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The Innovation Paradox of AI-Driven Development: Resource Allocation Distortion and Corporate R&D Motivation Loss

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As artificial intelligence technology rapidly develops, enterprises pursuing intelligent transformation may face innovation resource allocation dilemmas. On one hand, the construction and maintenance of AI systems require substantial financial investment, and this high-cost pressure may crowd out resources traditionally allocated to innovation activities. On the other hand, excessive dependence on AI may lead enterprises to neglect talent cultivation and equipment updates, resulting in technological path lock-in. Based on resource allocation theory, principal-agent theory, and path dependence theory, this paper uses Chinese A-share listed companies from 2013–2023 as research samples and employs text analysis methods to construct an enterprise AI application intensity index to explore the impact of AI on enterprise innovation behavior and its mechanisms. The research finds that: (1) AI application has a significant crowding-out effect on enterprise innovation; (2) this crowding-out effect is primarily realized through two channels: reducing innovation talent investment intensity and cutting professional technical equipment configuration; (3) heterogeneity analysis shows that characteristics such as state ownership, high market competition, low financing constraints, high technology intensity, and high management shareholding can effectively mitigate AI's inhibitory effect on innovation. This research not only deepens theoretical understanding of the relationship between AI and enterprise innovation but also provides practical guidance for optimizing innovation resource allocation during enterprise digital transformation.

Keywords: *Artificial Intelligence; Enterprise Innovation; Resource Allocation; Crowding-out Effect; Innovation Talent; Professional Technical Equipment.*

Introduction

With the vigorous development of the global digital economy, artificial intelligence, as the core driving force of a new round of technological revolution and industrial transformation, is reshaping the global industrial landscape and competitive situation at an unprecedented speed and depth (George & George, 2024). In recent years, with breakthrough progress in key technologies such as machine learning and deep learning, AI has demonstrated powerful technological potential in image recognition, natural language processing, intelligent decision-making, and other fields (Lu, 2019; Sarker, 2021). Facing increasingly intense market competition, enterprises are increasing their investment in AI technology research and development and application exploration to gain first-mover advantages in technological innovation (Chen *et al.,* 2024). However, it is worth noting that the development of AI technology has profoundly impacted enterprise innovation models, resource allocation methods, and value creation paths. The mechanism and effectiveness of this impact have not been systematically explained, which to a large extent constrains enterprises' understanding and practice of AI-enabled innovation .

Existing research on enterprise innovation mainly focuses on innovation factor input, innovation process management, and innovation performance evaluation. Numerous empirical studies have shown that effective allocation of innovation resources and coordinated development of organizational capabilities are key factors in improving enterprise innovation performance (Van Beers & Zand, 2014; Yam *et al.,* 2004; Yam *et al.,* 2011). Enterprises continuously enhance their innovation capabilities and market competitiveness through sustained R&D investment and technological accumulation. However, in the AI era, enterprise innovation activities increasingly rely on new production factors such as data, algorithms, and computing power, and traditional innovation resource allocation models face significant challenges. Research has found that enterprise investment in AI may crowd out resources for other innovation activities, leading to imbalances in innovation input structure. Particularly for small and medium-sized enterprises with relatively limited resource endowments, how to achieve optimal balance between AI investment and traditional innovation activities has become an urgent practical problem (Li *et al.,* 2024).

As AI technology develops further, its impact on enterprise innovation shows complex duality. On one hand, AI can significantly improve enterprises' data processing capabilities and decision-making efficiency, providing powerful technical support for enterprise innovation (Dewangan & Godse, 2014; Guan & Chen, 2010; Rese *et al.,* 2011). Through deploying AI systems, enterprises can more quickly identify market opportunities and more accurately predict technological development trends, thereby improving the scientific nature of innovation decisions (Kocoglu *et al.,* 2012; Li, 2011). On the other hand, the construction and maintenance of AI systems require continuous large investments, which may crowd out resources for basic research and innovation talent cultivation. More concerning is that excessive reliance on AI may lead enterprises into technological path lock-in, affecting the cultivation and development of long-term innovation capabilities. Some studies have shown that in the process of promoting AI applications, enterprises often focus excessively on short-term efficiency improvements while neglecting the accumulation of sustainable innovation capabilities, which may harm enterprises' long-term competitive advantages (Zhang *et al.,* 2024).

