The Application of Artificial Intelligence and the Resilience of Manufacturing Enterprises: Mechanisms of Action and Heterogeneity Boundaries

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Abstract. Against the backdrop of increasing external environmental uncertainties and accelerated intelligent transformation in the manufacturing sector, enhancing the resilience of manufacturing enterprises has become a critical issue for ensuring the security of industrial and supply chains and promoting high-quality development in manufacturing. This study uses China A-share listed manufacturing companies from 2015 to 2024 as research samples, constructs an indicator of corporate AI application levels based on annual report text mining methods, and measures corporate resilience across three dimensions: resistance capacity, recovery capacity, and innovation capacity, empirically examining the impact of AI application on manufacturing enterprise resilience and its underlying mechanisms. The findings reveal that AI application significantly enhances the resilience of manufacturing enterprises, with conclusions remaining robust even after substituting core variables, adjusting model specifications, controlling for cluster standard errors at the firm level, incorporating provincial fixed effects, and employing instrumental variable methods. Mechanism tests indicate that AI primarily strengthens corporate resilience by improving talent incentives, fostering technological innovation, and reducing management costs, with technological innovation serving as the primary transmission pathway; while internal control is partially influenced by AI, its mediating effect fails the Bootstrap robustness test. Further heterogeneity analysis demonstrates that the impact of AI on corporate resilience varies across ownership structures, firm size, regional differences, and industry attributes. This study enriches research on factors influencing corporate resilience in the digital economy context and provides empirical evidence for manufacturing enterprises to rationally advance AI adoption and enhance risk resistance and recovery capabilities.

Keywords: artificial intelligence, manufacturing enterprises, corporate resilience, mechanism of action, heterogeneity, technological innovation.

1. Introduction

Currently, the unprecedented global transformation of the century is accelerating rapidly, with external shocks—including the restructuring of global industrial and supply chains, geopolitical conflicts, trade frictions, and technological blockades interacting synergistically, creating an increasingly complex and challenging operating environment for China's manufacturing enterprises. As the foundation of the real economy and a critical pillar for building a modern industrial system and achieving high-quality development, the manufacturing sector faces significant challenges. Against a backdrop of growing external uncertainties, the ability of manufacturers to maintain essential operations, swiftly resume production, and sustain growth amid disruptions has become pivotal to ensuring stable industry development and supply chain security. Corporate resilience represents the core capability for navigating uncertain environments, encompassing not only recovery capacity post-disaster but also pre-crisis risk anticipation, crisis-induced shock absorption, and post-crisis resource reconfiguration alongside capability enhancement (Williams et al., 2017; Duchek, 2020).

Meanwhile, as a pivotal driver of the new wave of technological revolution and industrial transformation, artificial intelligence has become a fundamental technological foundation for advancing the intelligent transformation of China's manufacturing sector and fostering new types of productive forces. Since the introduction of the "New Generation Artificial Intelligence Development Plan" calling for accelerated development of AI innovation ecosystems, China has consistently reinforced AI's strategic role in industrial upgrading, economic restructuring, and smart manufacturing. The "14th Five-Year Plan for Smart Manufacturing Development" further emphasizes digitalization, networking, and intelligent transformation across the manufacturing industry, while the State Council's "Opinions on Deeply Implementing the'+' Initiative" advocates comprehensive integration of AI into all sectors of society and economy. Driven by both policy support and technological advancements, AI is rapidly permeating production, R&D, management, and decision-making processes in manufacturing enterprises, providing innovative solutions to enhance risk identification capabilities, resource allocation efficiency, and operational resilience.

Theoretically, artificial intelligence exhibits characteristics such as data mining, intelligent forecasting, autonomous learning, and decision support, enabling enterprises to transcend traditional information processing limitations and enhance their ability to identify market demand fluctuations, supply chain disruptions, and operational risks. Relevant studies indicate that as a general-purpose technology, AI helps companies improve environmental awareness, optimize operational processes, and strengthen organizational resilience (Boh et al., 2023; Han et al., 2025). However, AI technology does not automatically translate into tangible resilience advantages for enterprises. In practice, while some manufacturing firms actively adopt AI solutions, they still face challenges including high technological investment costs, weak data foundations, inadequate organizational adaptation, insufficient talent reserves, and difficulties in business process restructuring, leading to phenomena characterized by "high initial enthusiasm, slow implementation, and inconsistent outcomes." Brynjolfsson et al. (2019) noted that AI's productivity effects may be influenced by technology diffusion, organizational adjustments, and delayed complementary investments; Yang Yang et al. (2025) further observed that AI's impact on corporate resilience presents both opportunities and challenges. Therefore, whether AI can genuinely enhance the resilience of manufacturing enterprises depends not only on adoption rates but more critically on effective integration with internal governance, talent development, technological innovation, and operational management.

Based on this, this study takes China's A-share listed manufacturing companies from 2015 to 2024 as the research object, employs annual report text mining methods to construct corporate AI application indicators, empirically examines the impact of artificial intelligence on corporate resilience, and further analyzes its mechanisms from four perspectives: internal control, talent incentives, technological innovation, and management expenses. This research contributes to enriching studies on the factors influencing corporate resilience in the context of the digital economy, further revealing the micro-level pathways through which AI enhances the resilience of manufacturing enterprises; simultaneously, it provides empirical evidence for manufacturing companies to rationally advance AI applications under policy support, strengthen risk resilience and recovery capabilities, and offers insights for China's efforts to promote intelligent transformation in manufacturing, enhance the resilience of industrial and supply chains, and achieve high-quality development in the manufacturing sector.

2. Literature Review

Corporate resilience originated in fields such as physics, ecology, and engineering, and was later incorporated into organizational management and strategic management research to describe an enterprise's capacity to withstand shocks, resume operations, and achieve sustained growth in uncertain environments (Meyer, 1982; Williams et al., 2017). Current scholarship generally defines corporate resilience not merely as post-crisis recovery capability, but rather as a dynamic set of capabilities encompassing risk identification, shock absorption, resource reallocation, and capability restructuring throughout the pre-crisis, crisis, and post-crisis phases (Duchek, 2020). In measurement approaches, two main methodologies have emerged: one employs single financial or market indicators—such as profitability, revenue growth rate, return on assets volatility, or stock price fluctuations—for indirect assessment (Xiao Xingzhi & Xie Weimin, 2024; Qiao Penghua et al., 2025); the other develops multidimensional indicator systems based on capability or process perspectives, breaking resilience down into dimensions like resistance, recovery, adaptability, and innovation capabilities, with measurements using entropy analysis or comprehensive evaluation methods (Wang Peng & Chen Diexin, 2025; Cheng Qiongwen & Zhu Jingli, 2025). Key influencing factors include financial redundancy, managerial characteristics, human capital allocation, technological innovation capacity, supply chain management effectiveness, and external institutional environments (Sahebjamnia et al., 2018; Stoverink et al., 2020; Luo Ni et al., 2024).

Research on the relationship between artificial intelligence and corporate resilience has begun to explore this topic from both enterprise and industrial chain perspectives. Wang Peng and Chen Diexin (2025) developed an AI dictionary using machine learning methods, demonstrating that AI applications enhance corporate resilience through resource allocation optimization, information flow facilitation, and knowledge restructuring. Cheng Qiongwén and Zhu Jingli (2025), studying manufacturing enterprises, found that AI improves resilience by optimizing supply-demand matching, strengthening information governance coordination, boosting innovation capabilities, and alleviating financing constraints. Zhou Shitong et al. (2025) further examined industrial chain resilience, revealing how AI applications strengthen it through cost control effects, internal control improvements, and sustained innovation impacts. Some studies have used industrial robots or generative AI as proxy variables, showing their ability to enhance manufacturing resilience by improving labor productivity, fostering technological innovation, or boosting total factor productivity (Xiao Xingzhi & Jie Weimin, 2024; Qiao Penghua et al., 2025). However, the impact of AI on corporate resilience is not necessarily unidirectional: Yang Yang et al. (2025) noted a potential nonlinear relationship—AI may initially increase adjustment pressures for enterprises, but its empowering effects gradually manifest as technological maturity and organizational adaptability improve.

