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Research on the Impact of Artificial Intelligence on Enterprise Resilience

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Abstract

This paper uses A-share listed companies in Shanghai and Shenzhen from 2014 to 2023 as the research sample to empirically examine the impact effect of artificial intelligence on enterprise resilience, its underlying mechanisms, endogeneity tests, and heterogeneity analysis. The study finds that artificial intelligence has a significant inhibitory effect on enterprise resilience, and this core conclusion remains valid after endogeneity and robustness tests. The mechanism test results indicate that artificial intelligence inhibits enterprise resilience through three pathways: increasing the level of financing constraints, enhancing the intensity of R&D investment, and raising the management expense ratio. The heterogeneity test results further reveal the differences in its inhibitory effects, showing that artificial intelligence has a more pronounced inhibitory impact on enterprise resilience in the eastern region, in non-manufacturing industries, and among heavily polluting enterprises. This paper breaks through the current mainstream research' s singular optimistic perspective on the application of artificial intelligence, revealing its potential risks to the sustainable development of enterprises, and provides empirical evidence and decision-making references for enterprises to rationally promote digital transformation.

Keywords

artificial intelligence, enterprise resilience, financing constraints, R&D investment intensity, management expense ratio

1. Introduction

Currently, the new round of technological revolution represented by artificial intelligence is profoundly influencing the global economy and international landscape. China has elevated artificial intelligence to the height of national strategy, positioning it as the core driving force of new quality productive forces, and incorporating it into important policies such as the "14th Five-Year" Plan for Digital Economy Development [1]. Under this background, enterprises, as the main body of economic development and key forces of innovation, whether they can effectively respond to and integrate artificial intelligence not only concerns their own survival but also relates to industrial transformation and national economic development [2].

Artificial intelligence is at a critical stage of transitioning from technological innovation to industrial integration. At the macro level, the artificial intelligence industry has expanded rapidly in scale and, driven by policy initiatives, has empowered a wide range of industries. At the micro level, artificial intelligence has been deeply integrated into areas such as efficiency improvement in manufacturing and disciplinary development, continuously giving rise to new forms of business [3]. However, its development still faces challenges such as weak foundational technologies, reliance on foreign algorithms, shortage of high-end talents, high funding costs, and imperfect governance systems [4]. The impact of artificial intelligence also has duality: while enhancing productivity, it may exacerbate gaps between enterprises; while improving efficiency, it may lead to labor substitution. Therefore, its development path needs to be carefully planned.

At the same time, enterprise resilience has increasingly become a focus of attention in both academic and practical circles. In a complex and changeable environment, how to build and maintain resilience has become the key to enterprises' sustainable survival and competition [5]. Today, the goal of enterprise resilience has shifted from "restoring to the original state" to "achieving evolution and prosperity amid turbulence." However, its construction still faces issues such as difficulty in quantifying resilience, limitations in managerial cognition, decision-making difficulties, and the potential for excessive digitization to trigger new vulnerabilities. Strong enterprise resilience is not only a guarantee of survival but also an important competitive advantage for winning long-term market positions and customer trust [6].

Although there is a substantial body of research on artificial intelligence and enterprise resilience respectively, the literature that integrates the two and systematically examines their relationship remains limited. Existing studies mostly emphasize the positive impacts of artificial intelligence, with insufficient attention to the enterprise vulnerabilities it may trigger; theoretically, there is a lack of analysis from the micro-enterprise perspective on the transmission mechanisms through which artificial intelligence affects enterprise resilience; practically, due to issues such as low resource allocation efficiency, digital divide, and imprecise policy support, artificial intelligence has not effectively enhanced enterprise resilience and may even exacerbate survival pressures.

To this end, this paper takes A-share listed companies in Shanghai and Shenzhen from 2014 to 2023 as samples to study the impact of artificial intelligence on enterprise resilience. Through fixed effects models, instrumental variable methods, and propensity score matching methods, it systematically examines its mechanisms and heterogeneity. The core research questions include: How does artificial intelligence affect enterprise resilience? Do financing constraints, R&D investment intensity, and management expense ratio play mediating roles? Does this impact vary by region, industry, and enterprise characteristics? The innovations of this paper lie in: first, breaking through the existing optimistic bias toward artificial intelligence, empirically testing its inhibitory effect on enterprise resilience, and enriching the theoretical research on technological shocks and enterprise resilience; second, simultaneously verifying the three mechanism paths of financing constraints, R&D investment intensity, and management expense ratio, providing a more comprehensive internal logic analysis; third, based on heterogeneity analysis results, identifying the differentiated impacts of artificial intelligence in different contexts, thereby providing targeted resilience-building suggestions for various enterprises to avoid weakening long-term survival capabilities due to blind promotion of digitization.

2. Theoretical Analysis and Research Hypotheses

2.1 Artificial Intelligence and Enterprise Resilience

Under the dual background of increasing environmental uncertainty and deepening penetration of digital technologies, enterprise resilience, as a core capability for resisting risks and achieving sustainable development, is closely related to the integration process of artificial intelligence. Artificial intelligence is shifting from tool-based applications to deep integration with core enterprise processes. Traditional research has mostly focused on its empowering role, but the integration process inevitably involves reconstruction of structures, resources, and capabilities, so the impact of artificial intelligence on enterprise resilience is not a simple linear promotion [7]. This paper argues that this impact is essentially a paradoxical dynamic process of resource reallocation and capability reconstruction, where its introduction may disrupt the existing enterprise balance and thereby inhibit resilience. The following analysis is conducted by combining stakeholder theory, strategic management theory, and dynamic development theory.