Based on the review and analysis of existing research, this paper finds several important issues in the current academic discussion of the relationship between AI and enterprise innovation that require further study. First, the mechanism of AI's impact on enterprise innovation behavior remains unclear, particularly lacking systematic research from the perspective of resource allocation. Second, under different institutional environments, market structures, and resource endowment conditions, AI's impact on innovation may vary significantly, and these heterogeneous characteristics and their mechanisms await in-depth discussion. Third, the specific pathways through which AI affects enterprise innovation factor input structure and thereby influences innovation output also need further elucidation. The theoretical contributions of this paper are mainly reflected in three aspects: First, it constructs a theoretical analysis framework for AI's impact on enterprise innovation, systematically examining the mechanism of AI's influence on enterprise innovation behavior from the perspective of resource allocation, deepening theoretical understanding of the relationship between AI and enterprise innovation. Second, based on resource allocation theory, principal-agent theory, and path dependence theory, it deeply analyzes the internal mechanism of AI's impact on enterprise innovation, enriching the theoretical system of innovation management. Third, it systematically examines the moderating effect of enterprise heterogeneous characteristics on the AI-innovation relationship, providing theoretical basis for enterprises to promote intelligent transformation according to local conditions.

The structure of this paper is as follows: The second section proposes research hypotheses based on a review of relevant literature; the third section introduces the research design, including data sources, variable definitions, and model specifications; the fourth section reports empirical analysis results and conducts robustness tests; the fifth section explores potential mechanisms of AI's impact on enterprise innovation; the sixth section summarizes research conclusions and provides policy recommendations.

Literature Review and Hypothesis Development

Literature Review

In the context of the booming global digital economy, artificial intelligence, as the core driving force of a new round of technological revolution and industrial transformation, is reshaping the global industrial landscape and competitive situation at an unprecedented speed and depth. In recent years, with breakthrough progress in key technologies such as machine learning and deep learning, AI has demonstrated powerful technological potential in image recognition, natural language processing, intelligent decision-making, and other fields (Liu *et al.,* 2024). Facing increasingly intense market competition, enterprises are increasing their investment in AI technology research and development and application exploration to gain first-mover advantages in technological innovation. However, it is worth noting that the development of AI technology has profoundly impacted enterprise innovation models, resource allocation methods, and value creation paths. The mechanism and effectiveness of this impact have not been systematically explained, which to a large extent constrains enterprises' understanding and practice of AI-enabled innovation (Chen *et al.,* 2024).

Existing research on enterprise innovation mainly focuses on innovation factor input, innovation process management, and innovation performance evaluation. Numerous empirical studies have shown that effective allocation of innovation resources and coordinated development of organizational capabilities are key factors in improving enterprise innovation performance. Enterprises continuously enhance their innovation capabilities and market competitiveness through sustained R&D investment and technological accumulation (Li, 2011). However, in the AI era, enterprise innovation activities increasingly rely on new production factors such as data, algorithms, and computing power, and traditional innovation resource allocation models face significant challenges. Research has found that enterprise investment in AI may crowd out resources for other innovation activities, leading to imbalances in innovation input structure (Li *et al.,* 2024; Li *et al.,* 2021). Particularly for small and medium-sized enterprises with relatively limited resource endowments, how to achieve optimal balance between AI investment and traditional innovation activities has become an urgent practical problem (Wang *et al.,* 2024).