Overall, existing research provides a solid foundation for understanding how artificial intelligence enhances corporate resilience, yet there remains room for further expansion. Compared to prior studies, this paper's potential contributions are primarily reflected in the following three aspects.

First, in terms of research perspective, this paper integrates artificial intelligence applications with the resilience of manufacturing enterprises within a unified analytical framework, thereby expanding research on the factors influencing corporate resilience in the context of the digital economy. While existing literature often examines enterprise risk resilience from perspectives such as digital transformation, industrial robotics, generative AI, or supply chain resilience, this study focuses specifically on AI applications at the micro level of manufacturing firms. By constructing an indicator for corporate AI adoption levels based on annual report texts of listed companies, it measures enterprise resilience across three dimensions—resilience against risks, recovery capacity, and innovation capability—thus providing empirical evidence that reflects distinct characteristics at the firm level for understanding how AI enhances the resilience of manufacturing enterprises.

Second, regarding the mechanism of action, this paper systematically examines the internal pathways through which artificial intelligence influences corporate resilience, following the logical framework of "governance optimization – talent support – innovation-driven development – efficiency enhancement." Unlike existing studies that primarily focus on mechanisms such as resource allocation, supply-demand matching, financing constraints, or industrial chain synergy, this study incorporates internal control, talent incentives, technological innovation, and management costs into a unified analytical framework. By comparing the distinct roles of these mechanisms in enhancing corporate resilience through AI, it helps unravel the micro-level "black box" of how artificial intelligence impacts corporate resilience.

Third, regarding empirical identification, this study builds upon the benchmark regression by testing the robustness of conclusions through methods such as replacing core variables, adjusting model specifications, employing cluster standard errors at the firm level, incorporating provincial fixed effects, and using instrumental variable techniques. Additionally, the Bootstrap method was employed to examine indirect effects, thereby enhancing the reliability of identifying how artificial intelligence influences corporate resilience and its underlying mechanisms. Furthermore, the study examines heterogeneity boundaries from perspectives including property rights structure, firm size, and industry characteristics, providing supplementary evidence for understanding the conditions under which AI enhances the resilience of manufacturing firms.

3. Theoretical Analysis and Research Hypotheses

3.1. The Direct Impact of Artificial Intelligence Applications on the Resilience of Manufacturing Enterprises

From the perspectives of microeconomics and strategic management, corporate resilience encompasses not only an enterprise's capacity to absorb and withstand external shocks but also its ability to recover and achieve counter-cyclical growth during crises (Wu Xiaobo & Feng Xiaoya, 2022). As the VUCA characteristics of the global macro-environment become increasingly pronounced, traditional manufacturing industries' static defense models based on factor accumulation and linear processes prove inadequate in mitigating external uncertainties. Artificial intelligence (AI), as a core driver of new-generation productivity, is redefining production frameworks and governance paradigms within enterprises, endowing them with dynamic resilience. Research by Qi Yongxing and Cheng Junqi (2025) on listed manufacturing firms demonstrates that AI enhances total factor productivity by transforming research methodologies, optimizing workforce structures, and improving operational efficiency, solidifying its role as a pivotal technological force for efficiency enhancement and capability transformation in manufacturing. Firstly, AI exhibits robust risk identification and predictive capabilities. Leveraging foundational technologies like natural language processing (NLP) and computer vision (CV), companies can conduct real-time monitoring and in-depth analysis of heterogeneous information flows across supply chains, overcoming traditional information lag effects to enable agile responses prior to shocks (Wang Peng & Chen Diexin, 2025). Secondly, AI empowers manufacturing enterprises to achieve flexible production and optimized resource allocation. The deep integration of AI technology with smart manufacturing systems, the Industrial Internet, and digital production processes has transformed the rigid production line model of traditional manufacturing, significantly reducing product switching costs and enabling enterprises to rapidly adjust production strategies when facing supply chain disruptions or demand contraction, thereby mitigating operational fluctuations (Xiao Xingzhi & Xie Weimin, 2024; Cheng Qiongwen & Zhu Jingli, 2025). Furthermore, AI applications can foster organizational learning and adaptive collaboration, achieving precise resource allocation through algorithmic optimization to alleviate the adverse impacts of external shocks. Based on these findings, the following hypotheses are proposed:

Hypothesis 1: AI applications can significantly enhance the resilience of manufacturing enterprises.

3.2. Analysis of the Indirect Mechanisms by Which Artificial Intelligence Applications Influence the Resilience of Manufacturing Enterprises

To further unravel the micro-level mechanisms underlying how artificial intelligence enhances organizational resilience, this paper employs the theoretical framework of "factor restructuring – process governance – capability activation" to examine how AI delivers empowerment through four channels: organizational governance (internal control), human capital (talent incentives), technological innovation, and operational efficiency (management costs).

3.2.1. Applications of Artificial Intelligence, Internal Control, and Resilience in Manufacturing Enterprises

Internal control, as the cornerstone of micro-level corporate governance, serves as the first line of defense against external uncertainties. The theory of new-quality productive forces indicates that the introduction of novel production factors inevitably necessitates the optimization of internal governance relationships.

On one hand, the application of artificial intelligence has significantly reduced agency costs and information asymmetry within enterprises. Traditional internal controls heavily rely on manual audits and post-event accountability, suffering from severe data lag. The integration of AI algorithms and digital governance systems enables comprehensive, round-the-clock intelligent monitoring of corporate cash flows, material flows, and information flows, transforming traditional "post-event auditing" into "pre-event warnings and real-time controls," thereby enhancing the effectiveness of internal control boundaries. Digital-intelligent technologies enhance information governance by improving efficiency in information sharing, acquisition, and dissemination, thereby strengthening internal control quality (Gong Tingting et al., 2025); high-quality internal controls also serve as risk threshold management mechanisms during AI implementation, mitigating potential risks associated with digital transformation (Qi Yongxing et al., 2025). On the other hand, AI-driven improvements in internal control quality effectively curb managerial opportunism and impulsive expansion tendencies, preventing excessive consumption of redundant resources in routine operations. Robust internal controls ensure sufficient solvency capacity and resource buffers during crises, significantly enhancing organizational resilience. Based on these findings, the following hypotheses are proposed: Hypothesis 2a: AI applications can enhance the resilience of manufacturing enterprises by improving their internal control quality.

3.2.2. Applications of Artificial Intelligence, Talent Incentives, and Corporate Resilience

The fundamental essence of digital and intelligent transformation lies not merely in technological advancement, but in the creative reconfiguration of traditional labor elements. The introduction of artificial intelligence will drive enterprises to "reduce demand for conventional low-skilled workers while increasing demand for unconventional high-skilled workers," triggering a profound restructuring of the workforce's skill composition (Yao Jiaquan et al., 2024).

Digital and intelligent professionals serve as the core dynamic resource for enterprises to navigate VUCA environments, where their innovative commitment and work autonomy directly determine organizational recovery speed. To attract, retain, and activate these highly specialized digital talents, artificial intelligence applications will compel companies to optimize internal talent incentive mechanisms. AI in human resource management can drive digital transformation through data-driven decision support, talent pool development, precise talent matching, compensation management, and personalized training, thereby supporting the cultivation of high-quality talent teams (Zhou Hongguang, 2025). Such long-term, proactive incentive mechanisms can maximize the "individual resilience" and self-organizing creativity of digital professionals, enhancing employees' willingness to assume risks and demonstrate initiative in solving cross-functional challenges during external crises, thereby accelerating organizational recovery from disruptions. Based on this, the following hypothesis is proposed:

Hypothesis 2b: AI applications can enhance the resilience of manufacturing enterprises by strengthening their talent incentive mechanisms.

3.2.3. Applications of Artificial Intelligence, Technological Innovation, and Corporate Resilience

The Dynamic Capability Theory posits that sustained technological innovation serves as a key driver for manufacturing enterprises to achieve "counter-cyclical growth" and "catch-up growth" during crises. R&D innovation significantly enhances corporate resilience by increasing the proportion of highly educated and skilled workers, demonstrating that technological innovation and human capital upgrading form essential foundations for organizational resilience (Chu Siru et al., 2026). Furthermore, artificial intelligence enables knowledge reorganization and technological innovation through deep learning, big data processing, and cross-modal learning, thereby injecting new momentum into improving total factor productivity in manufacturing enterprises (Qi Yongxing et al., 2025). Consequently, AI technology applications exhibit strong knowledge spillover and innovation-enabling characteristics.