First, based on stakeholder theory, enterprise resilience depends on the balance and coordination of demands from stakeholders such as shareholders, customers, and employees [8]. The introduction of artificial intelligence will reshape internal and external interest patterns, easily triggering conflicts and eroding trust. At the internal level, intelligent substitution of low-skilled positions may lead to decreased employee identification and labor-capital conflicts; enterprises often tilt resources toward technical departments to promote artificial intelligence, compressing employee welfare and training, thus weakening organizational cohesion [9]. At the external level, automated services may reduce service warmth and damage customer trust, while deep dependence on supply chains may raise partners' concerns about data sovereignty. Management attention focused on technical aspects and high-end talents may neglect other stakeholder demands, making it difficult for enterprises to integrate resources when facing shocks, thereby weakening the foundation of resilience.

Second, based on strategic management theory, under resource-limited conditions, the optimal allocation of strategic resources is key to maintaining enterprise resilience. The introduction of artificial intelligence easily leads to resource misallocation: on one hand, its early-stage investments are huge with long return cycles, and continuous equipment updates, system upgrades, and talent introductions will crowd out resources needed for operations, diversified business cultivation, and non-artificial intelligence explorations; on the other hand, the enterprise's core competitiveness may shift to heavy reliance on specific data and algorithms, making it vulnerable when facing macro risks unrelated to artificial intelligence, such as public health events or geopolitical conflicts, due to lack of resource buffers and alternative capabilities, manifesting as strategic singularization weakening resilience [10].

Finally, based on dynamic development theory, enterprises are complex adaptive systems that co-evolve with technology, organization, and environment [11]. Healthy enterprise development requires approximate synchronization of organization, technology, personnel, and systems. However, the development speed of artificial intelligence often exceeds enterprises' organizational learning and debugging capabilities, causing technology to advance while systems lag, specifically manifesting as: established decision-making processes and hierarchical structures mismatched with the agility required by artificial intelligence, increasing coordination costs; employee skill updates lagging behind technological iterations, forming a human resource dilemma; and relevant laws, ethics, and industry norms remaining imperfect, exposing enterprises to compliance risks [12-14]. Thus, heavy investments in artificial intelligence and deep binding with core businesses easily form path dependence, limiting strategic adjustment flexibility in responding to external changes, damaging adaptation and recovery potential, and thereby weakening enterprise resilience.

Based on this, this paper proposes the hypothesis:

H1: Artificial intelligence has a significant inhibitory effect on enterprise resilience.

2.2 Artificial Intelligence, Financing Constraints, and Enterprise Resilience

Financing constraints reflect the financing difficulty and pressure faced by enterprises, which are important factors restricting their investments and long-term development [15]. As a strategic investment, artificial intelligence's unique attributes may worsen the enterprise financing environment, thereby weakening the financial foundation needed to build enterprise resilience.

Artificial intelligence investments have characteristics of high sunk costs, long return cycles, strong specificity, and low collateral value, easily exacerbating information asymmetry between enterprises and external investors [16]. According to pecking order financing theory, investors thus demand higher risk premiums, leading to increased financing costs and restricted channels for enterprises, thereby elevating financing constraint levels [17].

Financing constraints will weaken enterprise resilience from two aspects: first, directly eroding enterprise resource reserves, crowding out financial buffers available for responding to sudden risks and inhibiting short-term shock resistance; second, constraining long-term resilience construction, making key strategic investments such as emergency technology R&D and supply chain diversification difficult to advance due to insufficient funds, leading to a single business structure for enterprises and trapping them in passive risk response dilemmas [18].

Based on this, this paper proposes the hypothesis:

H2: Artificial intelligence inhibits enterprise resilience by increasing the level of financing constraints.

2.3 Artificial Intelligence, R&D Investment Intensity, and Enterprise Resilience

R&D investment is the core of enterprise innovative development, and its rational allocation directly concerns long-term competitiveness. Artificial intelligence, as a technological frontier, often attracts massive R&D resources from enterprises, and this unidirectional focus may lead to structural imbalances in resource allocation, thereby weakening the technological foundation needed to build enterprise resilience.

The transmission mechanism through which artificial intelligence increases R&D investment intensity mainly includes two aspects: first, from the perspective of technological competition, enterprises will continuously increase related R&D investments, such as algorithm optimization and system upgrades, to establish and maintain advantages in the artificial intelligence field and seize market opportunities; second, from the perspective of resource allocation, under resource-limited constraints, management tends to tilt R&D budgets toward artificial intelligence, thereby crowding out investments in other directions, such as traditional business upgrades and emergency technology R&D [19, 20].

