The 'Intelligent Trap' in Corporate Finance—A Study Based on New Energy Vehicle Enterprises

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A R T I C L E I N F O

A B S T R A C T

AI, as an emerging productive technology, has been widely adopted in production by technology and manufacturing firms engaged in cutting-edge product development. Academic research often incorporates corporate AI capability to examine its contributions to innovation, performance, and sustainable growth. However, in practice, many automotive firms, especially those developing new energy and intelligent vehicles, have suffered financial distress and even exited the market, attracting widespread concern.This study empirically investigates how AI dependence affects corporate financial risk using a sample of listed new energy vehicle and automobile manufacturers from 2013 to 2023. Results of data analysis show that AI dependency reduces financial safety and Moderation and Heterogeneity tests further reveal that strong knowledge or intelligent equipment output and patent transformation effectively mitigate such risks.Findings suggest that: (1) High AI dependency disclosed in financial reports does not improve financial health and may even endanger it; (2) AI can worsen financial and market performance if it crowds out normal R&D; (3) Efficient conversion of R&D into technological barriers is key to avoiding the AI trap. Amid intense competition, new energy vehicle firms should prioritize R&D efficiency, translate innovation into stable returns, and maintain sound financial conditions.

1.Research background

Since the 2010s, artificial intelligence has achieved significant breakthroughs in practical application, endowing enterprises with new productive forces for innovation and development. Major corporations began integrating deep learning algorithms into product development during this decade. Particularly within the automotive manufacturing sector, the synergistic advancement of computing power, big data, and AI technologies catalyzed comprehensive transformation across the entire industry chain — from upstream to downstream. This profoundly disrupted traditional automakers' perceptions of operational pathways, making AI adoption a critical imperative for enhancing competitiveness in today's market — especially for the new energy vehicle sector and its supply chain.

Amidst intensifying market competition and the emergence of new energy vehicle manufacturers forced to exit due to financial difficulties, academic research has consequently explored the relationship between corporate AI adoption and financial risk management. Numerous scholars globally have examined the impact of digitalization and AI adoption on debt risk, supply chain resilience, and factor productivity levels at both corporate and regional scales. However, comprehensive research integrating automotive manufacturing with financial risk assessment remains underdeveloped. This paper therefore conducts an empirical study on the correlation between AI dependency and financial risk among enterprises in the new energy and automotive manufacturing sectors.

1.1. Development of AI technology application in enterprises

The 2024 Generative Artificial Intelligence Application Development Report indicates that 230 million individuals in China have encountered or utilized generative AI. Regarding industrial applications, the Statistical Report on China's Internet Development reveals that digital R&D technology tools have achieved over 80% adoption rates among enterprises in key industrial sectors. As the nation that has led the world in intelligent robotics for over a decade, China now faces a critical challenge in its economic modernization and pursuit of high-level, high-quality development: how to widely deploy AI across society and the economy to boost productivity, particularly with the advancement and proliferation of generative AI technologies. In 2024, the Government Work Report first referenced "artificial intelligence", emphasizing the need to integrate AI technology with industrial development. The 2025 Government Work Report reiterated the importance of AI's industrial empowerment role, emphasizing its full application in the transformation and upgrading pathways of industries such as manufacturing and services. It highlighted the critical role of AI technologies, including large-scale model technologies, in driving innovative development and deployment within vertical sectors , demonstrating the nation's commitment to guiding AI's high-level penetration into the real economy through practical applications.

In summary, the technological convergence of artificial intelligence with traditional industries is charting a course for production model innovation, with its core value lying in injecting transformative momentum into high-quality economic development: through the deep mining and intelligent analysis of vast datasets, enterprises gain new dimensions for strategic decision-making; the precise capture of dynamic market trends and establishment of risk early-warning mechanisms effectively shorten information response cycles, making adjustments to innovation directions more forward-looking and proactive; Simultaneously, the automation of production processes and the introduction of intelligent decision-making systems not only enable the precise allocation of capital resources but also liberate foundational labor through human-machine collaboration, creating space for high-value-added innovation activities.

The permeation of artificial intelligence technologies within enterprises drives efficiency leaps and, through paradigm shifts in resource allocation, propels industries toward specialization and intensification. However, the immature application of AI in practical contexts may yield adverse effects. For instance, within corporate finance, the introduction, utilization, and maintenance of intelligent platforms incur substantial initial costs[1], with performance returns proving elusive in the short term; Similarly, within manufacturing, business owners may opt to replace human employees with artificial intelligence to maximize profits[2]. This risks creating social issues such as worker unemployment. Furthermore, it remains a matter for careful consideration how to measure the current input-output efficiency of artificial intelligence compared to human labor, and whether it can deliver higher returns over the long term of technological development[3]. Whether enterprises can

correctly, efficiently, and standardly embed artificial intelligence deeply into every link of the innovation chain is not only a key indicator for measuring their core competitiveness, but also a necessary test for building a modern industrial system as a participant in the market.

1.2. Development status and challenges facing new energy vehicle manufacturers

In recent years, alongside the proliferation of artificial intelligence technology, the automotive manufacturing industry represented by new energy intelligent vehicles has also gained widespread adoption. In terms of market scale, data disclosed by the China Passenger Car Association indicates that by 2024, China's new energy vehicle market share will exceed 70% of the global total. Concurrently, the penetration rate of new energy vehicles within China has surpassed 50%, with production and sales volumes exceeding ten million units, solidifying China's position as the world's largest market for new energy vehicles. Technologically, Chinese new energy vehicles have progressed beyond merely replacing petrol engines with lithium-ion or nickel-metal hydride batteries. Domestic manufacturers continuously innovate across connected vehicle systems, driver assistance technologies, and autonomous ride-hailing services, enhancing product competitiveness through technological advancement.

The development of new energy vehicles has long thrived in a favorable environment. Since the introduction of the "863 Program" in 2001, the state has implemented robust and constructive interventions to nurture electric vehicle enterprises and markets. Subsequently, new energy vehicle subsidy policies were progressively rolled out. The 2014 policy exempting new energy vehicles from purchase tax further attracted numerous consumers and enterprises into the market to benefit from these incentives. Coupled with subsequent locally introduced artificial intelligence subsidy schemes, domestic new energy and smart vehicles achieved rapid market expansion within a short timeframe. However, substantial market subsidies and the influx of numerous enterprises indirectly led to market disorder. Some manufacturers engaged in the development and sales of new energy vehicles despite lacking the requisite technological capabilities and operational capacity to meet market competition demands, triggering a series of adverse market conditions. The early domestic new energy vehicle brand ZHIDOU faced market scepticism over battery range and safety issues. Following the decline in vehicle subsidies in 2018, its sales plummeted, ultimately leading to bankruptcy and restructuring in 2019. It was subsequently acquired by capital from established automakers such as Geely and AIMA. What's more, HUATAI deliberately inflated its production figures and committed financial fraud to obtain huge technical subsidies. Then, it produced outdated vehicle models to satisfy the market but was met with consumer resistance. Eventually, HUATAI Automobile was punished by the Ministry of Industry and Information Technology and had to withdraw from the market.

New energy vehicle manufacturers entering the market typically emphasize their smart technology capabilities to gain

consumer trust. However, many struggle to meet market expectations in practice, leading to competitive defeat, unsustainable operations, and eventual withdrawal. In today's era of widespread artificial intelligence derivative technologies, the intelligent advantages disclosed in periodic reports, commercial promotions, or financial data do not directly translate into sustainable market viability. To enable enterprises in relevant sectors to comprehensively understand the advantages and disadvantages of AI technology for business development within real-world market operations, thereby enhancing their adaptability in the new wave of technological advancement, this paper delves into the automotive industry's capacity for applying AI-driven technological innovations. It thereby offers valuable insights into the developmental trajectory of the new energy vehicle market, holding significant practical relevance.