First, artificial intelligence can break down interdisciplinary and cross-domain knowledge barriers through efficient data mining and knowledge reorganization. AI algorithms enable researchers to swiftly identify technical bottlenecks within vast patent databases and cutting-edge literature, significantly shortening R&D cycles and reducing innovation-related trial-and-error costs. Second, AI-powered digital innovation exhibits network synergy effects that eliminate barriers to the flow of R&D assets within organizations, driving manufacturing enterprises to transition from low-value segments to high-value chains (Cheng Qiongwén & Zhu Jingli, 2025; Deng Feng & Wang Jindan, 2026). When facing severe external shocks such as geopolitical tensions, technological blockades, or market disruptions, robust independent innovation capabilities allow companies to rapidly develop alternative products, explore new markets, and flexibly restructure production processes, demonstrating exceptional growth resilience. Based on these findings, this paper proposes the following hypotheses:

Hypothesis 2c: AI applications can enhance the resilience of manufacturing enterprises by boosting their technological innovation capabilities.

3.2.4. Artificial Intelligence Applications, Administrative Costs, and Corporate Resilience

From the perspective of micro-level transaction cost economics, corporate management costs are largely determined by internal search costs, coordination costs, and information efficiency frictions. Artificial intelligence innovation can reduce labor input, external sales costs, and internal management costs, thereby enhancing cost efficiency across production, marketing, and management processes. From the perspective of industrial chain resilience, the application of AI technology strengthens industrial chain resilience through cost control effects, specifically by reducing information search costs, supervisory transaction costs, and financing transaction costs (Zhou et al., 2025).

The application of artificial intelligence demonstrates significant effects in digital operations management. Traditional hierarchical management structures suffer from multi-level decision-making distortions, leading to high administrative costs and poor resilience during crises. By leveraging automated workflows, intelligent production scheduling, and smart supply chain systems, AI applications achieve decentralization and flattening of organizational structures, substantially reducing friction costs associated with sourcing external intermediaries, transaction negotiations, and internal coordination. The streamlining of management expenses and the downward shift in rigid expenditure thresholds essentially free up valuable cash flow reserves and financial flexibility for enterprises. When facing external negative shocks or sharp declines in revenue, lower management costs mean a lower breakeven point and enhanced cash flow stabilization capabilities, thereby preventing organizations from going bankrupt due to capital chain crises. Based on this analysis, the paper proposes the following hypotheses:

Hypothesis 2d: AI applications can enhance the resilience of manufacturing enterprises by reducing management costs and improving operational efficiency.

4. Research Design

4.1. Data Sources and Sample Selection

This study initially selects manufacturing listed companies on China's A-share market from 2015 to 2024 as the research sample. The starting year of the sample is set as 2015, primarily based on the timeline when artificial intelligence technology began to penetrate micro-level enterprises on a large scale. The data mainly originate from the Guotai An (CSMAR) database. To ensure the reliability and robustness of the research conclusions, the original sample underwent the following treatments: First, only manufacturing listed companies were retained according to the industry classification standards of the China Securities Regulatory Commission (CSRC) in 2012; Second, companies with abnormal trading statuses such as ST or *ST during the observation period were excluded to eliminate interference from abnormal operating conditions on the empirical results; Third, missing values in key variables were handled by interpolation for partial observations, and firms with completely missing primary variables were removed; Fourth, to mitigate the potential impact of extreme outliers on the empirical findings, all continuous variables underwent bidirectional Winsorization at the 1th and 99th percentiles. After these screening procedures, a total of 21,630 annual observations were obtained for the period from 2015 to 2024.

4.2. Variable Definitions

4.2.1. Corporate Resilience

Corporate resilience refers to an enterprise's comprehensive capability to identify potential risks, absorb shocks, rapidly adjust strategies, restore operations, and achieve sustained growth and enhanced competitiveness through learning and innovation in complex, dynamic, and uncertain environments (the VUCA environment) or during emergencies. Theoretically, corporate resilience is not merely a static capacity to withstand shocks but rather a dynamic, multi-dimensional framework that reflects adaptability and antifragility (bouncing forward) under VUCA conditions. Drawing on research by Wang Peng and Chen Diexin (2025), Cheng Qiongwen and Zhu Jingli (2025), and other studies on multidimensional measurement of corporate resilience, we develop an evaluation system comprising three dimensions: resistance capacity, recovery capacity, and innovation capacity. Resistance capacity measures an enterprise's ability to mitigate external impacts on operations through financial stability and operational adjustments before or during initial shocks, serving as the fundamental prerequisite—assessed via financial robustness and operational volatility. Recovery capacity evaluates an enterprise's capability to swiftly resume operations, stabilize financial performance, and restore organizational functions post-shock, reflecting its post-crisis process optimization and operational efficiency—measured by operational efficiency and recovery scale. Innovation capacity denotes an enterprise's potential for capability enhancement and accelerated growth during recovery through increased R&D investment and innovative outputs, embodying the long-term developmental aspect of resilience—measured by input absorption and innovation output. Specific calculation methods for indicators are presented in Table 1. Additionally, the comprehensive resilience index (Resilience) is calculated using the entropy method.

Table 1. Corporate Resilience Evaluation Indicator System

Name of Index	Metric Abbreviation	Computational Method	Direction
Financial Stability	CH	Annualized operating cost / [(End-of-period inventory value + Net end-of-period inventory) / 2]	Positive Direction
Operational Volatility	CV	Standard Deviation of Total R&D Investment / Average Total R&D Investment	Negative Direction
Operational Efficiency	XJ	Annualized Operating Revenue / Net Operating Cash Flow	Positive Direction
Recovery Scale	R	Net operating cash flow – Average net operating cash flow – Average debt level – Total corporate debt	Positive Direction
Absorption Investment	YF	Total R&D Investment / Annualized Operating Revenue	Positive Direction
Innovation Output	ZL	Number of inventions granted independently in the year + Number of utility models granted independently in the year + Number of design patents granted independently in the year	Positive Direction

4.2.2. Artificial Intelligence (AI)

Drawing on the research of Yao Jiaquan et al. (2024), the approach of constructing enterprise-level AI indicators from listed companies' annual reports involves extracting AI-related keywords and calculating their frequency to determine corporate AI proficiency. Given that the original word frequency data contains numerous zero values and exhibits a right-skewed distribution, the frequency metrics were transformed by adding 1 and applying natural logarithmic transformation, yielding the final AI proficiency index.

4.2.3. Mechanistic Variables

The study identifies four key mechanism variables: internal control, talent management, technological innovation, and administrative expenses. Specifically, internal control (IC) is measured using an internal control index that comprehensively reflects a company's governance structure, risk management capabilities, and operational standardization – higher values indicate superior internal control quality. Talent motivation (Peop) is assessed by the combined proportion of PhD and master's degree holders within the workforce, reflecting the company's allocation of high-level human capital; a higher ratio signifies stronger reserves of specialized and knowledge-based professionals. Technological innovation (Inn) is quantified through the natural logarithm of annual patent applications to gauge innovation investment and output capacity, with greater patent filings indicating heightened innovation activity. Administrative expenses (Mfee) are measured as the natural logarithm of the ratio of administrative costs to operating revenue, reflecting cost control efficiency in operations – lower values typically indicate stronger expense management capabilities and higher operational efficiency.

4.2.4. Control Variables

To eliminate potential confounding effects from a company's inherent characteristics, financial condition, and corporate governance structure on its resilience and to ensure the robustness of the empirical results, a series of control variables were included in the model: firm size (Size), debt-to-asset ratio (Lev), revenue growth rate (Growth), board size (Board), dual leadership structure (Dual), shareholding proportion of the top five shareholders (Top5), firm age (Age), and institutional investor shareholding proportion (Inst). The definitions and calculation methods for the main variables are detailed in Table 2.