Therefore, excessively high R&D investment intensity overly concentrated in the artificial intelligence field will trigger structural imbalances in resource allocation, damaging the technological redundancy and adaptability required for enterprise resilience. On one hand, decreased technological diversity will weaken enterprises' response capabilities to non-artificial intelligence-related risks; on the other hand, artificial intelligence R&D has characteristics of long cycles and high uncertainty, and if projects fail to convert as scheduled or iterate too rapidly, it will lead to massive input waste, exacerbating enterprise operational pressures [21, 22]. This indicates that unreasonably configured high R&D intensity may damage enterprises' strategic flexibility in responding to dynamic environments, thereby weakening their resilience.

Based on this, this paper proposes the hypothesis:

H3: Artificial intelligence inhibits enterprise resilience by increasing the R&D investment intensity.

2.4 Artificial Intelligence, Management Expense Ratio, and Enterprise Resilience

The management expense ratio is an important indicator for measuring enterprise management efficiency and cost control capabilities [23]. The deep integration of artificial intelligence will trigger multi-dimensional organizational changes, and this process may push up management expenses, posing a threat to organizational resilience.

The introduction of artificial intelligence will give rise to a series of high management expenditures. First, increased human costs, involving high salaries for introducing top talents and continuous training for existing employees; second, rising process coordination costs, requiring redesign and integration of decision-making processes to adapt to human-machine collaboration; third, risk and compliance costs, requiring continuous investments in security reviews and ethical assessments [24-26]. These expenditures collectively drive a structural rise in the management expense ratio.

Increased management expenses will weaken enterprise resilience from three aspects: first, leading to organizational structural rigidity and decision-making delays, making it difficult for enterprises to agilely respond to external shocks; second, crowding out management attention resources, causing potential neglect of external environmental insights and long-term strategic layouts; third, inhibiting the formation of an organizational trial-and-error culture, where strong control systems established to prevent risks may frustrate enterprises' enthusiasm for learning and exploration in facing risks, thereby hindering resilience cultivation [27].

Based on this, this paper proposes the hypothesis:

H4: Artificial intelligence inhibits enterprise resilience by increasing the management expense ratio.

3. Research Design

3.1 Research Sample and Data Sources

Following the research of Li Xinru et al. (2024), this paper selects A-share listed companies in Shanghai and Shenzhen from 2014 to 2023 as the sample, excluding ST and PT category enterprise samples, financial industry enterprise samples, as well as samples with missing values and outliers, and applying a 1% Winsorization treatment to all data up and down, ultimately obtaining 20,649 observations. All data are sourced from the CSMAR database and the China Stock Market and Accounting Research Database [28].

3.2 Variable Explanation and Definition

3.2.1 Explained Variable

Enterprise Resilience (Res): Following the research of Li Xinru et al. (2024), evaluation indicators are constructed from two aspects—growth and volatility—to measure enterprise resilience [28]. Among them, growth is measured by the cumulative increase in operating revenue over 3 years, volatility is measured by the standard deviation of monthly stock returns within 1 year, and finally, the entropy weight method is used for comprehensive calculation to obtain the enterprise resilience variable.

3.2.2 Explanatory Variable

Artificial Intelligence (Lnwords): Following the research of Hu Jun et al. (2025), the degree of enterprise artificial intelligence usage is measured by extracting the frequency of artificial intelligence words in listed company annual reports, adding 1, and taking the logarithm [29]. Additionally, it can also be measured by the number of artificial intelligence patents applied for by the enterprise in that year plus 1 and taking the logarithm, as well as the MD&A management discussion and analysis keywords plus 1 and taking the logarithm.

3.2.3 Mechanism Variables

Financing Constraint Level (KZ): Following the research of Pan Yaqiong and Li Zixuan (2025), the KZ index is selected to measure the enterprise's financing constraint level [30]. The specific formula is:

$$KZ=-1.002CF+0.283Q+3.139TLTA-39.368DIV-1.315CASH$$

where CF is the ratio of cash flow to total assets, Q is the enterprise's Tobin's Q value, TLTA is the ratio of total liabilities to total assets, DIV is a dummy variable for whether dividends are paid, and CASH is the ratio of cash holdings to total assets.

R&D Investment Intensity (RDintensity): Following the research of Fan Qingquan and Guo Wen (2025), R&D investment intensity is selected as the mechanism variable, measured by the ratio of R&D expenditure to operating revenue, with all data used in the calculation sourced from the CSMAR database [31].

Management Expense Ratio (Mfee): Following the research of Wu Fei and Xu Siyan (2022), the management expense ratio is selected as the mechanism variable, which is the ratio of management expenses to operating revenue, with all data used in the calculation also sourced from the CSMAR database [32].

3.2.4 Control Variables

Following the research of Shao Mingzhen and Yang Tingyu (2025) and Yang Zhen et al. (2025), the control variables selected in this paper include: company size (Size), asset-liability ratio (Lev), enterprise age (ListAge), return on total assets (ROA), quick ratio (Quick), CEO-chairman duality (Dual), and operating revenue growth rate (Growth) [33, 34].

Specific variable definitions are shown in Table 1.