2.Literature review and research hypotheses

2.1.Literature review

Research on artificial intelligence in economic management has expanded alongside the proliferation of AI applications in production and operations. Measurement approaches encompass text analysis of corporate disclosures[4], industrial robot installations[5,6], employee resume characteristics[7], and survey-based assessments[8]. A broad consensus confirms that AI enhances firm innovation efficiency and productivity by restructuring knowledge boundaries, overcoming organizational inertia, and optimizing resource allocation. It also empowers precision marketing[9] and the intelligent upgrading of financial management[10]. Hodson pointed out that the combination of AI and big data can precisely match customer demands with product supply[11]. He et al. used innovation ability as the mediating variable to reveal that AI enhances the new quality productivity level of enterprises by strengthening their innovation ability[12].

Research specifically targeting the automotive manufacturing sector remains limited. Liu drawing on data from Chinese listed automotive firms, finds that AI significantly strengthens supply chain resilience by stimulating dynamic capabilities—an effect more pronounced in large, state-owned, or mature enterprises[13]. Zhu, through a case study, demonstrates the resource optimization role of AI expert systems in the financial management of auto parts suppliers[14].

While the positive effects of AI on firm innovation and competitiveness are widely acknowledged, measurement approaches remain heterogeneous due to limited and inconsistent disclosure of firm-level AI investment in financial reports. Concurrently, a growing body of research identifies constraints and adverse effects associated with AI adoption. These include high upfront costs and limited short-term returns lower input–output efficiency relative to human labor in certain manufacturing contexts, and "system isolation"—the inability to integrate data across fragmented systems, which undermines AI effectiveness in state-owned enterprises[15]. Fan and Qu et al. provide evidence for the "productivity paradox," showing that the relationship between AI investment and productivity gains is not linearly positive[16,17]; mismatches between digital tools and existing workflows, data infrastructure, and skill endowments may lead to short-term performance declines. Furthermore, in specific application domains such as autonomous driving, technological hazards—including system failures and decision errors — have triggered public distrust[18]. These contested findings underscore the significant heterogeneity of AI effects and point to the need for further investigation into the mechanisms and boundary conditions of AI deployment in automotive and other manufacturing contexts.

A review of existing research indicates that artificial intelligence applications in economic management have demonstrated significant innovation-driven effects. Its multidimensional empowerment pathways — from knowledge reconstruction to factor optimization, and from patent inventions to total factor productivity gains — have been extensively validated. However, current academic discourse on new energy vehicles and the automotive manufacturing sector remains somewhat underdeveloped. Select representative studies have revealed AI's positive impact on supply chain management and financial resource allocation within automotive manufacturers. Concurrently, AI's substantial initial costs, uncertain long-term returns, and issues of "system isolation" pose latent risks to enterprises' intelligent transformation and sustained productivity growth. Particularly in autonomous driving, technological safety concerns may trigger public trust crises. Failure to promptly address negative consequences accompanying emerging technologies could render AI a potential threat to corporate sales, operations, and financial security, the potential dark side of AI, especially its impact on financial risk in capital-intensive industries like NEV manufacturing — has received scant attention. This study aims to fill this gap by examining whether and how AI dependence can become an 'intelligent trap' that undermines financial stability.

Consequently, this paper focuses on listed companies in the new energy vehicle and automotive manufacturing sectors to examine how reliance on artificial intelligence impacts corporate financial security. It aims to reveal the potential risks of the "intelligent trap" and provide scientific grounds for financial decision-making during intelligent transformation, holding both academic value and practical significance.

2.2.Theoretical framework and hypothesis formulation

2.2.1.Direct effects of corporate AI applications on financial risk

The prevailing societal perspective on AI adoption within enterprises leans toward active acceptance and robust support. This stance is articulated not only in national policies such as the aforementioned Government Work Report and Made in China 2025, but also in academic research conclusions cited in literature reviews, which highlight AI's advantages in enhancing corporate productivity, competitiveness, and

promoting steady performance improvement[1]. This represents the ideal perspective for societal acceptance of emerging technologies, aligning closely with Wernerfelt's 1984 Resource-Based View (RBV)[19] . It posits that unique, immovable, or irreplicable tangible or intangible resources possessed by an enterprise can be transformed into unparalleled strengths, serving as invaluable sources for enhancing corporate competitiveness. As a strategic resource, artificial intelligence technology plays a vital role in helping enterprises optimize operations, reduce costs, and enhance efficiency, thereby strengthening financial robustness and performance. For automotive manufacturers and their upstream and downstream enterprises, the advantages of artificial intelligence can be applied across multiple fronts. For instance, within internal management, financial systems and marketing data analytics can substantially optimize resource allocation. In the manufacturing process, intelligent robots can enhance the specialization of assembly lines and boost production efficiency. Applications within products, such as intelligent driving systems and voice-assisted systems, can cater to the demands of new-era consumers and elevate the market competitiveness of products.

On the other hand, however, it is not uncommon to see automotive manufacturers that invest heavily in R&D for technological innovation grappling with high debt ratios, unstable supply chains, and cash flow issues. JIYUE, jointly established by Baidu and Geely, disclosed in its 2024 projected loss report that its annual deficit is expected to reach 7 billion yuan, with nearly half allocated to R&D expenditure. Coupled with equally substantial sales costs, this has sharply inflated the unit cost per vehicle sold for JIYUE, while its market reception has been underwhelming, precipitating an operational crisis. Such cases have become commonplace in the domestic market in recent years, with multiple automakers announcing their withdrawal from the market in the short term. Beyond the struggles of downstream manufacturers like LIFAN, JIYUE, and NEZHA, upstream supply chain enterprises are also severely impacted. Battery suppliers such as BAK Power and smart chip suppliers like NAXINWEI face difficulties recovering their own accounts receivable when downstream automakers encounter capital chain crises, triggering adverse chain reactions.

The phenomenon where companies invest heavily in product R&D yet struggle to sustain operations can be partially explained by the "productivity paradox" and "Baumol's cost disease". The "productivity paradox," proposed by Robert Solow (1987), suggests that substantial investments in information technology do not necessarily yield immediate performance improvements. Instead, factors such as learning costs, user proficiency, and utility lags may cause short-term performance declines, meaning technological advancements do not always translate into significant productivity gains. Baumol's cost disease, proposed by Baumol (1967), describes a two-sector macroeconomic growth model comprising a progressive sector and a stagnant sector. When the progressive sector experiences sustained rapid productivity growth, the relative costs of the stagnant sector gradually increase[20] . For automotive enterprises, sustained investment in artificial intelligence technologies may, on the one hand, exacerbate short-term difficulties in achieving returns, while on the other hand potentially increasing costs in non-automated, non-innovation sectors, thereby reducing overall capital return rates.

In light of the foregoing, this paper proposes the following research hypotheses:

H1a: The level of AI dependency in automotive manufacturing positively influences financial security;

H1b: The level of AI dependency in automotive manufacturing enterprises negatively impacts financial security .

2.2.2.The mediating effect of investor confidence in the relationship between AI dependency levels and financial risk

Investor confidence represents the subjective expectations formed by investors regarding investment prospects based on market conditions and corporate characteristics. It encompasses both rational assessments of fundamental factors such as corporate profitability and growth potential, and is influenced by irrational elements like market sentiment. When investor confidence is robust, enterprises can more readily secure equity or debt financing at lower costs, thereby reducing liquidity risk. Conversely, diminished confidence leads investors to adopt more conservative projections of a firm's future cash flows, thereby raising financing thresholds and costs while intensifying financial pressures[21]. In examining the financial health of automotive manufacturers— particularly those producing new energy and intelligent vehicles — external assessments of a company's ongoing viability constitute an indispensable variable. Key research questions include: whether adopting emerging technologies fosters capital trust; how reliance on artificial intelligence impacts the stability of operational capital investment; and consequently, how this influences overall financial robustness. This study thus proposes the following hypothesis:

H2: Investor confidence plays a mediating role in the path of AI dependency and financial security impact.

