Ni, H. (2024). The impact of corporate ESG performance on organizational resilience. *Journal of Industrial Technological Economics, 43*(12), 92–102.

[10] Chen, H., Guo, T. M., Zhang, Y., et al. (2024). The impact of internal control on organizational resilience in manufacturing firms: A corporate life cycle perspective. *Nankai Business Review*, Advance online publication, 1–28.

[11] Yang, Y., Li, Z. Q., Xie, G. Q., et al. (2021). Government-led mechanisms for enterprise work resumption under major public health emergencies. *Journal of Public Management, 18*(2), 70–82, 169.

[12] Ishak, W. A., & Williams, A. E. (2018). A dynamic model of organizational resilience: Adaptive and anchored approaches. *Corporate Communications, 23*(2), 180–196.

[13] Yang, Y., Liu, S. W., & Deng, X. Y. (2025). Crisis and opportunity: The dual effects of artificial intelligence on corporate resilience. *Nankai Business Review*, Advance online publication, 1–39.

[14] Ma, H. J., Tang, S. S., & Xiong, L. (2023). The mechanism of network market orientation on organizational resilience of new ventures. *Chinese Journal of Management, 20*(12), 1809–1817, 1877.

[15] Tao, F., Wang, X. R., Xu, Y., et al. (2023). Digital transformation, industrial chain and supply chain resilience, and firm productivity. *China Industrial Economics, 5*, 118–136.

[16] Briscoe, F., & Rogan, M. (2016). Coordinating complex work: Knowledge networks, partner departures, and client relationship performance in a law firm. *Management Science, 62*(8), 2392–2411.

[17] Cui, S. J., Wu, Z., & Yu, L. N. (2025). Evolution of industrial cooperation complex networks and resource allocation: Evidence from big data on Chinese artificial intelligence firms. *China Soft Science, 1*, 193–207.

[18] Schultz, T. W. (1961). Investment in human capital. *The American Economic Review, 51*(1), 1–17.

[19] Bertrand, M., & Schoar, A. (2003). Managing with style: The effect of managers on firm policies. *The Quarterly Journal of Economics, 118*(4), 1169–1208.

[20] Xie, W. M., Tian, W., & He, K. (2025). Industrial robot applications and upgrading of firms' human capital structure. *Systems Engineering—Theory & Practice, 45*(6), 1745–1763.

[21] Smith, K. W., & Tushman, M. L. (2005). Managing strategic contradictions: A top management model for managing innovation streams. *Organization Science, 16*(5), 522–536.

[22] Yin, X. N., Ming, H., & Geng, J. F. (2021). The impact of executive compensation incentives on resource allocation efficiency: Perspectives of ownership and industry heterogeneity. *China Soft Science, 36*(S1), 260–267.

[23] Yao, J. Q., Zhang, K. P., Guo, L. P., et al. (2024). How does artificial intelligence improve firm productivity? A labor skill structure adjustment perspective. *Management World, 40*(2), 101–116, 117–122, 133.

[24] Lv, W., Wei, Y., Li, X., et al. (2019). What dimension of CSR matters to organizational resilience? Evidence from China. *Sustainability, 11*(6), 1561. https://doi.org/10.3390/su11061561

[25] Zhao, W. T., & Wang, L. (2024). The impact of enterprise artificial intelligence exports on upstream climbing and resilience in global value chains. *South China Journal of Economics, 42*(7), 132–150.

[26] Liu, P., & Wu, A. K. (2022). Top management team heterogeneity and corporate growth: The mediating role of dynamic capabilities. *East China Economic Management, 36*(11), 117–128.

[27] Wu, Q., & Yao, Y. X. (2023). Corporate digital transformation and supply chain configuration: Centralization or diversification? *China Industrial Economics, 8*, 99–117.

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Conflicts of Interest

The authors declare no conflict of interest.

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