Table 1: Variable Definitions and Measurement Methods

Variable Type	Variable Name	Variable Symbol	Measurement Method
Explained Variable	Enterprise Resilience	Res	Comprehensive calculation using entropy weight method
Explanatory Variable	Artificial Intelligence	Lnwords	Logarithm of frequency of AI words in listed company annual reports +1
Mechanism Variables	Financing Constraint Level	KZ	KZ index
	R&D Investment Intensity	RDintensity	R&D expenditure / operating revenue
	Management Expense Ratio	Mfee	Management expenses / operating revenue

Control Variables	Company Size	Size	Natural log of total assets
	Asset-Liability Ratio	Lev	Total liabilities / total assets
	Enterprise Age	ListAge	Years since listing
	Return on Total Assets	ROA	Net profit / total assets
	Quick Ratio	Quick	(Current assets - inventory) / current liabilities
	CEO-Chairman Duality	Dual	1 if chairman and general manager are the same person, 0 otherwise
	Operating Revenue Growth Rate	Growth	(Current sales - previous sales) / previous sales × 100%

3.3 Empirical Model Construction

Based on the previous theoretical analysis and research hypotheses, this study constructs the following econometric models to verify the mechanisms through which artificial intelligence affects enterprise resilience via multiple paths.

Model 1: Tests hypothesis H1, the direct impact of artificial intelligence on enterprise resilience.

$$Res_{i,t} = \alpha_0 + \alpha_1 Lnwords_{i,t} + \alpha_2 controls_{i,t} + \delta_{Year} + \eta_{City} + \varepsilon_{i,t} \tag{1}$$

Models 2 to 4: Test hypotheses H2-H4, the impact of artificial intelligence on enterprise resilience

through three mechanism paths.

$$KZ_{i,t} = \alpha_0 + \alpha_1 Lnwords_{i,t} + \alpha_2 controls_{i,t} + \delta_{Year} + \eta_{City} + \varepsilon_{i,t} \tag{2}$$

$$RDintensity_{i,t} = \alpha_0 + \alpha_1 Lnwords_{i,t} + \alpha_2 controls_{i,t} + \delta_{Year} + \eta_{City} + \varepsilon_{i,t} \tag{3}$$

$$Mfee_{i,t} = \alpha_0 + \alpha_1 Lnwords_{i,t} + \alpha_2 controls_{i,t} + \delta_{Year} + \eta_{City} + \varepsilon_{i,t} \tag{4}$$

where i and t represent enterprise and year, Res represents enterprise resilience, Lnwords represents artificial intelligence, KZ represents enterprise financing constraint level, RDintensity represents R&D investment intensity, Mfee represents management expense ratio, controls represents control variables, δ_{Year} represents year fixed effects, η_{City} represents city fixed effects, and ε represents the random disturbance term.

4. Empirical Analysis

4.1 Descriptive Statistics

The descriptive statistics results for the main variables are shown in Table 2. The average value of the enterprise resilience (Res) indicator is 0.8840, the median is 0.8920, the maximum is 0.9890, and the minimum is 0.0259. This result indicates significant differences in enterprise resilience among the selected samples; the average value of the artificial intelligence (Lnwords) indicator is 0.9170, the standard deviation is 1.1210, the maximum is 4.8900, and the minimum is 0.0000. This result shows obvious differences in the penetration degree of artificial intelligence among different enterprises.

Table 2: Descriptive Statistics of Main Variables

Variable	N	Min	Max	Mean	p50	SD
Res	20649	0.0259	0.9890	0.8840	0.8920	0.0536
Lnwords	20649	0.0000	4.8900	0.9170	0.6930	1.1210
Size	20649	18.8200	26.7100	22.2600	22.0700	1.2900
Growth	20649	-0.9900	13.0600	0.3140	0.1030	1.1470
ROA	20649	-0.3700	0.2160	0.0331	0.0349	0.0690
Quick	20649	0.1180	28.4900	2.0980	1.3000	2.6620
Lev	20649	0.0191	1.0620	0.4090	0.4010	0.2010
Dual	20649	0.0000	1.0000	0.3060	0.0000	0.4610
ListAge	20649	1.7920	3.5260	2.7700	2.7730	0.4580

4.2 Baseline Regression

The regression results of artificial intelligence on enterprise resilience are shown in Table 3. Column (1) shows that, with only the core explanatory variable Lnwords included, the regression coefficient of regional artificial intelligence (Lnwords) on enterprise resilience (Res) is -0.0012, significant at the 1% level, indicating that artificial intelligence has a significant negative impact on enterprise resilience; Column (2) shows that, after incorporating control variables, the regression coefficient of artificial intelligence (Lnwords) on enterprise resilience (Res) is -0.0013, significant at the 1% level, and the magnitude remains stable, indicating that the inhibitory effect of artificial intelligence on enterprise resilience remains robust after controlling for a series of factors, so hypothesis H1 is established.

Table 3: Baseline Regression Results

	(1)	(2)
VARIABLES	Res	Res
Size		0.0056***
		(24.1805)
Growth		-0.0006***
		(-3.1746)
ROA		0.0001
		(0.0415)
Quick		-0.0004***
		(-4.2293)
Lev		-0.0223***
		(-13.7770)
Dual		-0.0012**
		(-2.2614)
ListAge		0.0022***
		(3.5272)
Constant	0.8849***	0.7656***
	(2,978.2372)	(167.0211)
Size		0.0056***
		(24.1805)
Observations	20,640	20,640
R-squared	0.6550	0.6680
Adj.R2	0.6620	0.6620

*Note: *, **, *** represent significance levels of 10%, 5%, and 1%, respectively.*

4.3 Endogeneity Tests

To alleviate potential endogeneity issues in the empirical model, such as lag effects, omitted variables, and reverse causality that may affect estimation results, this paper employs the instrumental variable method and propensity score matching (PSM) for endogeneity tests to ensure the validity and consistency of the research results.