2.2.3.The moderating effect of innovation efficiency on the relationship between AI dependency level and financial risk

Leibenstein's X-efficiency theory, proposed in the 1960s by Harvey Leibenstein, posits that a firm's operational performance fluctuates with variations in effort efficiency. Through refinement and expansion in practical application, its core business principle emerges: increased input factor costs do not necessarily entail proportional output cost increases. This relationship hinges on the X-convergence rate of internal coordination and employee effort levels: Should a firm strengthen management and optimize internal relations increased input costs may paradoxically reduce output costs. As the foremost means for enterprises to enhance competitiveness in emerging markets, the application efficiency of R&D expenditure directly reflects the actual value of investment in this area. Among new energy intelligent vehicle enterprises, disparities may exist between entities achieving high conversion rates of technological R&D investment into tangible asset outcomes or operational

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[1] "Made in China 2025" explicitly states: "Accelerate the deep integration of next-generation information technology with manufacturing, advance intelligent manufacturing, develop smart equipment and products, promote intelligent production processes, and cultivate new manufacturing models."

revenue performance, and those with lower conversion efficiencies. This disparity influences the path strength of the main effect. Consequently, this paper proposes the following hypothesis:

H3: Innovation efficiency moderates the relationship between AI dependency levels and financial security impacts.

3.Research approach and design

3.1.Sample selection

This study focuses on an analysis of listed companies within the new energy vehicle sector and the automotive manufacturing industry on the Shanghai and Shenzhen A-share markets from 2013 to 2023. The listed companies within the sector were selected from data compiled and summarized by East Money Information based on publicly disclosed business information. Data indicators were sourced from the GUOTAIAN database (CSMAR) and official corporate financial statements, supplemented by statistical information from the Wind platform as supporting documentation. To ensure empirical rigor, and considering the potential negative correlation between main effects and mediating effects in the research hypotheses, alongside the minimal proportion of ST-listed companies within the total sample, this paper retains observations from companies marked as ST. Concurrently, enterprises with substantial data gaps were excluded, while observations with minor variable omissions were imputed using mean values.

Given that indicators involving technological application and financial risk inherently exhibit substantial variation across enterprises in practice, the impact of excessively high or low values on financial status itself warrants consideration. To ensure sample authenticity and representativeness, this study refrained from applying tail trimming (Winsorization) during benchmark regression data processing. All original observations were retained for benchmark regression to more accurately reflect the actual relationship between corporate financial health and AI dependency levels.

Following a meticulous data cleansing and organization process, 4,266 valid samples were ultimately identified, laying a solid foundation for subsequent research.

3.2.Model specification

To examine the impact of corporate AI dependency on financial security, this study incorporates industry effects and time effects while absorbing relevant fixed effects to construct the following Model (1):

$$\text{Z-score}_{it}=\alpha_0+\alpha_1 AI_{it}+\sum\alpha_k\text{Controls}+\text{year}_t+\text{industry}_i+\varepsilon_{it} \quad (1)$$

Where *Z-score* represents the financial security index of a series of sample enterprises, α_0 denotes the constant term, α_1 and α_k are the regression coefficients for the core explanatory variable (AI dependency level) and the control variable respectively (the same applies to the following β, γ and so on), $year_t$ and $industry_i$ denote the time fixed effect and industry fixed effect respectively, and ε represents the residual value.

To further validate Hypothesis H2, Model (2) is expanded and designed upon this foundation. This study employs a

common three-step model to verify the mediating effect of corporate investor confidence in the relationship between AI dependency levels and financial risk, utilizing bootstrap sampling to test the mediating effect path:

$$IC_{it}=\beta_0+\beta_i AI_{it}+\sum\beta_k\text{Controls}+\text{year}_t+\text{industry}_i+\varepsilon_{it} \quad (2)$$
$$\text{Z-score}_{it}=\gamma_0+\gamma_1 AI_{it}+\gamma_2 IC_{it}+\sum\gamma_k\text{Controls}+\text{year}_t+\text{industry}_i+\varepsilon_{it} \quad (3)$$

Where represents the mediating variable investor confidence. Assuming the explanatory variable coefficient in Model (1) is significant, and the regression coefficient for AI_{it} in Model (2) is also significant, the following outcomes indicate mediation:
- If the regression coefficient for the mediating variable IC_{it} in Model (3) is significant while the explanatory variable coefficient becomes insignificant, this signifies full mediation. If the explanatory variable remains significant, this indicates partial mediation.

To test Hypothesis H3, this study introduces a moderator variable and its interaction term with the independent variable into the aforementioned Model (1), yielding the following model:

$$\text{Z-score}_{it}=\chi_0+\chi_1 AI_{it}+\chi_2 AI_{it}\times\text{eff}_{it}+\chi_3\text{eff}_{it}+\sum\chi_k\text{Controls}+\text{year}_t+\text{industry}_i+\varepsilon_{it} \quad (4)$$

Where *eff* denotes the moderator variable (innovation efficiency), and *AI × eff* represents the interaction term between the explanatory variable and the moderator variable. If both the explanatory variable and the interaction term exhibit significant regression coefficients, this indicates that the moderator variable either enhances or attenuates the main effect pathway.

3.3.Variable descriptions

Current academic approaches to measuring corporate AI-related levels primarily fall into three categories: Yao employs Jieba word segmentation technology to conduct textual analysis of AI keywords in listed companies' annual reports, quantifying keyword frequency[22]; He et al. calculate the ratio of disclosed intelligent industrial machinery asset value to employee numbers in corporate financial statement notes[23]Zhou et al. retrieved and measured the annual number of artificial intelligence patent applications filed by listed companies[24]. Given that the research sample primarily comprises automotive manufacturing enterprises, the ratio of intelligent machine asset value（*Machinery_{it}*）to employee (*employee_{it}*) count effectively measures corporate adoption levels of artificial intelligence technology. Hence, this method is employed to calculate the explanatory variable, marked as AImach.

$$AImach_{it}=\frac{\text{Machinery}_{it}}{\text{employee}_{it}} \quad (5)$$

Meanwhile, to ensure the robustness of the study, since the new energy vehicle-related enterprises in the sample are mainly engaged in manufacturing business, in accordance with the measurement characteristics of the explanatory variable AImach, this paper refers to the measurement methods for the degree of robot adoption in manufacturing firms proposed by Wang et al.[25] and Acemoglu & Restrepo[26]. We select the development level of artificial intelligence robots, measured using data on industrial robot penetration disclosed by the International Federation of

Robotics (IFR), as an alternative explanatory variable for the robustness test. The calculation is as follows: based on the idea of the Bartik instrument, with 2011 as the base period, we construct the artificial intelligence dependency indicator measured by industrial robot penetration.

$$AIrob_{it} = \frac{PL_{ijt=2011}}{medianPL_{t=2011}} \times \frac{Robots_{jt}^{CH}}{L_{jt=2010}^{CH}} \quad (6)$$

Among them, PL_{ijt} represents the proportion of employees engaged in production positions in firm i of industry j among the total employees in all manufacturing enterprises in 2011, $medianPL_t$ represents the median of the proportion of employees engaged in production positions across all manufacturing enterprises in 2011, $Robots_{jt}^{CH}$ represents the stock of industrial intelligent robots in industry j of China in year t, and L_{jt}^{CH} represents the number of employees in industry j in 2010.