Table 2. Variable Definitions Table

Variable Name	Variable Abbreviation	Variable Definition Explanation
Internal Control	IC	Internal Control Index
Talent Incentives	Peop	The sum of the proportions of doctoral and master's degree holders
Technical Innovation	Inn	The total number of patent applications in that year was taken logarithmically.
Administration Expenses	Mfee	The management expenses as a percentage of operating revenue are expressed using their natural logarithm.
Business Resilience	Resilience	According to the calculation results obtained using the entropy method presented in Table 1
Artificial Intelligence	AI	After adding 1 to the frequency of each word in the artificial intelligence dataset, take its natural logarithm.
Company size	Size	Natural logarithm of the company's total assets
Asset-Liability Ratio	Lev	The ratio of total liabilities to total assets
Enterprise Growth Potential	Growth	Increase rate of business revenue
Board Size	Board	Natural logarithm of the number of board members
Duality	Dual	Whether the Chairman and General Manager are the same person (Yes = 1, No = 0)
Equity Concentration Degree	Top5	The sum of the shareholding ratios of the top five shareholders
Enterprise Age	Firmage	Add 1 to the company's establishment year, then take the natural logarithm of the result.
Institutional Investors Hold Shares	Inst	The proportion of shares held by institutional investors to the total share capital

4.2.5. Model Configuration

To examine how corporate AI capabilities affect organizational resilience, the following regression model was established:

$$Resilience_{i,t}=\alpha_0+\alpha_1 AI_{i,t}+\alpha_2 Control_{i,t}+\mu_{i,t}+\lambda_{i,t}+\epsilon_{i,t} \quad (1)$$

Furthermore, to examine the mechanism by which corporate AI capabilities influence organizational resilience, we developed the following mediation model:

$$Mediator_{i,t}=\gamma_0+\gamma_1 AI_{i,t}+\gamma_2 Control_{i,t}+\mu_{i,t}+\lambda_{i,t}+\epsilon_{i,t} \tag{2}$$

$$Resilience_{i,t}=\theta_0+\theta_1 AI_{i,t}+\theta_2 Mediator_{i,t}+\theta_3 Control_{i,t}+\mu_{i,t}+\lambda_{i,t}+\epsilon_{i,t} \tag{3}$$

These variables *Resilience* represents the resilience level of firms, *AI* represents artificial intelligence capabilities, *Medidator* represents mechanism variables, and *Control* represents a set of control variables. μ is industry fixed effects, λ is year fixed effects, and ϵ is random disturbance terms.

Furthermore, to further test the robustness of the mediating effects, this study employs the Bootstrap method for repeated sampling tests of indirect effects. Specifically, we calculate the indirect effects of artificial intelligence on corporate resilience through internal control, talent incentives, technological innovation, and management costs, and determine whether the mediating effects are significant by examining whether the Bootstrap bias-corrected confidence intervals contain zero.

5. Emprical Result Analysis

5.1. Descriptive Statistics

Table 3 presents the descriptive statistics of the main variables and their correlation coefficients. The mean resilience score was 0.111, with a median of 0.095 and a standard deviation of 0.072, indicating some variation in resilience levels among the sample firms but relatively controlled overall fluctuations. The mean AI score was 1.077, with a standard deviation of 1.135, reflecting significant differences in AI adoption levels—some firms have not fully utilized AI technologies, while others have achieved high adoption rates. All other variables fall within reasonable ranges.

Furthermore, the correlation coefficient between artificial intelligence (AI) and corporate resilience is 0.272, which is statistically significant at the 1% level, indicating a strong positive relationship between AI adoption and improved corporate performance. This preliminary finding suggests that AI applications can enhance organizational resilience.

Table 3. Descriptive statistics of major variables

Variable Name	Average Value	Standard Deviation	Median
resilience	0.111	0.072	0.095
AI	1.077	1.135	0.693
size	22.158	1.162	22.005
lev	0.384	0.174	0.372
growth	0.130	0.339	0
board	2.093	0.181	2.197
dual	0.296	0.456	0
top5	0.527	0.144	0.531
firmage	2.998	0.280	3.037
inst	0.391	0.235	0.405

5.2. Benchmark Regression Results

Table 4 presents the benchmark regression results of artificial intelligence (AI) on corporate resilience. To control for the effects of different fixed effects, three model specifications were constructed sequentially: Column (1) shows the regression results without controlling for fixed effects; column (2) incorporates a year-specific fixed effect; and column (3) further controls for industry and year-specific fixed effects. The regression results indicate that across all three models, the AI regression coefficient is positive and statistically significant at the 1% level. Specifically, after controlling for industry and year-specific fixed effects, the AI regression coefficient for corporate resilience is 0.010, demonstrating that AI adoption significantly enhances corporate resilience. By introducing and applying AI technologies, enterprises can optimize production processes, improve operational efficiency, and strengthen their capacity to withstand external shocks, thereby substantially boosting corporate resilience.

Table 4. Regression Results of Artificial Intelligence and Corporate Resilience

Variable	(1) Resilience	(2) Resilience	(3) Resilience
AI	0.015***	0.015***	0.010***
	(42.776)	(40.083)	(23.105)
Size	0.031***	0.030***	0.031***
	(68.685)	(66.643)	(63.728)
Lev	-0.003	-0.004	-0.017***
	(-1.150)	(-1.582)	(-5.721)
Growth	-0.005***	-0.005***	-0.009***
	(-4.444)	(-4.453)	(-5.428)
Board	-0.007***	-0.004*	-0.004*
	(-3.043)	(-1.745)	(-1.746)
Dual	0.005***	0.005***	0.006***
	(5.532)	(5.143)	(6.000)
Top5	0.038***	0.042***	0.036***
	(11.145)	(12.396)	(9.686)
Firmage	0.003**	-0.005***	-0.001
	(2.234)	(-3.130)	(-0.363)
Inst	-0.006***	-0.005**	-0.002
	(-2.707)	(-2.128)	(-0.869)
Constant Term	-0.606***	-0.571***	-0.597***
	(-57.042)	(-51.681)	(-49.484)
Industry Fixed Effect	no	no	yes
Year Fixed Effect	no	yes	yes
Sample Size	21630.000	21630.000	18230.000
Adjust R^2	0.311	0.318	0.356

Note: Values in parentheses represent the robust standard deviation; *, **, and *** indicate significance at the 10%,5%, and 1% levels, respectively.

5.3. Robustness Test

5.3.1. Replace Core Variables

To mitigate potential estimation biases arising from measurement errors in variables, a substitution test was conducted between the core explanatory variable Artificial Intelligence (AI) and the dependent variable Corporate Resilience.

For explanatory variables, the logarithm of the number of enterprise-related AI patents (ln_ai_patent) was used as a proxy indicator for AI development level. As shown in Column (1) of Table 5, the estimated coefficients of the core explanatory variables are significantly positive at the 1% significance level, indicating that the conclusions of this study are independent of the specific construction method employed for AI metrics.

Regarding the dependent variable, this study employs the three-year rolling standard deviation of a company's ROA to measure profit volatility and takes its reciprocal to construct a proxy variable for operational stability (ROA-resilience). A higher value of this indicator indicates lower profit volatility and stronger operational stability. As shown in Column (2) of Table 5, the estimated coefficient for the artificial intelligence variable is significantly negative at the 1% level, suggesting that AI application may exacerbate corporate profit volatility in the short term, thereby reducing operational stability. It should be noted that since constructing the rolling standard deviation requires continuous annual data, some samples were excluded due to missing values, resulting in a reduced sample size.

Table 5. Results of robustness tests for substitute variables

	(1)	(2)
Explained Variable	Replace the core explanatory variable Resilience	Replace the dependent variable roa_resilience
ln_ai_patent	0.0588***	
	(0.0022)	
AI		-0.0024***
		(0.0009)
Controlled Variable	control	control
Industry Fixed Effect	control	control
Year Fixed Effect	control	control
Sample Size	18210	16902
Adjust R^2	0.2739	0.1185

Note: Values in parentheses represent the robust standard deviation; ***, **, and * indicate significance at the 1%,5%, and 10% levels, respectively.

5.3.2. Robustness Bias in Model Specification

To further verify the robustness of the benchmark regression results, a multi-dimensional robustness test was conducted from a model specification perspective, addressing potential sample selection biases, error term correlations, and missing variable issues.