4.3.1 Instrumental Variable Method

The instrumental variable method is a way to mitigate the impact of potential endogeneity issues on research conclusions, utilizing an exogenous instrument that is correlated with the core variable to isolate the exogenous variation in the explanatory variable, obtaining unbiased estimates of causal effects and ensuring the consistency and validity of estimation results. Based on this, this paper introduces two sets of instrumental variables.

Considering that the impact of enterprises adopting artificial intelligence may not manifest immediately, following the research of Yang Huimei and Jiang Lu (2021), this paper selects the one-period lag of the core explanatory variable (Lnwords), denoted as LLnwords, as the first instrumental variable [35]. As a lagged variable, LLnwords is determined prior to the current period and is less susceptible to the influence of the explained variable Res or other shocks, satisfying the exogeneity assumption; in the first-stage regression, as shown in Column (1), the coefficient of LLnwords is 0.8736, significant at the 1% level, indicating that the instrumental variable is highly positively correlated with the endogenous variable, satisfying the relevance assumption; in the second-stage regression, as shown in Column (2), the coefficient of Lnwords is -0.0014, significant at the 1% level, consistent in direction with the baseline regression, indicating that after controlling for endogeneity, artificial intelligence (Lnwords) still has a significant inhibitory effect on enterprise resilience (Res).

Following the research of Mo Yalin and Ni Hao (2024), this paper further selects the mean value of Lnwords for other enterprises in the same city and same industry in the same year (medianLnwords) as the second instrumental variable. This instrumental variable excludes the individual enterprise itself and is calculated solely from information of other enterprises, unrelated to individual-specific shocks, satisfying the exogeneity assumption; as shown in Column (3), in the first-stage regression, the coefficient of the instrumental variable medianLnwords is 0.8881, significant at the 1% level, indicating that the instrumental variable is highly correlated with the core explanatory variable Lnwords, satisfying the relevance assumption; as shown in Column (4), in the second stage, the regression coefficient of Lnwords is -0.0017, significant at the 1% level, consistent in direction with the baseline regression, further reinforcing the reliability of this paper's core conclusions [36].

Table 4: Instrumental Variable Method Results

	(1)	(2)	(3)	(4)
	First	Second	First	Second
VARIABLES	Lnwords	Res	Lnwords	Res
FittedLnwords		-0.0014***		-0.0017***
		(-5.6454)		(-4.2584)
LLnwords	0.8736***			
	(207.8824)			
medianLnwords			0.8882***	
			(98.1708)	
Size	0.0117**	0.0047***	0.0670***	0.0055***
	(2.5522)	(20.2308)	(7.4369)	(15.7112)
Growth	0.0087**	-0.0009***	0.0068	-0.0005*
	(2.1151)	(-4.4713)	(0.9207)	(-1.7248)
ROA	0.2126***	0.0074**	-0.4491***	0.0071
	(3.0611)	(2.1348)	(-3.2893)	(1.3394)
Quick	0.0014	0.0000	-0.0041	-0.0002
	(0.6009)	(0.3791)	(-1.0265)	(-1.3780)
Lev	-0.0221	-0.0153***	-0.1526**	-0.0211***
	(-0.6715)	(-9.2810)	(-2.3858)	(-8.4688)
Dual	0.0168	-0.0012**	0.0496**	-0.0005
	(1.6367)	(-2.4060)	(2.5427)	(-0.6572)
ListAge	-0.0674***	0.0023***	-0.0612**	0.0023**
	(-5.6784)	(3.8808)	(-2.5480)	(2.5056)
Constant	0.1162	0.7150***	-1.0638***	0.7873***
	(1.2575)	(153.8182)	(-5.9700)	(113.5977)
Observations	16335	16,335	8,550	8,550
R-squared	0.7370	0.7070	0.5460	0.6450
Adj. R2	0.7360	0.7060	0.5460	0.6440

*Note: *, **, *** represent significance levels of 10%, 5%, and 1%, respectively.*

4.3.2 Propensity Score Matching (PSM) Method

Following the research of Wang Yonggui and Li Xia (2023), this paper adopts the propensity score matching (PSM) method to address selection bias caused by observable confounding variables. The specific research design is as follows: first, based on the median of the core explanatory variable artificial intelligence (Lnwords), the full sample is divided into a high-frequency group (treatment group, high_Lnwords = 1) and a low-frequency group (control group, high_Lnwords = 0); second, using high_Lnwords as the explained variable and all control variables (Size, Lev, ListAge, ROA, Quick, Dual, Growth) as explanatory variables, a Logit model is constructed to predict the propensity score for enterprises entering the high-frequency group; finally, a one-to-one nearest neighbor matching without replacement is used to match the samples, retaining only enterprise samples within the common support domain. After matching, 15,545 observations are ultimately obtained for subsequent further analysis [37].