In the actual operation process, there may be certain discrepancies between enterprises' external communication and their operational behaviors, and "talking much but doing little" is a typical phenomenon reflecting such characteristics. Li et al. examined the impact of discrepancies between enterprises' external communication volume and digital transformation behavior on analysts' market forecasts during enterprises' digital transformation, concluding that "talking much but doing little" behavior can lead to excessively optimistic market forecasts[27]. Returning to the topic of this study, on the one hand, enterprises disclose favorable outcomes of AI-enabled production processes in their financial statements; as mentioned earlier, the academic community therefore adopts the method of counting the frequency of AI-related keywords to measure enterprises' artificial intelligence application level. On the other hand, enterprises' investment in fixed assets or intangible assets related to artificial intelligence in a given year is not necessarily fully consistent with the AI level measured by textual keyword frequency. Therefore, this empirical study introduces the variables AItext and AIinv: AItext represents the natural logarithm of the number of mentions of artificial intelligence-related keywords in the annual financial report, and AIinv represents the ratio of total investment in artificial intelligence-related fixed assets and intangible assets to total assets as disclosed in the notes to the financial report. These variables respectively capture the differences between high/low communication intensity and high/low investment behavior in enterprises' artificial intelligence dependence, facilitating subsequent heterogeneity grouping analysis.

The Z-score model, widely employed in academic circles for assessing corporate financial risk, was introduced by Edward Altman in 1968[28]. This model incorporates five corporate financial indicators to generate an estimated risk score. A Z-score exceeding 2.99 indicates sound financial security, whilst a score below 1.8 signifies severe bankruptcy risk. The model is presented as follows:

$$Z\text{-}score_{it} = 1.2X_{1it} + 1.4X_{2it} + 3.3X_{3it} + 0.6X_{4it} + 0.999X_{5it} \quad (7)$$

Where X_{nit} respectively denote: working capital as a proportion of total assets; retained earnings relative to total assets; EBIT relative to total assets; market value of equity to book value of total liabilities; and operating revenue relative to total assets.

As a positive assessment model, the Z-score is termed "financial security level" within this paper's assumptions to enhance interpretability. Furthermore, the Z-score model originates from Edward Altman's measurements for manufacturing enterprises, aligning with this study's sample. Hence, this indicator is selected as the dependent variable for measuring corporate financial security.

Drawing upon Lei et al.'s methodology for measuring investor confidence, this study employs the Investor Confidence Index (IC) as the dependent variable. Considering the industry characteristics and research context of new energy vehicle manufacturers, three complementary proxy variables are selected: the annual price-to-book ratio (PB), annual price-to-earnings ratio (PE), and annual turnover rate (TR). The investor confidence index is constructed via principal component analysis. For missing data in individual proxies — such as rare observations lacking PE for a given year — the index is directly derived using the remaining two proxies. This investor confidence variable comprehensively captures investors' value-based confidence levels, providing a reliable metric to examine the mediating effect of investor confidence on financial risk when assessing AI applications in new energy vehicle enterprises. The formula is as follows:

$$IC_{it} = \omega_1 PB_{it} + \omega_2 PE_{it} + \omega_3 TR_{it} \quad (8)$$

When measuring corporate innovation efficiency, one may also quantify it from the perspective of actual returns on knowledge output. This paper references the methodology employed by Hu et al. (2017) in their study on the relationship between corporate innovation efficiency and performance. Under this method, this study simplifies the measurement approach to a certain extent. It uses the ratio of patent output to R&D expenditure[29]. The calculation model is as follows:

$$eff_{it} = Ln(patent_{it} + 1)/Ln(Inv_{it} + 1) \quad (9)$$

$Patent_{it}$ refers to the number of patent applications filed by the firm in a given year, and Inv_{it} denotes the firm's R&D investment in the same year.

A higher value of eff_{it} indicates that the enterprise is at the leading edge of the sample in terms of scientific research patent conversion efficiency. Conversely, a lower value suggests that the enterprise may be experiencing waste of R&D resources and inefficiency.

Table 1. Control variable descriptions

Variable Symbol	Variable Description	Calculation Method
Size	Enterprise Size	Ln (Current Year's Number of Employees + 1)
ROE	Return on Equity	Net profit / Average balance of shareholders' equity
Loss	Whether loss incurred	Recorded as 1 if net profit for the year is negative, otherwise 0
FIXED	Scale of Fixed Assets	Annual fixed asset account total / total assets
Board	Number of directors	Ln(Annual Number of Directors + 1)
Indep	Director independence	Number of Independent Directors/Total Number of Directors
Dual	Dual role	Chairman and Chief Executive Officer held by one individual counted as 1; otherwise 0

To enhance the persuasiveness of empirical findings, this study adopts typical financial indicators as control variables in accordance with academic conventions. Variable descriptions and calculation methods are presented in the Table 1.

4.Research findings

4.1.Descriptive statistics

Following variable screening, exclusion, and imputation, the basic statistical results are presented in the table below. The core dependent variable, financial risk (Z-score), exhibits a mean of 4.092 and a standard deviation of 4.267, with a wide range of extremes (-3.777 to 73.931). This indicates significant heterogeneity in financial risk across the sample of new energy vehicle enterprises.

Regarding AI dependency, AImach exhibited a mean of 161,000 and a standard deviation of 215,000, reflecting pronounced volatility and divergent AI hardware investments among enterprises. The mean value of AIrob is 27.816, and the mean value of AIinv is 0.0045, the median is approximately 0.002, with its maximum value not exceeding 0.1. AItext displayed a mean of 1.032 with a relatively concentrated distribution, the median is approximately 0.69. The contrasting data characteristics of these two variables are suitable for subsequent robustness testing. The mediator variable Investor Confidence (IC) exhibits a mean of 0.041 and standard deviation of 0.559, with values ranging from -0.842 to 2.834. This reasonable volatility satisfies requirements for mediator effect testing.

Among the control variables, the distributions of firm size (Size) and ROE were generally reasonable. The standard deviation of ROE (0.158) indicated some variation in corporate profitability. The mean proportion of independent directors (Indep) was 38.7%, while the proportion of dual directors (Dual) was 35.8%, consistent with industry governance norms.

Overall, the sample exhibits significant heterogeneity in core variables, providing a sound data foundation for subsequent empirical analysis.

Table 2. Descriptive statistics

VarName	Obs	Mean	SD	Min	Median	Max
Z-score	4266	4.092	4.267	-3.777	2.959	73.931
AImach	4266	1.61×10^5	2.15×10^5	0.000	1.01×10^5	2.52×10^6
AIrob	4266	27.816	20.187	0.000	28.181	77.524
AItext	4266	1.032	1.148	0.000	0.693	5.518
AIinv	4266	0.005	0.007	0.000	0.002	0.089
Size	4266	7.954	1.238	3.497	7.873	13.464
ROE	4266	0.061	0.158	-2.094	0.076	1.751
Loss	4266	0.130	0.337	0.000	0.000	1.000
FIXED	4266	0.202	0.111	0.001	0.188	0.872
Board	4266	2.092	0.194	0.000	2.197	2.890
Indep	4266	0.387	0.075	0.211	0.375	0.714
Dual	4266	0.358	0.479	0.000	0.000	1.000
IC	4266	0.041	0.559	-0.842	-0.136	2.834
eff	4266	0.125	0.088	0.000	0.136	0.314

4.2.Benchmark regression results

To ensure that the linear regression results are not affected by high multicollinearity between variables, a variance inflation factor (VIF) test is conducted on the variables involved in the estimation before the baseline regression, so as to ensure low mutual interference among variables. Generally, a VIF value below 5 indicates that the selected variables do not suffer from severe multicollinearity. As shown in the Table 3 below, the VIF values among the dependent variable, explanatory variables, alternative explanatory variables, and control variables are 1.26, suggesting the absence of high multicollinearity.