First, given that municipalities exhibit distinct characteristics in terms of economic development levels and resource allocation that may influence estimation results, this study excludes the municipal sample from the regression analysis to verify whether the conclusions are sample-dependent. Second, considering potential correlations among error terms at the firm level in the panel data, we employ cluster-standardized errors at the firm level to enhance the robustness of standard error estimates. Finally, to address potential missing variables, the study incorporates additional control variables such as firm financial characteristics into the baseline model and introduces provincial fixed effects to account for unobservable regional factors affecting firm behavior.

The regression results are presented in Table 6. Under various specifications, the estimated coefficients of the core explanatory variables remain significantly positive with no substantial changes in magnitude, demonstrating strong robustness of the study's conclusions.

Table 6. Results of robustness testing for model specifications

	(1)	(2)	(3)	(4)
	Excluding municipalities directly under the central government	Cluster Standard Error	Add Control Variables	Provincial Fixed Effect
AI	0.0134***	0.0119***	0.0102***	0.0093***
	(0.0007)	(0.0020)	(0.0005)	(0.0005)
Controlled Variable	control	control	control	control
Industry Fixed Effect	yes	yes	yes	yes
Year Fixed Effect	yes	yes	yes	yes
Provincial Fixed Effect	deny	deny	deny	yes
Sample Size	15,603	18,230	18,230	18,230
Adjust R^2	0.1612	0.1478	0.3615	0.3741

Note: Values in parentheses represent the robust standard deviation; column (2) shows the cluster-standard error at the firm level; ***, **, and * indicate significance at the 1%,5%, and 10% levels, respectively.

5.3.3. Endogeneity Test: Instrument Variable Method

To further address potential reverse causality and omitted variable issues between AI adoption and corporate resilience, this study employs the instrumental variable method for endogeneity testing.

Following established methodologies (Wang Shuo et al., 2024; Li Rongrong & Yang Rui, 2026; Li Bin et al., 2025), we use the average AI adoption level of all enterprises within the same province and year (excluding the target firm) as the instrumental variable, denoted as IV.AI_proyr. On one hand, firms within the same province share similar digital infrastructure, policy environments, and technology diffusion conditions; thus, other firms 'AI adoption levels can influence the target firm's adoption through regional technological spillovers, imitation learning, and competitive pressures, satisfying the instrumental variable relevance requirement. On the other hand, this variable eliminates the impact of the target firm's own AI capabilities during construction—since other firms' AI adoption typically does not directly affect corporate resilience but rather influences it indirectly through its impact on the target firm's AI adoption, thereby exhibiting exogenous characteristics.

Table 7 results show that in the first stage, the estimated coefficient of the instrumental variable IV_AI_proyr is 0.5727 and significant at the 1% level, indicating a significant correlation between the instrumental variable and corporate AI adoption. The Kleibergen-Paaprk-Wald F-statistic is 68.277, exceeding the critical value of 16.38 under the Stock-Yogo 10% significance threshold, confirming no weak instrumental variable problem exists. The Kleibergen-Paaprk-LM statistic is 64.339 and significant at the 1% level, demonstrating no model identification problem. The second-stage results reveal an estimated coefficient for artificial intelligence of 0.0382, also significant at the 1% level, indicating that even after accounting for potential endogeneity issues, AI adoption still significantly enhances corporate resilience, thereby reinforcing the core conclusions of this study.

Table 7. Test Results Using the Tool Variable Method

Variable	AI	Resilience
IV_AI_proyr	0.5727*** (8.26)	
AI		0.0382*** (3.80)
Controlled Variable	control	control
Industry Fixed Effect	yes	yes
Year Fixed Effect	yes	yes
Sample Size	18,230	18,230
Kleibergen-Paap rk LM	64.339***	
Kleibergen-Paap rk Wald F	68.277	
Anderson-Rubin Wald test	14.68***	

Note: Values in parentheses represent the robust standard deviation; ***, **, and * indicate significance at the 1%,5%, and 10% levels, respectively.

6. Mechanism Testing

6.1. Artificial Intelligence and Corporate Resilience: A Mechanism Test Based on Internal Control

Columns (1) and (2) of Table 8 examine the mechanism through which internal control influences corporate resilience under artificial intelligence (AI) impact. Column (1) reveals that the regression coefficient between AI and internal control (IC) is 0.0135, statistically significant, indicating that AI application significantly enhances corporate internal control effectiveness. Column (2) further shows a regression coefficient of 0.0117 between internal control and corporate resilience, significant at the 1% level, demonstrating that higher internal control quality correlates with stronger corporate resilience. Notably, even after incorporating internal control variables, the AI-regression coefficient remains significantly positive, suggesting that internal control does not fully absorb AI's impact on resilience—AI exerts a direct effect. Thus, internal control serves as a mediating factor in AI-driven corporate resilience enhancement, albeit partially rather than fully. Existing research indicates that digital transformation promotes high-quality corporate development by improving internal control and social responsibility performance (Zhang Ruichen et al., 2023), while also significantly enhancing internal control quality (Hua Junguo et al., 2025). This is because AI improves information processing efficiency, risk identification capabilities, and process standardization, thereby elevating internal control quality; conversely, robust internal controls help mitigate information asymmetry and operational risks, enabling companies to rapidly allocate resources and adjust strategies during external shocks, ultimately strengthening corporate resilience.

6.2. Artificial Intelligence and Corporate Resilience: A Mechanism Analysis Based on Talent Incentives

Columns (3) and (4) of Table 8 examine the mediating effects of talent incentive mechanisms. Column (3) reveals that the regression coefficient for artificial intelligence on talent incentives (Peop) is 0.0116, statistically significant, indicating that AI application significantly enhances corporate talent incentive levels. Column (4) shows a regression coefficient of 0.1466 for talent incentives on organizational resilience, which is significant at the 1% level, demonstrating that higher talent incentive levels correlate with stronger organizational resilience. Furthermore, after incorporating the talent incentive variable, the regression coefficient between AI and organizational resilience remains significantly positive, suggesting that talent incentives do not fully replace AI's direct impact on organizational resilience but rather serve as a partial mediator. Niu Hua et al. (2024) argue that digital transformation drives high-quality corporate development by promoting upgrades in human capital structure; Bresnahan et al. (2002) also found that IT adoption increases demand for highly skilled workforce and drives organizational restructuring. Specifically, AI applications elevate enterprises' demand for digital professionals, technical experts, and interdisciplinary talents, prompting companies to optimize compensation incentives, performance evaluations, and promotion mechanisms, thereby enhancing employee motivation and organizational cohesion. When facing external uncertainties, robust talent incentive mechanisms strengthen employees' adaptability and organizational synergy efficiency, ultimately improving corporate resilience and recovery capabilities.

6.3. Artificial Intelligence and Corporate Resilience: A Mechanism Test Based on Technological Innovation

Columns (5) and (6) of Table 8 present the estimation results for technological innovation mechanisms. Column (5) shows that the regression coefficient of artificial intelligence on technological innovation (Inn) is 0.2701, significant at the 1% level, indicating that AI significantly promotes corporate technological innovation. Column (6) further reveals that the regression coefficient of technological innovation on corporate resilience is 0.0293, also significant at the 1% level, demonstrating that stronger technological innovation capabilities correlate with higher corporate resilience. Notably, after incorporating the technological innovation variable, the AI's positive coefficient for corporate resilience remains significant but decreases compared to the baseline regression, suggesting that technological innovation partially absorbs the impact of AI on corporate resilience without fully capturing it. Thus, technological innovation plays a distinct partial mediating role in how AI enhances corporate resilience. Existing research also confirms that AI applications significantly drive corporate innovation through mechanisms such as knowledge spillover, optimization of human capital structure, and efficient allocation of innovation resources (Fang Haochao, 2024). From the perspective of digital innovation theory, digital technologies have transformed the organizational logic of corporate innovation activities, enabling knowledge, data, and technical modules to be recombined and integrated into R&D processes (Yoo et al., 2010; Nambisan et al., 2017). The underlying mechanism lies in AI's ability to enhance R&D efficiency, reduce trial-and-error costs, and shorten product/technology iteration cycles through data mining, algorithmic optimization, and intelligent decision-making. Enhanced technological innovation capabilities enable enterprises to more rapidly implement product substitutions, process adjustments, and resource reorganization when facing changing demands, supply chain disruptions, or market competition pressures, thereby strengthening their resilience.