The regression results for the matched observations are shown in Table 5. After incorporating all control variables, the regression coefficient of Lnwords on Res is -0.0012, significant at the 1% level, consistent in direction with the previous baseline regression and instrumental variable method results, once again verifying the reliability of the conclusion that artificial intelligence has an inhibitory effect on enterprise resilience.

Table 5: Propensity Score Matching Results

	(1)	(2)
VARIABLES	Res	Res
Lnwords	-0.0013***	-0.0012***
	(-5.5841)	(-5.3486)
Size		0.0056***
		(20.3287)
Growth		-0.0007***
		(-3.2799)
ROA		0.0034
		(0.8777)
Quick		-0.0005***
		(-3.8861)
Lev		-0.0209***
		(-11.0947)
Dual		-0.0015***
		(-2.6726)
ListAge		0.0016**
		(2.1542)
Constant	0.8836***	0.7647***
	(2,383.6175)	(143.5319)
Observations	15,545	15,545
R-squared	0.6600	0.6740
Adj. R2	0.6660	0.6660

*Note: *, **, *** represent significance levels of 10%, 5%, and 1%, respectively.*

4.4 Robustness Tests

To further verify the reliability of the research conclusions, this paper employs three methods for robustness tests, with regression results shown in Table 6.

First, changing the Winsorization treatment. Following the research of Li Benqing and Yue Hongzhi (2022), this paper applies a stricter Winsorization treatment to continuous variables, changing from the 1%-99% to the 5%-95% quantiles [38]. As shown in Column (1), the regression coefficient of Lnwords is -0.0012, significant at the 1% level, consistent in direction with the baseline regression coefficient, indicating that this paper’s core conclusions are not affected by changes in extreme outliers.

Second, excluding municipality samples. Considering that municipalities directly under central government (Beijing, Shanghai, Tianjin, Chongqing) have significant advantages in resource concentration, policy support, and economic foundations, their uniqueness may interfere with overall regression results, so this paper re-estimates after excluding these four municipalities. The results, as shown in Column (2), show that the regression coefficient of Lnwords is -0.0009, significant at the 1% level, consistent in direction with the baseline regression, indicating that this paper’s core conclusions are not affected by special samples.

Finally, extending the time span. To exclude the influence of time span factors on the core relationship, following the research of Li Xiumin and Lin Zhaohe (2025), this paper extends the sample time range from 2013 onward to 2009 onward and then conducts regression analysis. The results, as shown in Column (3), show that the regression coefficient of Lnwords is -0.0012, significant at the 1% level, consistent with the aforementioned test results, indicating that this paper’s core conclusions are not affected by changes in time span and possess universality and robustness [39].

Table 6: Robustness Test Results

	(1)	(2)	(3)
	Changing Winsorization	Excluding Municipalities	Extending Time Span
VARIABLES	Res	Res	Res
Lnwords	-0.0012***	-0.0009***	-0.0012***
	(-5.4855)	(-4.0723)	(-5.9968)
Size	0.0060***	0.0053***	0.0053***
	(22.5544)	(20.4719)	(24.4772)
Growth	-0.0018***	-0.0004*	-0.0007***
	(-3.1733)	(-1.7113)	(-3.8635)
ROA	-0.0024	-0.0014	-0.0005
	(-0.4812)	(-0.3882)	(-0.1527)
Quick	-0.0003	-0.0006***	-0.0004***
	(-1.1842)	(-4.7129)	(-4.5511)
Lev	-0.0206***	-0.0233***	-0.0215***
	(-10.2466)	(-13.2927)	(-14.3626)
Dual	-0.0012**	-0.0007	-0.0012***
	(-2.2814)	(-1.1936)	(-2.5872)
ListAge	0.0023***	0.0026***	0.0022***
	(3.4261)	(3.9139)	(3.7595)
Constant	0.7553***	0.7715***	0.7645***
	(143.2845)	(150.9459)	(176.3122)
Observations	20,640	17,341	22,458
R-squared	0.6670	0.6800	0.7170
Adj. R2	0.6610	0.6730	0.7120

*Note: *, **, *** represent significance levels of 10%, 5%, and 1%, respectively.*

4.5 Mechanism Tests

The regression results regarding the mechanism effects of artificial intelligence on enterprise resilience are shown in Table 7.

Column (2) shows that the regression coefficient of artificial intelligence (Lnwords) on financing constraint level (KZ) is 0.0202, significant at the 10% level, indicating that investment in artificial intelligence significantly increases enterprises' financing constraints; this may be because the introduction of artificial intelligence requires substantial early-stage investments, leading to a large outflow of enterprises' liquid resources, deteriorating financing conditions and restricting external financing, which reduces long-term investments and thereby weakens risk resistance, i.e., inhibiting enterprise resilience.

Column (3) shows that the regression coefficient of artificial intelligence (Lnwords) on R&D investment intensity (RDintensity) is 0.7795, significant at the 1% level, indicating that investment in artificial intelligence significantly increases enterprises' R&D investment intensity, which also implies that, under resource-limited conditions, massive R&D in artificial intelligence may lead enterprises to reduce investments in other key areas, lowering resource allocation efficiency and resulting in a relatively singular technological structure, damaging enterprise resilience; additionally, the introduction and R&D of artificial intelligence are long-cycle projects with high risks, and if enterprises face shocks in the future, artificial intelligence may instead become a burden, exerting an inhibitory effect on enterprise resilience.