Table 3. Variance inflation factor analysis

Variable	VIF	1/VIF
ROE	1.510	0.661
Loss	1.490	0.670
FIXED	1.330	0.753
AImach	1.320	0.756
Board	1.300	0.767
Indep	1.210	0.829
Size	1.080	0.924
AIrob	1.050	0.952
Dual	1.040	0.963
Mean VIF	1.260	-

Table 4. Benchmark regression results

	(1) Z-score	(2) Z-score	(3) Z-score
AImach	-0.00000208*** (0.000000303)	-0.00000213*** (0.000000316)	-0.00000173*** (0.000000337)
Size		-1.207*** (0.0500)	-1.252*** (0.0518)
ROE		6.221*** (0.463)	5.557*** (0.454)
Loss		-0.358* (0.216)	-0.353* (0.210)
FIXED		1.086* (0.614)	-0.427 (0.660)
Board		0.470 (0.348)	0.600* (0.346)
Indep		0.887 (0.866)	0.556 (0.847)
Dual		-0.0681 (0.126)	-0.0356 (0.124)
_cons	4.426*** (0.0812)	12.18*** (0.930)	12.66*** (0.917)
Control	No	Yes	Yes
Year Fe	No	No	Yes
Industry Fe	No	No	Yes
N	4266	4266	4266
R^2	0.011	0.173	0.241

Standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Table 4 presents the regression results between automotive enterprises' AI dependency levels and the financial safety

indicator Z-score. The first column of regression analyses was conducted without incorporating control variables and without fixing time and industry effects. The results indicate that the regression coefficient for AImach is -0.00000208, with a p-value below 0.01, indicating a significant negative correlation between AI dependency and corporate financial security. After sequentially incorporating control variables and fixing time and industry effects in the second and third columns, the benchmark regression results remained highly significant. The level of AI dependency among automotive manufacturers negatively impacts the security of their financial position.

4.3. Robustness tests

4.3.1. Substitution of explanatory variables

As mentioned above, the measurement method based on the penetration rate of industrial intelligent robots in enterprises is also widely used in academic research to measure the artificial intelligence level of enterprises, which is widely recognized and suitable for the new energy vehicle industry sample dominated by manufacturing enterprises. The VIF test has shown that the variables measured by the two methods do not have excessively high multicollinearity. As shown in Table 5 below, AImach and AIrob pass the Pearson correlation test, with a correlation coefficient of only 0.0852. AIrob is suitable as an variable substitute for the robustness test both in terms of definition and from an econometric perspective.

Table 5. Correlation test for explanatory variables

	AImach	AIrob
AImach	1.0000	
AIrob	0.0852*	1.0000

We conduct the baseline regression using AIrob as the new explanatory variable. After including control variables, time fixed effects and industry fixed effects, the results are shown in Column 1 of Table 6. Under the industrial intelligent robot measurement method, the degree of enterprise artificial intelligence dependence is still negatively correlated with the financial safety indicator Z-score, with a coefficient of -0.0131 and a p-value still less than 0.1, which is statistically significant and rejects the null hypothesis. This further confirms that financial risk increases as sample enterprises raise their level of artificial intelligence dependence, providing basic support for Hypothesis H1b.

4.3.2. Truncated variable treatment

Trimmed data for both the dependent and independent variables effectively mitigates the bias introduced by extreme values in benchmark regression analyses. Following robustness testing, where the core independent variable AImach and core dependent variable Z-score underwent 1% trimming before re-running the benchmark regression (as shown in the second column of Table 6), the results remained statistically significant at the 1% level.

Table 6. Robustness analysis

	(1) Z-score	(2) Z-score {Trimmed}
AIrob	-0.0131* (0.00768)	
AImach		-0.00000192***

		(0.000000332)
Size	-1.265*** (0.0524)	-1.147*** (0.0434)
ROE	5.528*** (0.455)	5.031*** (0.380)
Loss	-0.377* (0.210)	-0.436** (0.176)
FIXED	-1.768*** (0.606)	-0.756 (0.558)
Board	0.459 (0.346)	0.496* (0.290)
Indep	0.635 (0.850)	0.348 (0.710)
Dual	-0.0167 (0.125)	-0.0627 (0.104)
_cons	13.38*** (0.954)	12.20*** (0.769)
Control	Yes	Yes
Year Fe	Yes	Yes
Industry Fe	Yes	Yes
N	4266	4266
R^2	0.237	0.277

Standard errors in parentheses

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

4.3.3. Dual machine learning

To further eliminate the potential nonlinear bias of high-dimensional covariates and model specification bias from interfering with the benchmark regression results, this paper adopts the double machine learning method for robustness tests, following the research of Chernozhukov et al. (2018)[30]. Through a 5-fold cross-fitting and 5 repeated sampling processes, overfitting bias and sample random splitting noise are eliminated. Ridge regression and Post-Lasso algorithms are respectively used as auxiliary estimators to capture the complex nonlinear predictive relationship of the control variable set on AImach and Z-score. The first stage of Post-Lasso, selects the regularization parameter using 3-fold cross-validation. To ensure the rigor of the inference, the model automatically selects the regularization parameters through cross-validation within each fold, centralizes the high-order terms of continuous control variables, and strictly controls the industry and year fixed effects. The empirical results show that under four different model specifications, the estimated coefficient of AImach on Z-score is significantly negative at the 1% level: the estimated coefficients of the first-order and second-order terms based on the Ridge algorithm in columns (1) and (2) are -1.7387×10^{-6} and -1.7264×10^{-6} respectively; the estimated coefficients of the first-order and second-order terms based on the Post-Lasso algorithm in columns (3) and (4) are -1.7922×10^{-6} and -1.8066×10^{-6} respectively. This indicates that after introducing machine learning algorithms to handle high-dimensional features and correct regularization bias, the inhibitory effect of artificial intelligence transformation on corporate financial stability remains highly robust, and its negative impact does not change substantially with the change of estimation methods or functional forms, strongly supporting the benchmark research conclusion of this paper.

Table 7. Dual machine learning tests

	(1) Ridge DML	(2) Ridge DML	(3) Post-Lasso DML	(4) Post-Lasso DML
AImach	-1.7387×10^{-6}***	-1.7264×10^{-6}***	-1.7922×10^{-6}***	-1.8066×10^{-6}***
	(3.3149×10^{-7})	(3.5062×10^{-7})	(3.3051×10^{-7})	(3.4199×10^{-7})
Control Variable Term	Yes	Yes	Yes	Yes
Control Variable quadratic term	No	Yes	No	Yes
Year Fe	Yes	Yes	Yes	Yes
Industry Fe	Yes	Yes	Yes	Yes
Obs	4266	4266	4266	4266

Standard errors in parentheses

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

4.4.Testing for mediating effects

Table 8. Mediating effect test results

	(1) IC	(2) Z-score
AImach	-0.000000168***	-0.00000184***
	(4.45×10^{-8})	(0.000000337)
Size	-0.165***	-1.358***
	(0.00684)	(0.0551)
ROE	0.160***	5.660***
	(0.0599)	(0.453)
Loss	-0.0115	-0.360*
	(0.0277)	(0.209)
FIXED	0.120	-0.351
	(0.0871)	(0.658)
Board	-0.0924**	0.540
	(0.0456)	(0.345)
Indep	0.0783	0.606
	(0.112)	(0.844)
Dual	0.0988***	0.0278
	(0.0164)	(0.124)
IC		-0.642***
		(0.116)
_cons	1.473***	13.61***
	(0.121)	(0.930)
Control	Yes	Yes
Year Fe	Yes	Yes
Industry Fe	Yes	Yes
N	4266	4266
R^2	0.230	0.246

Standard errors in parentheses

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

To test Hypothesis H2, this paper employs a three-step mediation analysis to examine the role of investor confidence in the direct effect pathway. The results of Model (1) in Table 8 reveal a significant negative correlation between the AI dependency level of the sampled automotive enterprises and investor confidence. In Model (2), after incorporating the mediating variable into the main effect regression, the mediating variable IC coefficient is significant. Meanwhile, AImach continues to exhibit a significant negative correlation with Z-score. This suggests that external investor expectations partially mediate the relationship between AI adoption and financial risk. The introduction of AI technology results in the inherent negative impact of operational performance expectations leading to financial security issue.