6.4. Artificial Intelligence and Corporate Resilience: A Mechanism Test Based on Administrative Costs

Columns (7) and (8) of Table 8 examine the mechanism through which management costs influence corporate resilience under artificial intelligence (AI) impact. Column (7) reveals that the regression coefficient for AI on management costs (Mfee) is-1.3428, statistically significant, indicating that AI application significantly reduces corporate management expenses. Column (8) shows a regression coefficient of-0.0013 for management costs on corporate resilience, significant at the 1% level, suggesting higher management costs correlate with weaker corporate resilience. Notably, even after incorporating management costs as a variable, the AI's positive correlation with resilience remains statistically significant, demonstrating that management costs do not fully explain AI's impact on resilience—AI continues to enhance corporate resilience via other direct or indirect pathways. Thus, management costs play a partial mediating role in AI's effect on corporate resilience. Specifically, AI reduces repetitive management tasks through process automation, intelligent decision-making, and digital management, lowering organizational coordination and information transmission costs; meanwhile, reduced management costs free up resources for risk mitigation, technological upgrades, and operational adjustments, thereby improving resource allocation efficiency and strengthening enterprises' resilience against external shocks. Tan Zhidong et al. (2022) found from the perspective of corporate cash holdings that digital transformation enhances the value of corporate cash reserves and strengthens financial resilience under both transactional and precautionary motivations; Mithas et al. (2011) also demonstrated that information management capabilities improve corporate performance by optimizing process, customer, and performance management.

Table 8. Testing the Mechanisms by Which Artificial Intelligence Influences Corporate Resilience

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IC	Resilience	Peop	Resilience	Inn	Resilience	Mfee	Resilience
AI	0.0135*	0.0117***	0.0116***	0.0102***	0.2701***	0.0040***	-1.3428***	0.0101***
	(18.182)	(22.558)	(15.110)	(27.690)	(7.955)	(-28.818)	(15.150)	(1.925)
IC		0.0117***						
		(16.854)						
Peop				0.1466***				
				(9.536)				
Inn						0.0293***		
						(48.630)		
Mfee								-0.0013***
								(-24.989)
Controlled Variable	control	control	control	control	control	control	control	control
Industry Fixed Effect	yes	yes	yes	yes	yes	yes	yes	yes
Year Fixed Effect	yes	yes	yes	yes	yes	yes	yes	yes
Sample Size	18,230	18,230	18,230	18,230	18,230	18,230	18,230	18,230
Adjust R^2	0.0073	0.1680	0.0898	0.1567	0.1875	0.4188	0.2620	0.1627

Note: Values in parentheses represent the robust standard deviation; ***, **, and * indicate significance at the 1%,5%, and 10% levels, respectively.

6.5. Bootstrap Mediation Effect Test

To further enhance the reliability of mediation effect estimation results, we adopted the Bootstrap mediation testing methodology proposed by Preacher and Hayes (2008) and Hayes (2013), conducting repeated sampling tests for indirect effects. Specifically, we performed 1,000 repeated sampling trials using cluster sampling at the firm level to examine the indirect effects of four mechanism pathways: internal control, talent incentives, technological innovation, and management expenses. A significant mediation effect is indicated when the Bootstrap 95% bias-corrected confidence interval does not include zero.

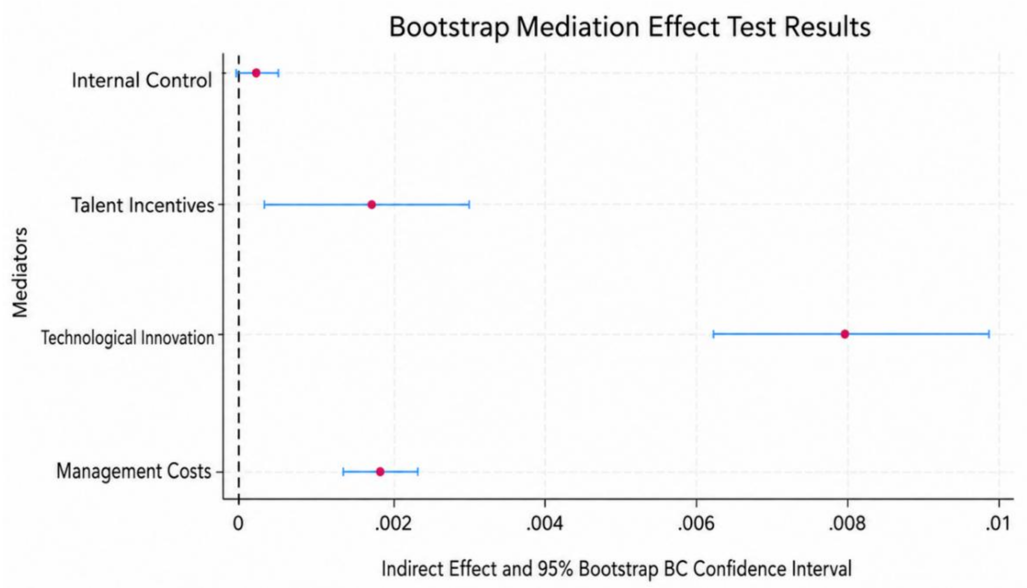

Figure 1. Results of the bootstrap mediation effect test

Note: Dots represent estimated indirect effects; horizontal lines indicate 95% confidence intervals adjusted for bias based on 1,000 Bootstrap replicates. Dashed lines show the zero-effect baseline. If a confidence interval crosses zero, the mediating effect is not significant.

The Bootstrap test results indicate that the indirect effect of the internal control pathway is 0.0001995, with a 95% bias-adjusted confidence interval of [-0.0000412,0.0004878], which includes zero, demonstrating that the mediating effect of internal control does not pass the Bootstrap significance test. The indirect effect of the talent incentive pathway is 0.0016971, with a 95% bias-adjusted confidence interval of [0.0003188,0.0029643], excluding zero, indicating that talent incentives play a significant mediating role in how artificial intelligence enhances corporate resilience. The indirect effect of the technological innovation pathway is 0.0079195, with a 95% bias-adjusted confidence interval of [0.0062356,0.0098816], also excluding zero and exhibiting the highest value among all pathways, confirming that technological innovation serves as the primary mechanism through which AI improves corporate resilience. The indirect effect of the management expense pathway is 0.0018070, with a 95% bias-adjusted confidence interval of [0.0014426,0.0022612], similarly excluding zero, suggesting that artificial intelligence enhances corporate resilience by reducing management costs and improving operational efficiency.

Overall, the Bootstrap test further demonstrates that the mediating effects of the three pathways—talent incentives, technological innovation, and management costs—are statistically significant, with the indirect effect of the technological innovation pathway being the most pronounced and serving as the primary mechanism through which artificial intelligence enhances corporate resilience. In contrast, although the indirect effect of the internal control pathway is positive, its Bootstrap bias-corrected confidence interval includes zero, indicating that it does not exhibit a robust mediating effect. Consequently, Hypotheses 2b,2c, and 2d are supported, while Hypothesis 2a is not supported by the Bootstrap test.

7. Heterogeneity Test

To further examine the scope of how artificial intelligence impacts corporate resilience, this study conducts heterogeneity tests across dimensions such as corporate and industry characteristics.

7.1. Differences in Property Rights Nature: The Amplifying Effect of Resources and Governance Capacity

From the perspective of property rights structure, this study categorizes firms into state-owned enterprises (SOEs) and non-state-owned enterprises based on their ultimate controlling ownership, conducting separate regressions to compare how artificial intelligence enhances resilience across different ownership types. Table 9-1 reveals that AI has a significantly positive impact on resilience in both groups: the AI coefficient for SOEs is 0.0142, while that for non-SOEs is 0.0096, indicating stronger reinforcement effects for SOEs. Inter-group comparison tests show a statistically significant difference (P = 0.0069), likely due to SOEs 'superior resource acquisition capabilities, policy support, and fewer constraints in digital infrastructure development, technological investment, and data integration—factors facilitating AI integration into operational processes. This aligns with findings from digital transformation research regarding ownership differences. The impact of digital transformation on high-quality corporate development varies across ownership types, reflecting how resource foundations, governance structures, and institutional support shape digital technology's value realization (Niu et al., 2024). Moreover, SOEs' robust governance frameworks and organizational coordination mechanisms reduce implementation uncertainties, enabling AI to enhance risk identification, shock response, and operational recovery capabilities—thereby amplifying its resilience-improving effects.