Column (4) shows that the regression coefficient of artificial intelligence (Lnwords) on management expense ratio (Mfee) is 0.0017, significant at the 1% level, indicating that investment in artificial intelligence significantly increases enterprises' management expense ratio; as one of the frontier high-tech fields today, the maintenance and operation of artificial intelligence systems require professional teams, and enterprises also need to conduct a series of related trainings internally. These additional processes greatly increase management complexity and enterprise management expenses, leading to reduced response speed when facing shocks, i.e., weakening enterprise resilience.

The regression results indicate that financing constraints, R&D investment intensity, and management expense ratio all play mediating roles in the inhibitory effect of artificial intelligence on enterprise resilience, so research hypotheses H2, H3, and H4 are established.

Table 7: Mechanism Effect Test Results

	（1）	(2)	(3)	(4)
VARIABLES	Res	KZ	RDintensity	Mfee
Lnwords	-0.0012***	0.0202*	0.7795***	0.0017***
	(-4.7296)	(1.7300)	(23.6608)	(3.9205)
Size	0.0055***	-0.3333***	-0.2194***	-0.0131***
	(16.1524)	(-21.5700)	(-5.0297)	(-23.0254)
Lev	-0.0227***	6.0907***	-4.3584***	-0.0356***
	(-10.5157)	(61.5866)	(-15.6125)	(-9.7519)
ROA	-0.0000	-12.1125***	-8.6641***	-0.2804***
	(-0.0067)	(-64.5635)	(-16.3608)	(-40.5070)
ListAge	0.0016*	0.3768***	-0.3938***	0.0202***
	(1.8344)	(9.3156)	(-3.4492)	(13.5660)
Dual	-0.0011*	0.0314	0.2545***	0.0017*
	(-1.8996)	(1.1761)	(3.3786)	(1.7646)
Quick	-0.0003**	-0.0256***	0.1906***	0.0026***
	(-2.3345)	(-4.6503)	(12.2471)	(12.7581)
Growth	-0.0016***	0.0508***	0.1094**	0.0035***
	(-4.5767)	(3.0829)	(2.3503)	(5.7394)
Constant	0.7701***	5.6463***	11.4353***	0.3296***
	(116.7700)	(18.6967)	(13.4144)	(29.5781)
观测值	12,960	12,960	12,960	12,960
R-squared	0.6870	0.5990	0.2500	0.3580

*Note: *, **, *** represent significance levels of 10%, 5%, and 1%, respectively.*

4.6 Heterogeneity Analysis

Table 10 reports the heterogeneity test results of artificial intelligence on enterprise resilience from three aspects: regional differences, industry differences, and enterprise differences.

4.6.1 Regional Differences

The regional heterogeneity analysis reveals significant regional differences in the inhibitory impact of artificial intelligence on enterprise resilience. Following the research of Han Honghua (2025), this study conducts grouped regressions on the selected enterprise samples according to eastern, central, and western regions [40]. Column (1) shows that in the eastern region, the regression coefficient of artificial intelligence (Lnwords) on enterprise resilience (Res) is -0.0014, with a significance level of 1%; Column (2) shows that in the central region, the regression coefficient of artificial intelligence (Lnwords) on enterprise resilience (Res) is -0.0011, with a significance level of 10%; Column (3) shows that in the western region, the regression coefficient of artificial intelligence (Lnwords) on enterprise resilience (Res) is -0.0002, which is insignificant.

The regional heterogeneity analysis regression results indicate that the eastern region, due to its developed economy and widespread adoption of artificial intelligence, may lead to partial labor substitution, affecting enterprise internal structures, while enterprises also need to invest substantial resources in system upgrades and employee training, causing increased operational costs and reducing risk response capabilities; the significance in the central region is markedly lower than in the east, and completely insignificant in the west, possibly because the central and western regions develop more slowly, with artificial intelligence applications still in the pilot stage, not yet deeply integrated into core businesses, and low penetration rates reducing shocks to enterprise operational structures, i.e., the inhibitory effect of artificial intelligence on enterprise resilience is not prominent.

4.6.2 Industry Differences

The industry heterogeneity analysis reveals the differential characteristics of artificial intelligence's impact on enterprise resilience across different industries. Following the research of Li Kaichao and Liu Liping (2025), this paper conducts grouped regressions on the selected enterprise samples based on whether they belong to manufacturing [41]. Column (4) shows that in manufacturing, the regression coefficient of artificial intelligence (Lnwords) is -0.0003, insignificant; Column (5) shows that in non-manufacturing, the regression coefficient of artificial intelligence (Lnwords) is -0.0022, significant at the 1% level.

The above results indicate that in non-manufacturing, artificial intelligence has a significant inhibitory effect on enterprise resilience. For enterprises in manufacturing, intelligent transformations are typically closely integrated with core links such as production processes and supply chain management, possibly having formed relatively stable resilience support systems, so the negative impact of artificial intelligence on their enterprise resilience is insignificant; whereas for non-manufacturing enterprises, such as those in services, artificial intelligence technologies have not yet been fully integrated with business processes and organizational structures, and coupled with high initial investment costs, enterprise resilience is significantly inhibited by artificial intelligence.