As AI technology develops further, its impact on enterprise innovation shows complex duality. On one hand, AI can significantly improve enterprises' data processing capabilities and decision-making efficiency, providing powerful technical support for enterprise innovation. Through deploying AI systems, enterprises can more quickly identify market opportunities and more accurately predict technological development trends, thereby improving the scientific nature of innovation decisions (Ali *et al.,* 2024). On the other hand, the construction and maintenance of AI systems require continuous large investments, which may crowd out resources for basic research and innovation talent cultivation. More concerning is that excessive reliance on AI may lead enterprises into technological path lock-in, affecting the cultivation and development of long-term innovation capabilities (Xiao *et al.,* 2024). Some studies have shown that in the process of promoting AI applications, enterprises often focus excessively on short-term efficiency improvements while neglecting the accumulation of sustainable innovation capabilities, which may harm enterprises' long-term competitive advantages (Zhang *et al.,* 2024).

Against this background, in-depth research on the relationship between AI and enterprise innovation has important theoretical value and practical significance. From a theoretical perspective, this research helps reveal the inherent laws of enterprise innovation in the digital age, enriching and developing the theoretical system of innovation management. Traditional innovation theory emphasizes technological breakthroughs and resource integration, but in the AI era, the data-driven characteristics and intelligent trends of innovation activities require new theoretical explanatory frameworks. In particular, research on how AI affects enterprise innovation resource allocation, innovation path selection, and innovation performance mechanisms will provide new research perspectives for the development of innovation theory (Su *et al.,* 2022). From a practical perspective, this research can provide valuable decision-making references for enterprises to formulate innovation strategies, optimize resource allocation, and improve innovation efficiency. Only by accurately grasping the mechanism of AI's impact on innovation activities can enterprises achieve continuous improvement of innovation capabilities during digital transformation. Currently, global technological competition and industrial transformation are accelerating, and in-depth research on the relationship between AI and enterprise innovation has important guiding significance for enhancing enterprise competitiveness and promoting industrial upgrading.

Research Hypotheses

Enterprise innovation is the core driving force of economic development and technological progress, with innovation behavior directly affecting the commercialization process of new technologies in the market and the realization of innovation outcomes (Lei & Xu, 2024, 2025; Rajapathirana & Hui, 2018). Enterprises continuously enhance their technological capabilities and market competitiveness through sustained innovation activities, a process that often involves complex resource integration and strategic decision-making. Research shows that enterprise innovation capability depends not only on the ability to acquire and utilize various resources but also on the comprehensive literacy of enterprises in evaluating and applying new technologies (MacMillan *et al.,* 2022). Enterprise innovation behavior is a multi-dimensional decision-making process influenced by multiple internal and external factors. Internally, enterprise product development strategy, organizational structure, and resource allocation methods have profound impacts on innovation behavior (Bieberstein *et al.,* 2005); externally, market competition patterns, technological development trends, and policy institutional environments also significantly influence enterprise innovation decisions (Teece, 2007).

This paper constructs a research framework based on resource allocation theory, principal-agent theory, and path dependence theory. Resource allocation theory suggests that enterprise innovation activities depend on the rational allocation of limited resources, and when enterprises invest substantial resources in AI systems, they may crowd out critical resources needed for traditional innovation activities (Yuan & Pan, 2023). Principal-agent theory emphasizes that under information asymmetry, management may overemphasize efficiency improvements brought by AI while neglecting the cultivation of long-term innovation capabilities due to pressure for short-term performance (Laverty, 1996). Path dependence theory indicates that once enterprises form dependence on specific technological paths, it may limit their exploration space in other innovation directions (Brekke & Development, 2015).

In the digital economy era, AI, as a revolutionary general-purpose technology, is profoundly changing enterprise innovation models and development paths. However, this technological transformation also brings unprecedented challenges to enterprises. First, the construction and maintenance of AI systems require substantial financial investment, and this high cost pressure may crowd out resources for other innovation activities. Specifically, enterprises need to make continuous investments in hardware facility procurement, algorithm development, technical personnel training, and system upgrades and maintenance, and this resource concentration may reduce enterprise investment intensity in other innovation areas. Second, AI technology itself has high uncertainty, and enterprises face multiple challenges in application processes, including technological path selection, market demand forecasting, and investment return evaluation. This uncertainty may lead enterprises to adopt more conservative innovation strategies and reduce investment in high-risk innovation projects.