7.2. Differences in Enterprise Size: The Synergistic Effect of Scale Economics and Data Factors

To examine whether the impact of artificial intelligence on corporate resilience exhibits heterogeneity across firm sizes, this study divided the sample into large and small firms based on the median firm size variable and conducted separate group regressions. Table 9-1 shows that AI has a significantly positive effect on resilience in both large and small firms: the AI coefficient was 0.0194 for large firms and 0.0027 for small firms, indicating a more pronounced positive effect on large firms. From the perspective of absorptive capacity theory, a firm's ability to identify, absorb, and utilize external knowledge influences the realization of technological benefits (Cohen & Levinthal, 1990). Large firms typically possess richer data resources, greater technological investment, and more specialized talent, enabling them to more effectively apply AI in risk identification, resource integration, and organizational recovery. Further intergroup comparison tests revealed a statistically significant difference (P = 0.0000), demonstrating strong scale dependence in how AI enhances corporate resilience. The reason may lie in the fact that large-scale enterprises typically possess richer data resources, more robust digital infrastructure, and stronger financial capacity, enabling them to cover the upfront costs required for AI implementation and integrate AI technologies across various operational areas—including production processes, supply chain management, and crisis response—thereby more effectively enhancing systemic resilience. In contrast, small-scale enterprises, constrained by limited data foundations, capital investment, and technical talent reserves, are more likely to confine their AI applications to localized optimizations or isolated improvements, with relatively limited impact on overall organizational resilience.

7.3. Regional Differences: Marginal Improvement and Development Stage Effects

Tan Zhidong et al. (2022) pointed out that the realization of digital transformation value is influenced not only by internal factors such as corporate scale but also by external factors like regional digital environments. Differences across regions in digital infrastructure, policy support, market maturity, and technology diffusion ecosystems may lead to varying effects of artificial intelligence on corporate resilience. Considering disparities in digital economic development levels, industrial foundations, and resource endowments among regions, this study further categorized samples by corporate registration locations into eastern, central, and western regions for analysis. Table 9-1 results demonstrate that AI significantly enhances corporate resilience across all three regions: 0.0146 for western regions, 0.0098 for eastern regions, and 0.0060 for central regions, indicating stronger

AI-driven resilience improvements in western areas. Inter-regional comparisons revealed a statistically significant difference (P=0.0004), with pairwise analyses showing marked differences between central and eastern regions, as well as between western and central regions, while no significant difference was observed between western and eastern regions. These findings suggest regional heterogeneity: AI's impact on corporate resilience is relatively weaker in central regions compared to eastern and western regions, potentially reflecting marginal improvement effects. For enterprises in western regions with relatively weaker development foundations, the adoption of artificial intelligence can yield significant marginal benefits in enhancing production efficiency, optimizing information processing, improving resource allocation, and strengthening risk identification capabilities, thereby substantially boosting their ability to withstand external shocks and resume business operations. In eastern regions, where the digital economy is more advanced and corporate digital infrastructure along with technological application capabilities are relatively well-developed, AI's role primarily involves optimization and enhancement based on existing foundations. In contrast, central regions may face challenges stemming from differences in industrial structure, technology absorption capacity, and digital infrastructure, resulting in an underutilized potential for AI in enhancing corporate resilience.

Table 9-1 Heterogeneity test on the impact of artificial intelligence on corporate resilience (across firms and regions)

Variable	State-Owned Enterprise	Non-State-Owned Enterprises	Large-Scale	Small-Scale	East	Central	West
AI	0.0142***	0.0096***	0.0194***	0.0027***	0.0098***	0.0060***	0.0146***
	(0.0013)	(0.0005)	(0.0002)	(0.0009)	(0.0006)	(0.0011)	(0.0023)
Controlled Variable	control	control	control	control	control	control	control
Industry Fixed Effect	yes	yes	yes	yes	yes	yes	yes
Year Fixed Effect	yes	yes	yes	yes	yes	yes	yes
Sample Size	4915	13314	8438	9791	13337	2848	1952
Adjust R^2	0.394	0.345	0.469	0.422	0.382	0.329	0.355
P-value for Difference Test	0.0069***		0.0000***		0.0004***		

Note: Values in parentheses represent the robust standard deviation; ***, **, and * indicate significance at the 1%,5%, and 10% levels, respectively.

7.4. Differences in Technical Attributes: Mechanisms of Technological Complementarity and Innovation-Driven Development

The technological attributes of an industry may influence the effectiveness of artificial intelligence in enhancing corporate resilience. This study categorizes firms into high-tech and non-high-tech enterprises based on their industry classification, conducting separate group regressions. Table 9-2 reveals that AI has a significantly positive impact on resilience for both groups: the AI coefficient is 0.0098 for high-tech firms and 0.0066 for non-high-tech firms, indicating a stronger promotional effect of AI on resilience in high-tech enterprises. Further inter-group comparison tests show a statistically significant difference (P = 0.0002), demonstrating a strong complementary relationship between AI adoption and existing technological foundations. High-tech firms typically possess more robust R&D systems, enhanced technology absorption capabilities, and superior talent pools, enabling seamless integration of AI into R&D design, production optimization, and innovation management processes. This improves knowledge integration efficiency, research productivity, and risk identification capacity, thereby strengthening dynamic adaptability and resilience in uncertain environments. Digital innovation theory posits that digital technologies exhibit reconfigurability, modularity, and cross-scenario applicability, fundamentally transforming the organizational logic of corporate innovation activities (Yoo et al., 2010; Nambisan et al., 2017). Therefore, in industries with higher technological intensity, richer data resources, or stronger innovation demands, artificial intelligence is more likely to translate into corporate resilience advantages through knowledge reorganization and process optimization. In contrast, non-high-tech enterprises typically have weaker technical foundations and digital application capabilities, so AI adoption tends to remain limited to localized management improvements or single-process enhancements, making it difficult to fully realize its technological empowerment potential.

7.5. Differences in Pollution Characteristics: Regulatory Constraints and Resourcecrowding Effects

The pollution nature may also influence the effectiveness of artificial intelligence in enhancing corporate resilience. This study categorized firms into heavy-pollution and non-heavy-pollution groups based on their industry classification, conducting group-specific regression analyses. Table 9-2 reveals that artificial intelligence has a significantly positive impact on resilience for both groups: the AI coefficient was 0.0056 for heavy-pollution firms and 0.0082 for non-heavy-pollution firms, indicating a more pronounced positive effect on the latter. Further inter-group comparison tests showed a statistically significant difference (P = 0.0000), confirming substantial variations in coefficient values between the two groups.

This disparity may stem from resource allocation constraints and cost displacement effects imposed by environmental regulations. Heavy-polluting enterprises typically face stricter environmental oversight and higher compliance costs, requiring greater investments in pollution control, equipment upgrades, and compliance measures, which to some extent reduces funding for AI technology adoption, digital infrastructure development, and recruitment of highly skilled talent. Moreover, production processes in heavy-polluting industries often exhibit strong asset specificity and technological path dependence, making intelligent transformation challenging in the short term and limiting AI's potential to optimize production, predict risks, and allocate resources effectively. In contrast, non-heavy-polluting enterprises experience relatively lower regulatory pressures and enjoy greater flexibility in resource allocation, enabling them to more readily leverage AI applications to enhance corporate resilience.

Table 9-2 Heterogeneity test on the impact of artificial intelligence on corporate resilience (by industry attribute)

Variable	High-Tech	Non-High-Tech	Pollution	Non-Pollution
AI	0.0098***	0.0066***	0.0056***	0.0082***
	(0.0006)	(0.0007)	(0.0009)	(0.0006)
Controlled Variable	control	control	control	control
Industry Fixed Effect	yes	yes	yes	yes
Year Fixed Effect	yes	yes	yes	yes
Sample Size	14238	3992	4839	13391
Adjust R^2	0.387	0.290	0.344	0.399
P-value for Difference test	0.0002***		0.0000***	

Note: Values in parentheses represent the robust standard deviation; ***, **, and * indicate significance at the 1%,5%, and 10% levels, respectively.