4.6.3 Enterprise Differences

The enterprise-level difference analysis reveals the individual difference characteristics of artificial intelligence's impact on enterprise resilience. Following the research of Xu Minli et al. (2025), this paper conducts grouped regressions on the selected samples based on whether they are heavily polluting enterprises [42]. Column (6) shows that in heavily polluting enterprises, the regression coefficient of artificial intelligence (Lnwords) is -0.0017, with a significance level of 10%; Column (7) shows that in non-heavily polluting enterprises, the regression coefficient of artificial intelligence (Lnwords) is -0.0009, with a significance level of 1%.

The above results indicate that artificial intelligence has an inhibitory effect on the resilience of both types of enterprises, but the negative impact is greater on non-heavily polluting enterprises. This may be because heavily polluting enterprises' primary task is to cope with environmental compliance pressures, and artificial intelligence is not their main transformation option, so the inhibitory effect of artificial intelligence on them is diluted by more pressing environmental risks, resulting in lower significance; whereas non-heavily polluting enterprises face no significant environmental monitoring pressures and, under innovation policy incentives, actively introduce artificial intelligence to pursue growth, with more widespread application, making them more sensitive and strengthening the significance of the inhibitory effect.

Table 8: Heterogeneity Analysis Results

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	（7）
	Eastern	Central	Western	Manufacturing	Non-Manufacturing	Heavily Polluting Enterprises	Non-Heavily Polluting Enterprises
Lnwords	-0.0014***	-0.0011*	-0.0002	-0.0003	-0.0022***	-0.0017*	-0.0009***
	(-6.2882)	(-1.6872)	(-0.2139)	(-1.1578)	(-3.5375)	(-1.7598)	(-3.3057)
Constant	0.7640***	0.7437***	0.7989***	0.8083***	0.7711***	0.7991***	0.7755***
	(151.8515)	(53.1290)	(51.3044)	(115.6691)	(73.2932)	(62.5249)	(122.3283)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Observations	14,715	3,269	2,562	10956	3632	3,481	11,102
R-squared	0.6900	0.6350	0.6150	0.6110	0.6090	0.5830	0.6220

*Note: *, **, *** represent significance levels of 10%, 5%, and 1%, respectively.*

5. Conclusion and Implications

Based on 20,649 samples of A-share listed companies in Shanghai and Shenzhen from 2014 to 2023, this study systematically conducted baseline regressions, mechanism tests, endogeneity tests, robustness tests, and heterogeneity analyses on the impact of artificial intelligence on enterprise resilience. Integrating all results, the findings are: (1) artificial intelligence has a significant and robust inhibitory effect on enterprise resilience; (2) this inhibitory effect is realized through three mechanism paths: increasing the enterprise's financing constraint level, R&D investment intensity, and management expense ratio; (3) the inhibitory effect of artificial intelligence on enterprise resilience varies across different regions, industries, and individual enterprises. At the regional level, the eastern region is more affected by artificial intelligence compared to the central and western regions; at the industry level, non-manufacturing enterprises are more sensitive to the inhibitory effect of artificial intelligence; at the enterprise level, the inhibitory effect of artificial intelligence on the resilience of non-heavily polluting enterprises is more pronounced.

Current mainstream discourses mostly emphasize the positive impacts of artificial intelligence on empowering enterprises and enhancing efficiency, but this study reveals the "other side" of artificial intelligence: technological progress can also have complex and contradictory effects on enterprises, rather than a simple linear promotion relationship. Therefore, while embracing the AI revolution, enterprises must remain vigilant and avoid losing their survival foundation in the blind pursuit of efficiency [43]. Accordingly, this paper proposes the following suggestions.

First, whether entrepreneurs, scholars, or policymakers, when facing artificial intelligence, should shift from an optimistic attitude of unconditional adoption to a prudent one that involves trade-offs; not only learning to apply artificial intelligence but also committing to building resilient intelligent enterprises.

Second, investments in artificial intelligence easily trigger enterprises' "resource crowding-out effect," necessitating coordinated policy support to alleviate financing constraints. For example, government-led or third-party authorized assessments of the resilience impact of AI-related projects before enterprise adoption, with policy guarantees or subsidies for those with better assessment results, to ease financing pressures caused by substantial short-term investments.

Third, the high-intensity R&D driven by artificial intelligence brings efficiency improvements but may sacrifice enterprises' exploration and response capabilities to risk changes. This requires enterprise management to plan R&D investment budgets for both efficiency enhancement and resilience consolidation, with the latter specifically allocated to projects such as enterprise operating risk prediction models and disruptive scenario simulations, ensuring that R&D investments not only enhance efficiency but also improve survival capabilities or explore new survival scenarios.

Fourth, the increase in management expenses from introducing artificial intelligence, if solely used for new system maintenance and employee training, will become consumptive costs for enterprises. This necessitates enterprises to promote deep integration between core management departments such as finance and operations with AI operation teams, fostering the formation of a "digital office" [44]. This new department utilizes artificial intelligence for comprehensive risk scanning of the enterprise and multiple simulations of emergency plans, transforming these management expenses into strategic assets for sustained risk resistance

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