More notably, excessive dependence on AI may produce technological path lock-in effects. Some enterprises may view AI as an omnipotent tool for improving efficiency while neglecting the value of traditional innovation methods. This cognitive bias may cause enterprises to lose innovation advantages in certain specific scenarios because AI's performance in handling unstructured problems and creative tasks may not match that of humans. Additionally, the widespread application of AI also brings adjustment pressure on employment structure, potentially causing employee concerns about career prospects (Frey & Osborne, 2017). This sense of insecurity may affect employees' innovation enthusiasm, making them more inclined to complete routine tasks rather than exploratory innovation activities. Based on the above analysis, this paper proposes:

H1: AI has a crowding-out effect on enterprise innovation behavior.

From the perspective of enterprise resource allocation, AI technology development is changing enterprise resource structure and allocation methods. Enterprise investment in technical equipment in specific fields often reflects their innovation capabilities and competitive advantages in those fields (Teece, 2007). However, AI, as a general-purpose technology, its powerful adaptability and flexibility are changing enterprise resource dependence patterns. Enterprises face increasingly complex market environments and accelerating technological update speeds, challenging traditional resource allocation methods. AI application may promote enterprises to rely more on external resources and market transactions to obtain innovation momentum while reducing investment in internal specialized technical equipment.

Regarding innovation talent, AI technological progress is reshaping enterprise talent demand structure. Traditionally, core technical talent has been an important driver of enterprise innovation, with their professional knowledge and innovation capabilities directly determining enterprise technological innovation levels. However, as AI capabilities continue to improve in data analysis, pattern recognition, and other fields, enterprise talent demand structure is changing (Tschang & Almirall, 2021). Research finds that enterprises are increasingly inclined to invest resources in AI system development and maintenance rather than traditional talent cultivation and technical team building (Liang *et al.,* 2022). This shift in investment preference may lead to insufficient human resource investment in basic research and innovation projects, affecting enterprises' long-term innovation capabilities. Therefore, this paper proposes:

H2: AI inhibits enterprise innovation behavior by reducing innovation talent investment intensity.

Regarding technical equipment, AI application is changing enterprise investment strategies. Professional technical equipment, as an important material foundation for enterprise innovation, its configuration efficiency directly affects enterprise innovation output (Auranen & Nieminen, 2010). AI systems, with their powerful computing capabilities and data processing abilities, can greatly improve resource utilization efficiency (Huang & Rust, 2018). Meanwhile, the popularization of AI also accelerates the speed of technological updates and iterations, causing professional technical equipment to face faster depreciation risks. This change may lead enterprises to reduce investment in professional technical equipment and instead pursue more flexible technological solutions. Considering the important supporting role of professional technical equipment in enterprise innovation capabilities, this shift in investment strategy may affect enterprise innovation performance. Accordingly, this paper proposes:

H3: AI inhibits enterprise innovation behavior by reducing professional technical equipment configuration.

Research Design

Data Sources

The research sample for this paper consists of Chinese A-share listed companies from 2013-2023. The data sources for this research mainly include the following aspects: First, enterprise-level patent data comes from the China Patent Research and Service System (CPRS), which provides detailed information on enterprise patent applications and grants. Through screening and organizing information on patent types and application times, accurate data on sample enterprises' invention patent application numbers can be obtained. Second, AI-related text data comes from the Wind Financial Terminal, through which complete PDF documents of enterprise annual reports can be obtained. This paper uses Python programming to process and analyze these text files and extract AI-related keyword information.

Enterprise financial data and corporate governance data mainly come from the CSMAR database. This database provides standardized financial statement data such as balance sheets, income statements, and cash flow statements of listed companies, as well as corporate governance information such as ownership structure and executive characteristics. Innovation input data such as R&D personnel numbers come from the Wind Financial Terminal and corporate social responsibility reports. Through cross-checking different data sources, the accuracy and reliability of data can be effectively improved. Industry classification follows the "Guidelines for the Industry Classification of Listed Companies" (2012 revision) issued by the China Securities Regulatory Commission.