To ensure experimental rigour, the study employed bootstrap sampling with 1000 path tests to validate the mediating effect of investor confidence. Results confirmed all paths remained statistically significant, with none falling within the 95% confidence interval of 0, thus substantiating mediation. Among the sample of new energy and other automotive manufacturing industry chain enterprises, artificial intelligence adjusts financial risk by diminishing corporate investor confidence and worsening financial security, yielding a total effect of -1.73×10^{-6}.

Table 9. Bootstrap sampling test results for each path of the mediating effect

	Observed coefficient	Bootstrap std. err.	z	P>|z|	Normal-based [95% confidence interval]	
Indirect effect	1.08×10^{-7}	3.25×10^{-8}	3.33	0.001	4.44×10^{-8}	1.72×10^{-7}
Direct effect	-1.84×10^{-6}	3.43×10^{-7}	-5.35	0.000	-2.51×10^{-6}	-1.16×10^{-6}
Total effect	-1.73×10^{-6}	3.35×10^{-7}	-5.17	0.000	-2.38×10^{-6}	-1.07×10^{-6}

However, the analysis of the path coefficients in the mediation model reveals a suppression effect of investor confidence, with the effect size measured as | Indirect effect / Direct effect | ≈ 5.87%. Although the total effect remains negative, higher AI dependence in new energy vehicle firms indirectly improves financial safety slightly by reducing investor confidence, which appears inconsistent with the theoretical framework and conventional understanding.

Decomposing the results shows that market expectations and internal operational conditions reflect each other. When regressing Z-score on IC alone, the coefficient is 0.9829 (p = 0.000), highly significant and consistent with the view that stronger investor confidence lowers financing costs and enhances financial stability. In the new energy vehicle industry, however, investor confidence consists of two components: expectations about firm fundamentals and cautiousness toward AI transformation, which is usually

accompanied by heavy R&D and aggressive capital expenditure. Such firms attract high market attention but bear greater financial risk.

Controlling for AImach in the mediation model filters out AI-related sentiment, leaving the remaining variation in IC as a mixture of fundamental confidence and residual market sentiment. This residual sentiment tends to identify firms with high valuations driven by technological narratives but weak operational capabilities, resulting in a negative association between IC and Z-score. Firms that initially attract investor favor and adopt more aggressive AI investment will endanger financial stability and depress investor confidence, pushing managers into a vicious cycle. Conversely, Firms with lower AI dependence can avoid being trapped in aggressive strategic investment driven by overly optimistic market expectations, thus maintaining financial stability.

Table 10. Grouping mediating effect test results

	(1) IC High PB	(2) Z-score High PB	(3) IC Low PB	(4) Z-score Low PB
AImach	-0.000000185**	-0.00000386***	-6.98×10^{-8}*	-0.000000777***
	(8.68×10^{-8})	(0.000000759)	(3.90×10^{-8})	(0.000000232)
Size	-0.191***	-2.017***	-0.0917***	-0.804***
	(0.0121)	(0.113)	(0.00632)	(0.0397)
ROE	0.785***	9.828***	0.250**	8.365***
	(0.162)	(1.420)	(0.124)	(0.737)
Loss	-0.136*	0.661	0.0308	-0.216
	(0.0726)	(0.634)	(0.0408)	(0.243)
FIXED	0.267*	3.131**	0.104	-1.495***
	(0.156)	(1.367)	(0.0790)	(0.470)
Board	-0.107	1.259*	0.00627	0.129
	(0.0768)	(0.671)	(0.0417)	(0.248)
Indep	-0.168	1.030	0.0423	-0.0743
	(0.195)	(1.707)	(0.0984)	(0.585)
Dual	0.0812***	0.210	0.0644***	-0.133
	(0.0275)	(0.241)	(0.0154)	(0.0922)
IC		-1.732***		-0.772***
		(0.204)		(0.139)
_cons	1.879***	17.41***	0.499***	9.046***
	(0.210)	(1.876)	(0.108)	(0.648)
Control		Yes		
Year Fe		Yes		
Industry Fe		Yes		
N	1885	1885	1890	1890
R^2	0.179	0.215	0.188	0.291

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To deeply deconstruct the generative logic of the suppression effect and verify the aforementioned theoretical derivation, this paper partitions the sample into high- and low-valuation groups based on the median PB ratio for a multi-group path analysis. To maintain the consistency of valuation metrics, observations with a negative PE ratio were excluded from the subsample analysis. The empirical results manifest that the negative impact of AI dependence on financial security exhibits significant heterogeneity across different valuation environments. Specifically, in the high-valuation group, AI dependence significantly inhibits investor confidence, which subsequently exerts a potent negative backlash on financial security. The absolute value of the regression coefficient (-1.732) is approximately 2.2 times that of the low-valuation group (-0.772).

Concurrently, the direct financial destruction power of AI reliance in the high-valuation group is nearly five times that of its low-valuation counterpart, with both coefficients reaching high levels of statistical significance. Furthermore, the inter-group coefficient difference test conducted via the bdiff (permutation test) method reveals that the influence paths of IC to Z-score and AImach to Z-score differ significantly between the two groups (p < 0.01), attesting that valuation levels indeed moderate the mediation variable's counter-action against financial risks.

Table 11. Between-group coefficient difference test

Variables	b0-b1	Freq	p-value
AImach	0.000	0	0.000
IC	0.960	0	0.000
Control		Yes	
Year Fe		Yes	
Industry Fe		Yes	

These findings attest that within a narrative-driven market environment, surging investor confidence often serves as an incentive for enterprises to pursue aggressive expansion at the expense of operational robustness. In this context, while the total and direct effects remain negative, the indirect effect path coefficient is positive, statistically constituting a suppression effect on the primary risk. Although the basic direct regression between IC and Z-score yields a significant positive correlation—aligning with conventional economic intuition—technology stacking detached from fundamentals is inherently more prone to inducing financial collapse in bubble-heavy samples. Consequently, while AI reliance directly undermines corporate financial security, it marginally alleviates the operational burdens arising from the blind pursuit of valuation premiums by inhibiting excessive irrational exuberance within the capital market.

4.5. Endogeneity test

It must be acknowledged that finding an instrumental variable that is closely related to investment in AI but unrelated to indicators involving numerous financial data is quite difficult. Therefore, this paper will use lagged independent variables as instrumental variables to alleviate the endogeneity problem to some extent. According to Path Dependency Theory, an enterprise's current technological trajectory and resource allocation are heavily influenced by its

prior strategic commitments and technical endowments. In the context of digital transformation, the implementation of artificial intelligence—encompassing intelligent production systems and data-driven algorithmic frameworks—is a continuous process characterized by high adjustment costs and structural inertia. Therefore, an enterprise's AI dependency in the previous period serves as a foundational precursor that significantly shapes its current AImach, satisfying the relevance requirement of a valid instrumental variable.Conversely, the exclusion restriction is satisfied because the prior year's AI investment decisions represent "predetermined" strategic facts. While current AI dependency may directly impact an enterprise's immediate financial security through operational burdens, the lagged technological state from the previous year is unlikely to exert a direct, contemporaneous shock on the current year's debt-paying capacity or profitability, except through its influence on the current AI implementation. Thus, the lagged variable effectively isolates the exogenous variation in AI dependency, mitigating potential endogeneity arising from reverse causality or omitted contemporaneous factors.

The results of the 2SLS instrumental variable test reveal that the under-identification test statistic is 47.02, significant at the 1% level, rejecting the null hypothesis that the model is under-identified. This confirms that the selected instrumental variable possesses sufficient correlation with the endogenous variable. Furthermore, the weak instrumental variable test yielded a value of 200.15, substantially exceeding the conventional threshold of 10 and the stringent Stock-Yogo critical value of 16.38. This confirms the absence of weak instrument bias, establishing the statistical validity of the lagged AI dependency as an instrument.The first-stage regression results show that the coefficient for the lagged instrument (L. AImach) on AImach is 0.8874, significant at the 1% level , validating the strong technical persistence within the sample firms. The second-stage regression results indicate that, after addressing endogeneity, the regression coefficient for AImach on financial security is -1.78×10^{-6}, significant at the 5% level ($p = 0.037$). This result demonstrates that even after purging endogenous bias, increased AI dependency continues to exert a significant negative impact on the financial security of enterprises. This confirms that the "AI trap" identified in the benchmark regression is a robust causal relationship rather than a statistical artifact, further corroborating the reliability of this study's core conclusions which have been tested by alternative measure test(AIrob) based on Bartik method and DML approach before. This part of the test can serve as an auxiliary tool.