8. Research Conclusions and Policy Recommendations

8.1. Research Conclusion

Against the backdrop of continuously rising uncertainties in the global economic environment, supply chain disruptions faced by manufacturing enterprises, technological transformations, and fluctuations in market demand, enhancing corporate resilience has become a critical issue for promoting high-quality development in the manufacturing sector. This study uses China A-share listed manufacturing companies from 2015 to 2024 as the research sample, constructs an indicator of corporate AI application levels based on annual report texts, and calculates a comprehensive corporate resilience index across three dimensions: resistance capacity, recovery capacity, and innovation capability, systematically examining the impact of AI application on corporate resilience and its underlying mechanisms. The study yields the following key conclusions.

First, AI applications can significantly enhance the resilience of manufacturing enterprises. Benchmark regression results demonstrate that AI has a markedly positive impact on corporate resilience, indicating that higher levels of AI adoption correlate with stronger capabilities in risk identification, shock absorption, operational recovery, and sustained innovation. Through data analysis, intelligent forecasting, and process optimization, AI improves enterprises 'responsiveness to external shocks and resource allocation efficiency, thereby enhancing their adaptability in uncertain environments. Furthermore, this study validates its conclusions by substituting core explanatory variables, excluding specific sample cases, employing clustered standard errors, adding control variables, and incorporating provincial fixed effects. Substitution analyses reveal that AI may increase profit volatility in the short term, suggesting differential impacts across resilience dimensions. Instrumental variable tests also confirm that AI's positive effect on corporate resilience remains significant even after accounting for potential endogeneity issues, demonstrating strong reliability of the findings.

Second, artificial intelligence primarily influences corporate resilience through three robust mechanisms: talent incentives, technological innovation, and management costs. Econometric tests demonstrate that AI applications enhance the allocation of high-caliber talent, strengthen employees' adaptability and organizational collaboration efficiency; drive technological innovation to improve product updates, process optimization, and sustainable growth capabilities in response to market fluctuations and external shocks; and reduce management costs by minimizing internal coordination expenses and operational friction, thereby providing greater resource buffers for risk mitigation and business recovery. Bootstrap mediation tests further reveal that the bias correction confidence intervals for all three mechanisms—including talent incentives, technological innovation, and management costs—exclude zero, confirming their strong robustness. Among these, technological innovation exhibits the strongest indirect effect, serving as the primary transmission mechanism through which AI enhances corporate resilience. In contrast, while AI improves internal control effectiveness, its mediation effect via the internal control pathway shows a zero-value bootstrap confidence interval, indicating insufficient robustness.

Third, the impact of artificial intelligence on corporate resilience exhibits significant heterogeneity. In terms of property rights structure, AI demonstrates a more pronounced positive effect on the resilience of state-owned enterprises, indicating that resource acquisition capabilities, policy support, and governance foundations influence its empowering effects. Regarding enterprise size, AI shows greater efficacy in enhancing the resilience of small-scale enterprises, suggesting these firms may achieve substantial marginal improvements through AI adoption. From a regional perspective, AI has a more notable impact on corporate resilience in western regions, highlighting how its application can leverage late-mover advantages in areas with relatively weaker digital infrastructure but substantial development potential. By industry type, AI exerts stronger promotional effects on high-tech enterprises and non-heavy-polluting industries, demonstrating that stronger existing technological foundations and fewer external constraints facilitate greater transformation of AI into enhanced corporate resilience.

8.2. Policy Recommendations

Based on the aforementioned research findings, this paper proposes the following policy recommendations.

First, the government should enhance the foundational environment for AI-driven manufacturing development. The enhancement of corporate resilience through AI relies on robust digital infrastructure, abundant data resources, and practical application scenarios. Therefore, efforts should be accelerated to develop industrial internet platforms, data centers, intelligent computing platforms, and digital public service platforms for manufacturing, thereby reducing technical barriers and costs for enterprises adopting AI. Concurrently, improvements should be made in data circulation mechanisms, data security governance frameworks, and algorithmic application standards to create a stable, secure, and open institutional ecosystem for AI adoption. In manufacturing clusters, regional AI service platforms and smart manufacturing demonstration bases should be established to facilitate broader implementation of AI technologies across various manufacturing contexts.

Second, manufacturing enterprises should integrate artificial intelligence into their long-term development strategies. Companies must not view AI merely as a tool for partial technological upgrades, but rather embed it throughout the entire process of production operations and risk management. Specifically, enterprises can apply AI technologies in areas such as risk early warning, intelligent production scheduling, supply chain management, inventory control, quality inspection, customer demand forecasting, and business decision-making to enhance their ability to perceive external environmental changes and respond more swiftly. By deeply integrating AI with business processes, companies can more effectively identify potential risks, optimize resource allocation, and improve operational resilience.

Third, enterprises should leverage AI applications to optimize talent structures and enhance organizational capabilities. Whether AI can truly become a competitive advantage for enterprises depends not only on technological investment but also on the availability of high-caliber professionals capable of understanding, applying, and managing AI. Manufacturing companies should prioritize the needs of intelligent transformation by intensifying efforts to recruit and cultivate digital specialists, technical experts, and interdisciplinary talents. They should establish comprehensive compensation systems, performance evaluation frameworks, career advancement pathways, and long-term incentive mechanisms to boost employee engagement in digital transformation and innovation initiatives. Additionally, enterprises must strengthen cross-departmental collaboration by fostering coordinated approaches among R&D, production, supply chain, finance, and management teams regarding AI implementation, enabling employees to swiftly identify issues, develop solutions, and restore operational stability during external disruptions.

Fourth, enterprises should strengthen artificial intelligence's role in supporting technological innovation and operational efficiency. Technological innovation serves as a critical foundation for manufacturing companies to adapt to market changes and external shocks. Enterprises should actively apply AI across key areas such as R&D design, patent analysis, process optimization, product iteration, quality control, and market forecasting. By leveraging data analytics and intelligent decision-making, they can shorten development cycles, reduce trial-and-error costs, enhance innovation efficiency, and thereby bolster sustainable growth capabilities in uncertain environments. Additionally, AI should be utilized to streamline management processes, minimize repetitive tasks, and lower internal coordination costs, driving digital transformation in areas including office approvals, production scheduling, inventory management, supply chain collaboration, and customer engagement. Higher operational efficiency coupled with lower management costs enables companies to allocate more resources, providing stronger financial resilience and recovery capacity when facing market fluctuations, supply chain volatility, or operational pressures.

Fifth, enterprises should continue to prioritize the development of internal control and risk governance systems. While artificial intelligence's role in enhancing corporate resilience primarily lies in areas such as talent development, innovation, and operational efficiency, robust internal controls remain a fundamental pillar for sustainable business operations. Manufacturing enterprises implementing AI applications should concurrently strengthen mechanisms for risk identification, financial monitoring, compliance review, data security, and process management to prevent issues like internal management chaos, data risks, or reckless expansion resulting from premature technology adoption. By integrating intelligent monitoring, risk alerts, and standardized processes into daily governance frameworks, companies can enhance the standardization and transparency of decision-making, thereby establishing a solid foundation for improved organizational resilience.

Sixth, targeted support policies should be implemented tailored to different enterprise types and regional characteristics. For small-scale enterprises, priority should be given to reducing AI implementation costs by providing modular, low-barrier technical services and digital training programs, enabling them to maximize the marginal benefits of technology adoption. For enterprises in western regions, efforts should be intensified to develop digital infrastructure and enhance technical service offerings, positioning artificial intelligence as a key tool for narrowing regional development gaps. For non-state-owned enterprises, the financing environment and technical support systems should be improved to alleviate funding and resource constraints during their digital transformation. For heavily polluting enterprises, guidance should be provided to apply AI in green production, energy consumption management, and pollution monitoring, thereby improving production efficiency and corporate resilience while complying with environmental standards.

In summary, artificial intelligence has become a key driver for manufacturing enterprises to enhance their resilience. Governments should lower the barriers to corporate digital transformation across infrastructure, institutional frameworks, and public services, while enterprises should systematically advance AI adoption through strategic planning, talent development, technological innovation, operational efficiency, and risk management. Only by fostering deep integration of AI with manufacturing can technological advantages be truly transformed into resilient capabilities that enable enterprises to withstand uncertain shocks.

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