To ensure the validity of the research sample, this paper processed the original sample as follows: First, financial industry listed companies were eliminated due to their significant differences from other industries in asset structure and operating models; Second, ST and *ST companies were eliminated, as their operational difficulties may cause abnormal fluctuations in innovation behavior; Third, companies that underwent major asset restructuring during the research period were eliminated to avoid interference from structural changes in research results; Fourth, observations with missing values in key variables were eliminated. After these screening procedures, 10,827 company-year observations were finally obtained. To eliminate the influence of extreme values, this paper winsorized all continuous variables at the 1 % and 99 % percentile levels.

Variable Definitions

The measurement of enterprise innovation behavior has always been an important topic in innovation management research. This paper selects patent application numbers as the main indicator for measuring enterprise innovation behavior. Specifically, the natural logarithm of annual invention patent application numbers (LN_PAT) is used as the dependent variable. The reason for choosing patent application numbers rather than granted numbers is that patent applications can more timely reflect enterprise innovation willingness and input, avoiding the lag effect brought by patent examination cycles. Meanwhile, invention patents have higher technical content and innovation levels compared to utility model patents and design patents, better reflecting enterprises' substantive innovation achievements. To handle possible zero values, 1 is added as a correction term when performing logarithmic transformation on patent application numbers. In robustness tests, this paper will use the natural logarithm of invention patent grant numbers (LN_GPAT) as an alternative indicator to verify the reliability of research conclusions.

For the measurement of the core explanatory variable AI, this paper adopts text analysis methods, constructing based on AI-related information disclosure in enterprise annual reports. Specifically, referring to the keyword dictionary related to AI level measurement published by Chinese domestic scholars (Yao *et al.,* 2024). In the specific calculation process, this paper first uses Python programming to perform word segmentation processing on enterprise annual reports, counting the frequency of each keyword in the text. Considering the differences in document length among different enterprises, this paper adopts a standardization processing method, dividing the total frequency of each keyword by the total number of words in the document to obtain a relative word frequency indicator. To avoid the influence of extreme values and make data distribution closer to normal distribution, this paper takes the natural logarithm after adding 1 to the standardized word frequency value to form the final enterprise AI application intensity index (AI). This processing method can not only eliminate the influence of document length differences but also to some extent alleviate the problem of data skewness.

Mechanism variables. To verify the mechanisms through which AI influences enterprise innovation behavior, this paper sets up the following mechanism variables: (1) Innovation talent ratio (RDRATIO): Uses the proportion of R&D personnel to total enterprise personnel to measure enterprise innovation talent input situation. This indicator can directly reflect the resource allocation status of enterprises in innovation talent and is an important carrier for examining AI's substitution effect on enterprise innovation talent. (2) Professional equipment configuration (FARATIO): Uses the ratio of enterprise net fixed assets to total assets to measure enterprise professional technical equipment input level. Although fixed assets include multiple categories, changes in this ratio can to some extent reflect enterprise investment intensity in professional technical equipment, helping to examine AI's substitution effect on enterprise professional equipment.

Control variables. To control for other factors that may influence enterprise innovation behavior, this paper introduces the following control variables: First, enterprise size (Size) is an important factor affecting innovation input and output, measured by the natural logarithm of total enterprise assets. Larger enterprises usually have stronger resource integration capabilities and risk resistance capabilities, more likely to conduct sustained innovation input. Second, enterprise age (Age) may affect its innovation strategy and capabilities, calculated as the natural logarithm of the number of years from enterprise establishment to the sample year. Mature enterprises may have richer innovation experience but may also face organizational inertia constraints.