Table 12. Instrumental variables method test results

Variables	AImach	Z-score
L.AImach	0.8874*** (0.06)	
AImach		-1.78×10^{-6}** (8.51×10^{-7})
Controls	Yes	Yes
Year Fe	Yes	Yes
Industry Fe	Yes	Yes
Kleibergen-Paap rk LM statistic	47.02 ***	
Kleibergen-Paap Wald rk F statistic	200.15 [16.38]	
R²		0.1756
Obs		3619

4.6. Moderation effect test

Differences in resource allocation efficiency arise from variations in corporate operational strategies and capabilities. Where R&D expenditure translates into patent outcomes, it facilitates the formation of intangible assets possessing both value and technological applicability. Comparative analysis within the same industry sector adequately reflects a firm's efficiency in converting innovation into tangible results.

The moderation effect results are presented in Table 13. As an exogenous moderator variable, R&D-to-patent conversion efficiency exerts an inverse effect on the main effect pathway. The coefficient for the interaction term is 0.00000791, significantly positive. This indicates that under the moderation of innovation efficiency in patent conversion, enterprises with strong knowledge innovation and patent output capabilities experience a significant buffering of AI's negative effects. Consequently, the main effect's detrimental impact on financial security is mitigated.

The results validate Hypothesis H3: when patent conversion efficiency is high, enterprises possess stronger knowledge absorption and technology transformation capabilities. AI investment is more readily converted into patents or new products, effectively empowering business operations and thereby mitigating the financial chain and organisational friction costs associated with AI implementation.

Table 13. Results of moderation effect tests

	(1) Z-score	(2) Z-score
AImach	-0.00000173*** (0.000000338)	-0.00000155*** (0.000000347)
eff	-0.0592 (0.731)	0.0600 (0.732)
AImach_eff		0.00000791** (0.00000343)
cons	12.66 *** (0.920)	12.69*** (0.920)
Control	Yes	Yes
Year Fe	Yes	Yes
Industry Fe	Yes	Yes
N	4266	4266
R²	0.241	0.242

Standard errors in parentheses

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

4.7. Heterogeneity analysis

Our previous empirical results have examined the suppression role of market investor confidence in the mechanism through which corporate AI applications affect financial safety, and the moderating role of corporate research efficiency in the main effect. However, whether the characteristics of corporate AI transformation disclosed in public annual reports lead to heterogeneous outcomes in the main effect chain remains a question to be explored. Academics have conducted research on phenomena such as "high voice but low action" in corporate digital transformation, and similar inconsistencies are also inevitable in AI

transformation that empowers corporate operations. Moreover, different measures of corporate AI intensity in the literature confirm that firms' emphasis on AI-related keywords in financial reports does not fully align with their actual investment in intelligent equipment, or their R&D and acquisition of AI technologies. Accordingly, we divide the sample into four groups based on the sample medians of AItext and AIinv. Specifically, the High Voice & High Action group refers to firms whose natural logarithm of AI-related keyword mentions (AItext) in the annual report is above the sample median, and whose ratio of AI-related fixed asset and intangible asset investment to total assets (AIinv) disclosed in the notes is also above the sample median.

The decoupling of AI Voice and Action captures the tension between symbolic management and substantive resource commitment, where tangible technological assets function as a critical buffer against the inherent risks of AI adoption. Firms with high AI reliance but low substantive action are more susceptible to financial shocks because they lack the absorptive capacity and organizational resilience required to internalize complex technical transitions. Consequently, this analytical framework reveals that the AI trap is not a universal threat, but a selective penalty primarily targeting firms that prioritize narrative valuation over fundamental productivity enhancement.

Table 14. Group-wise heterogeneity results

	(1) High Voice & High Action	(2) High Voice & Low Action	(3) Low Voice & High Action	(4) Low Voice & Low Action
AImach	-0.000000390	-0.00000412***	-0.00000144*	-0.00000203***
	(0.000000489)	(0.000000828)	(0.000000869)	(0.000000657)
Size	-0.908***	-1.412***	-1.477***	-1.457***
	(0.0739)	(0.115)	(0.142)	(0.122)
ROE	5.165***	7.813***	3.648***	6.412***
	(0.671)	(1.099)	(0.967)	(1.017)
Loss	-0.766**	0.633	-1.142**	0.0743
	(0.311)	(0.483)	(0.490)	(0.438)
FIXED	-2.137**	5.578***	-1.031	-2.032
	(0.967)	(1.644)	(1.570)	(1.381)
Board	-0.222	1.561*	0.659	0.461
	(0.483)	(0.803)	(0.860)	(0.755)
Indep	1.214	5.766***	-1.532	-1.715
	(1.218)	(2.022)	(2.014)	(1.727)
Dual	-0.0625	0.212	-0.0496	-0.173
	(0.180)	(0.283)	(0.304)	(0.271)
Control	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
Industry Fe	Yes	Yes	Yes	Yes
Chow Test P-Value		0.0563*		
N	1384	1082	745	1045
R^2	0.274	0.259	0.301	0.315

Standard errors in parentheses

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

The results are shown in the Table 14[2]. In the High Voice & Low Action group, the coefficient of AImach is -0.00000412 and significantly negative at the 1% level, indicating that AI transformation has the strongest negative impact on investor confidence. In the Low Voice & Low Action group, the coefficient is -0.00000203 and significantly negative at the 1% level, showing a weaker negative effect. The baseline regression results are no so significant in the

other two groups with above-median AIinv especially in the group of High Voice & High Action.

The Chow Test shows that the F-statistic for the joint significance test of the interaction terms between AImach and group dummies is 2.52, with a corresponding p-value of 0.0563, which rejects the null hypothesis of equal coefficients across groups at the 10% significance level. The heterogeneity conclusion is supported both statistically and economically.

The heterogeneity analysis sufficiently indicates that new energy vehicle firms that claim high-level AI applications in their public reports but do not achieve substantial intelligent production transformation in their asset structure suffer more severely from the AI dependence trap, which undermines the

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[2] When conducting the regression analysis, the fixed effects of year and industry were controlled. After grouping, a very small number of isolated observations were automatically excluded. Ultimately, 4,256 observations participated in the calculation.

trust of investors and consumers and further endangers corporate financial stability.

To further eliminate potential sensitivity regarding grouping thresholds and ensure the robustness of our findings, this study employs a tercile split method to examine the heterogeneity of the main effect across two dimensions: AI Voice and AI Action. Regressions were performed on sub-samples representing the top and bottom 33% of the observations for each variable.

The empirical results indicate that the negative impact of AI reliance on financial security is predominantly concentrated in the "Low Voice" and "Low Action" groups. Specifically, for firms characterized by Low AI Action, the negative impact of the AImach coefficient is most pronounced, reaching -0.00000296 and attaining statistical significance at the 1% level. In contrast, within the high-level groups, AI reliance does not significantly deteriorate financial security. This finding reinforces the premise that substantive technological output is a critical prerequisite for mitigating technical risks and achieving a robust strategic transformation.