Enterprise financial condition is also a key factor affecting innovation behavior. This paper selects asset-liability ratio (Lev) as the indicator measuring enterprise financial leverage level, calculated by dividing total liabilities by total assets. Higher debt levels may limit enterprise innovation input, but moderate financial leverage may also provide necessary funding support for innovation activities. Meanwhile, enterprise profitability will also affect its willingness and ability for innovation input, therefore return on total assets (ROA) is included as a control variable, calculated by dividing net profit by total assets. Better profitability performance not only provides internal funding support for innovation activities but also reflects enterprise operational efficiency. Considering the influence of enterprise governance characteristics on innovation decisions, this paper includes the shareholding ratio of the largest shareholder (First) in the control variable system. The degree of control concentration may affect enterprise innovation strategy and resource allocation efficiency. Additionally, enterprise growth may affect its innovation input tendency, therefore revenue growth rate (Growth) is selected as a control variable. Rapidly growing enterprises may be more inclined to increase innovation input to maintain competitive advantages. Finally, to control for the influence of industry and time characteristics on enterprise innovation behavior, this paper also includes industry dummy variables (Industry) and year dummy variables (Year).

Model Specification

For the empirical testing needs of this research, this paper constructs an econometric model framework based on Poisson regression. The main consideration for choosing Poisson regression is that the dependent variable patent application number has count characteristics, and the data shows obvious non-negative integer distribution characteristics. Accordingly, the baseline model set by this paper is as follows:

$$E\left(LN\_PAT_{i,t} \mid x_{i,t}\right) = exp\begin{pmatrix} \rho_0 + \rho_1 AI_{i,t} + \sum_{k=1}^{n} \rho_2 x_{i,t} \\ +\mu_i + \delta_i + \tau_i + \varepsilon_{i,t} \end{pmatrix} \quad (1)$$

In this model, $LN\_PAT_{i,t}$ represents enterprise i's innovation behavior in year t, measured by the natural logarithm of invention patent application numbers; $AI_{i,t}$ represents the enterprise AI application intensity index; $x_{i,t}$ is a series of control variables that may affect enterprise innovation behavior, including enterprise characteristics such as size, age, asset-liability ratio, profitability, ownership concentration, and growth. To control for the influence of unobservable heterogeneity factors on estimation results, the model also includes time fixed effects μ_i, industry fixed effects δ_i, and province fixed effects τ_i, to eliminate the influence of macroeconomic fluctuations, industry characteristics, and regional development level differences on enterprise innovation behavior.

Empirical Results

Descriptive Statistics

This section first conducts descriptive statistical analysis of the main variables in the research sample. As shown in Table 1, regarding the dependent variable, the logarithm of enterprise invention patent applications (LN_PAT) has a mean value of 1.847, a median of 1.609, and a standard deviation of 1.413, indicating significant differences in innovation output among Chinese listed companies. From the distribution characteristics, the minimum value is 0 and the maximum value is 5.338, indicating that the sample includes both enterprises with no patent applications and highly innovation-active enterprises. The core explanatory variable AI application intensity index (AI) has a mean value of 0.186, a median of 0.142, and a standard deviation of 0.201, reflecting evident heterogeneous characteristics in AI application levels among Chinese listed companies.

Table 1

Descriptive Statistics

Variable	Mean	Std Dev	Min	Median	Max
LN_PAT	1.847	1.413	0.000	1.609	5.338
AI	0.186	0.201	0.000	0.142	0.893
RDRATIO	0.132	0.088	0.009	0.119	0.427
FARATIO	0.224	0.154	0.021	0.202	0.689
Size	22.314	1.326	19.875	22.106	26.249
Age	2.843	0.426	1.792	2.890	3.611
Lev	0.456	0.201	0.059	0.449	0.873
ROA	0.058	0.049	-0.124	0.052	0.198
First	0.343	0.148	0.089	0.327	0.748
Growth	0.164	0.329	-0.415	0.128	1.569

Regarding mechanism variables, the mean value of enterprise R&D personnel ratio (RDRATIO) is 13.24 %, with a median of 11.87 %, indicating that sample enterprises generally value R&D talent input but maintain moderate input intensity. The professional equipment configuration (FARATIO) has a mean value of 22.36 % and a median of 20.15 %, indicating that fixed assets occupy an important proportion of total enterprise assets, which is consistent with the characteristics of China's real economy. Regarding control variables, enterprise size (Size) has a mean value of 22.314, asset-liability ratio (Lev) has a mean value of 45.62 %, and return on total assets (ROA) has a mean value of 5.84 %. These indicators all fall within reasonable ranges, reflecting the overall robust operating conditions of sample enterprises.

Baseline Model Results

To test the impact of AI on enterprise innovation behavior, this paper first conducts baseline regression analysis based on equation (1). Table 2 reports the baseline regression estimation results. Column (1) includes only the core explanatory variable AI and year and industry fixed effects, while column (2) further includes all control variables. From the regression results, when controlling only for fixed effects, the coefficient of AI is -0.284, significantly negative at the 1 % level. After adding control variables, AI's coefficient maintains a significant negative relationship, with the coefficient value changing to -0.246, indicating that AI application indeed has a significant inhibitory effect on enterprise innovation behavior, verifying hypothesis H1. From an economic significance perspective, holding other factors constant, for every standard deviation increase in AI application intensity, enterprise innovation level decreases by approximately 4.94 % (-0.246×0.201), an effect that is significant both statistically and economically.

Table 2

Baseline Regression Results

Variable	(1) LN_PAT	(2) LN_PAT
AI	-0.284^{***}	-0.246^{***}
	(-3.42)	(-3.18)
Controls	No	Yes
N	10,827	10,827
YEAR	Yes	Yes
Industry	Yes	Yes
City	Yes	Yes
Adj_R^2	0.342	0.385

Note: t-statistics in parentheses, ***, **, * indicate significance levels at 1 %, 5 %, 10 % respectively.

Regarding control variables, the coefficient of enterprise size (Size) is significantly positive, indicating that larger enterprises tend to have stronger innovation capabilities, consistent with expectations from economies of scale theory. The coefficient of enterprise age (Age) is significantly negative, suggesting that enterprises established for longer periods may face organizational inertia, unfavorable to innovation activities. The coefficient of asset-liability ratio (Lev) is negative but not significant, indicating that the impact of financial leverage on innovation is not clear. The coefficients of return on total assets (ROA) and revenue growth rate (Growth) are both significantly positive, reflecting that good operating performance can provide financial support for enterprise innovation. The coefficient of the largest shareholder's shareholding ratio (First) is significantly negative, suggesting that excessive concentration of ownership may be unfavorable to enterprise innovation.

Robustness Tests

To verify the reliability of baseline regression results, this paper conducts a series of robustness tests. First, the instrumental variable method is employed to address potential endogeneity problems. Following the previous research approach (Goldsmith-Pinkham et al., 2020), a Bartik instrumental variable (AI_IV) based on the shift-share method is constructed. Table 3 columns (1) and (2) report the regression results of the two-stage least squares (2SLS) method. The first-stage regression shows that the instrumental variable is significantly positively correlated with AI application intensity, with an F-statistic of 24.86, greater than the critical value for weak instrument testing, indicating no weak instrument problem. The second-stage regression results show that after controlling for endogeneity, AI's negative impact on enterprise innovation remains significant, with the absolute value of the coefficient slightly larger than the baseline regression, suggesting that ordinary least squares estimation may underestimate AI's inhibitory effect.

Table 3

Robustness Test Results

Variable	(1) IV_1st	(2) IV_2nd	(3) ALT_DV	(4) Trim
AI_IV	0.642^{***}			
	(4.98)			
AI		-0.312^{***}	-0.238^{***}	-0.251^{***}
		(-3.46)	(-3.12)	(-3.24)
Controls	Yes	Yes	Yes	Yes
N	10,827	10,827	10,827	10,610
YEAR	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
Adj_R^2	0.426	0.372	0.368	0.379

*Note: t-statistics in parentheses, ***, **, * indicate significance levels at 1 %, 5 %, 10 % respectively.*

Second, this paper also employs other methods for robustness tests. From the variable measurement perspective, replacing the explained variable with the logarithm of invention patent grant numbers (LN_GPAT), the regression results as shown in column (3) of Table 3 maintain robustness. From the sample selection perspective, eliminating extreme value samples of patent application numbers in the top and bottom 1% percentiles, the estimation results as shown in column (4) still hold. These test results all support the basic conclusion that AI has a significant inhibitory effect on enterprise innovation.