Table 15. Tercile heterogeneity test

	AI Voice		AI Action	
	(1)	(2)	(3)	(4)
	High	Low	High	Low
AImach	-0.000000324	-0.00000164***	-0.000000364	-0.00000296***
	(0.000000483)	(0.000000508)	(0.000000520)	(0.000000650)
Size	-0.821***	-1.468***	-1.037***	-1.433***
	(0.0636)	(0.0904)	(0.0795)	(0.109)
ROE	5.468***	4.958***	5.123***	7.411***
	(0.621)	(0.687)	(0.645)	(1.013)
Loss	-0.461*	-0.490	-0.753**	-0.132
	(0.272)	(0.323)	(0.312)	(0.434)
FIXED	-1.776*	-1.878*	-2.393**	1.791
	(0.924)	(1.005)	(0.977)	(1.370)
Board	-0.442	0.400	0.0770	1.336*
	(0.429)	(0.561)	(0.511)	(0.706)
Indep	1.480	-2.015	-0.975	1.538
	(1.104)	(1.298)	(1.274)	(1.731)
Dual	-0.129	-0.178	-0.124	0.209
	(0.162)	(0.199)	(0.190)	(0.257)
_cons	10.85***	16.10***	12.98***	11.79***
	(1.134)	(1.499)	(1.345)	(1.843)
Control		Yes		
Year Fe		Yes		
Industry Fe		Yes		
N	1325	1794	1422	1419
R^2	0.274	0.295	0.268	0.277

Standard errors in parentheses

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

5. Conclusions and implications

5.1. Summary of research findings

The study employs panel data of listed firms in the new energy vehicle and conventional automobile manufacturing industries from 2013 to 2023 to demonstrate the double-edged sword effect of artificial intelligence technology on corporate financial safety. Baseline regression results show that firms' artificial intelligence dependence is significantly negatively related to their financial safety levels: higher reliance on AI technology corresponds to increased financial risks.

This empirical result contradicts the "technology empowerment" logic in theoretical expectations and differs sharply from the general perception that AI improves resource allocation efficiency and corporate performance. A reasonable explanation can be found in the practice of the automobile manufacturing industry. In the short run, large R&D investment in AI crowds out a firm's existing R&D resources, making it difficult for the organization to effectively transform external knowledge and resulting in technological liabilities. On the one hand, core operational capabilities

cannot be effectively improved; on the other hand, the adoption of emerging technologies fails to generate promising return expectations. This may be because high R&D expenses are not converted into reliable intangible assets, or because intelligent equipment does not reduce costs or improve efficiency, creating a vicious cycle.

Especially in the emerging new energy vehicle sector, firms often emphasize heavy investment in AI technology to seize market opportunities, but the long return cycle and high learning costs of technology further amplify the risk of resource misallocation. Midstream and downstream manufacturers such as JIYUE Auto, GAOHE Auto, and QIDIAN Motors, as well as some upstream component suppliers, have experienced unsustainable financial conditions amid market-linked crises. Once financial safety cannot be guaranteed, no so-called advanced intelligent technology can be transformed into corporate profits. Firms will then face a series of practical operational difficulties, including declining industry status, weakening consumer interest, and reduced investment funding, ultimately landing in a precarious position.

Moderation effect tests and heterogeneity analysis further clarify the complexity of the contradiction between technology investment and financial safety. The study finds that the negative effect of AI dependence is significantly buffered when patent transformation efficiency is high. Meanwhile, compared with firms that merely claim artificial intelligence transformation, firms that truly achieve high-level asset intelligent transformation are less likely to fall into financial distress. This fully indicates that the potential financial risk effect of AI is not unilaterally harmful. Its mechanism highly depends on the allocation logic of a firm's innovation resources — specifically, whether technological achievements can be rapidly transformed into market value or knowledge barriers determines whether the application of AI in enterprises becomes a "trap" that triggers financial crises or a "springboard" that enhances competitiveness.

5.2. Practical implications and recommendations

For firms along the new energy vehicle and automobile manufacturing chain, avoiding the AI "intelligence trap" requires rebalancing technology investment and financial health. The potential financial risks of AI do not mean firms should adopt conservative strategies or reject new production tools. Instead, firms should evaluate their financial conditions and pursue efficient R&D to strengthen technological barriers and enhance market competitiveness only when their capital and technical capacity can support AI investment.

First, new energy smart vehicle firms should guard against the strategic impulse of "AI for AI's sake" and direct resources to areas with high technology conversion efficiency and clear market demand, rather than blind technological stacking. Second, they should optimize R&D resource allocation and shorten the return cycle of AI technologies industry-university-research collaboration or open innovation networks, so as to improve product competitiveness while reducing financial risks. Third, they should strengthen dynamic capabilities and deeply integrate AI investment with organizational learning to avoid disconnection between

technology application and internal management, resource waste, or even improper market behaviors driven by distress.

Finally, from a market-wide perspective, firms can achieve sustainable development only by formulating emerging technology R&D strategies matching their capital conditions. Xiaomi, over 10 billion CNY investment in new energy smart vehicles was supported by its strong financing capacity after listing in 2018 and its solid capital base. Beyond the automobile industry, Cambricon, a leading Chinese AI chip firm, can maintain high R&D investment exceeding annual revenue despite years of losses due to strong state-backed capital reserves and ample idle working capital, enabling long-term technological breakthroughs and successful flagship AI chip development.

For new market entrants, however, blind pursuit of cutting-edge technological competitiveness and excessive investment in AI or other advanced technologies will lead to financial distress if achievement transformation efficiency fails to support operations. This is irresponsible not only to the firm itself and shareholders, but also to society and supportive consumers.

Financial regulators should establish a dynamic intelligent debt early-warning mechanism specifically tailored for the New Energy Vehicle and intelligent automobile sectors. Given that intensive capital expenditure on intelligent hardware serves as a primary driver of financial risk, regulatory focus should shift from the qualitative auditing of technical patents to the direct monitoring of cash flow health. During credit approval processes, commercial banks should decrease the collateral weight of intelligent hardware assets and potentially implement specific AI debt ceilings. By utilizing these financial levers, regulators can compel firms reliant on technological narratives to return to financial rationality, preventing them from being overwhelmed by high depreciation and debt burdens before their innovations translate into stable returns.

Furthermore, government subsidy frameworks should transition from direct industry-based grants toward "computing power as a public utility". NEV manufacturers, particularly startups, frequently encounter a strategic paradox: they cannot maintain competitiveness without technological investment, yet they lack the capital to sustain operations after acquiring expensive equipment or funding massive R&D. To resolve this financial deadlock, policy priorities should shift from domain-specific corporate subsidies to the construction of regional intelligent computing and data platforms. By providing low-cost public resources through government-purchased services—similar to essential utilities such as water or electricity — firms can lease computing resources on demand. This would fundamentally alleviate the heavy burden of fixed assets and enhance financial security levels. Simultaneously, it allows the government to derive authentic insights into industrial innovation activity via actual platform usage data, rather than being misled by the "word games" often found in public financial disclosures.

5.3. Academic summary and reflections on improvements

This paper provides micro-evidence for the productivity paradox and related management theories from the

perspective of a specific industrial chain. Nevertheless, its methodology has certain limitations: the empirical research in this paper merely uses the lagged explanatory variables by one period to alleviate the endogeneity problem. Although the robustness test replacing the explanatory variable with AIrob and the double machine learning test provide solid evidence for the main effect conclusion, the academic community can try more sophisticated methods to alleviate the endogeneity problem in the future to support the relevant topics. The measurement of AI focuses on indicators including the ratio of AI-related equipment to employees, potentially neglecting softer factors such as managerial decisions and data application, though such indicators are indeed difficult to measure at present, and future research may consider more comprehensive approaches to quantifying corporate AI adoption. In addition, the sample does not distinguish between automakers and component suppliers or incorporate other heterogeneity dimensions such as state ownership, while the heterogeneity analysis only captures differences in firms' AI disclosure and investment profiles. Future studies may further explore the heterogeneous role of industrial chain positioning or use real-world cases to examine how organizational and institutional factors moderate corporate AI dependence and transformation, opening new directions for technology-driven financial risk management.

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