Heterogeneity Analysis

To deeply explore the heterogeneous characteristics of AI's impact on enterprise innovation behavior, this paper examines from five dimensions: (1) Constructing state-owned enterprise dummy variable (SOE) based on enterprise actual controller type, with state-owned enterprises taking value 1 and non-state-owned enterprises taking value 0; (2) Using the Herfindahl index (HHI) calculated as the sum of squares of enterprises' revenue shares within the industry to measure market competition degree, and using the industry annual median as the boundary, samples above the median taking value 1 (low competition) and below the median taking value 0 (high competition); (3) Using the SA index to measure financing constraint level, with samples above the annual median (high financing constraint) taking value 1 and below the median (low financing constraint) taking value 0; (4) Constructing technology intensity dummy variable (TECH) according to CSRC industry classification standards, with technology-intensive industries such as computer, communication and other electronic equipment manufacturing, pharmaceutical manufacturing, and specialized equipment manufacturing taking value 1, and other industries taking value 0; (5) Calculating management shareholding ratio (MSH) as the proportion of shares held by directors, supervisors and senior management to total shares, and distinguishing based on annual sample median, with samples above median (high management shareholding) taking value 1 and below median (low management shareholding) taking value 0. The selection of these heterogeneity dimensions is based on resource-based theory and principal-agent theory, aiming to comprehensively reveal the boundary conditions of AI's impact on enterprise innovation. All grouping variable divisions are conducted at the annual level to control for time trend effects.

This paper examines the heterogeneous characteristics of AI's impact on enterprise innovation from dimensions such as enterprise ownership nature, market competition degree, financing constraint level, technology intensity, and internal governance. Through constructing interaction term models for testing, Table 4 reports the regression results of heterogeneity analysis. The research finds that AI's impact on enterprise innovation has significant boundary condition effects, providing more detailed theoretical insights for understanding enterprise innovation resource allocation during digital transformation.

Table 4

Heterogeneity Analysis Results

Variable	(1) LN_PAT	(2) LN_PAT	(3) LN_PAT	(4) LN_PAT	(5) LN_PAT
AI	-0.312^{***}	-0.228^{***}	-0.235^{***}	-0.298^{***}	-0.289^{***}
	(-3.86)	(-3.24)	(-3.42)	(-3.75)	(-3.68)
AI × SOE	0.183^{***}				
	(2.92)				
AI × HHI		-0.156^{**}			
		(-2.45)			
AI × SA			-0.142^{**}		

Variable	(1) LN_PAT	(2) LN_PAT	(3) LN_PAT	(4) LN_PAT	(5) LN_PAT
			(-2.38)		
AI × TECH				0.165^{***}	
				(2.85)	
AI × MSH					0.178^{***}
					(2.96)
YEAR	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N	10,827	10,827	10,827	10,827	10,827
Adj_R^2	0.396	0.389	0.388	0.392	0.394

*Note: t-statistics in parentheses, ***, **, * indicate significance levels at 1 %, 5 %, 10 % respectively.*

First, from the ownership nature perspective, as shown in column (1) of Table 4, the interaction term coefficient between AI and SOE is 0.183, significantly positive at the 1 % level. Further calculation of marginal effects finds that in non-state-owned enterprises, AI's marginal effect is -0.312, while in state-owned enterprises this effect weakens to -0.129 (-0.312+0.183). This result indicates that state-owned enterprises can better balance the relationship between AI application and traditional innovation input. This difference may stem from several aspects: First, state-owned enterprises have stronger resource acquisition capabilities, able to maintain both AI input and traditional innovation activities; Second, state-owned enterprises bear social responsibilities for technological innovation, therefore considering more long-term benefits of innovation when allocating resources; Third, state-owned enterprises have more diversified assessment mechanisms and will not excessively pursue short-term efficiency improvements brought by AI.

Second, the moderating effect of market competition environment is equally noteworthy. Column (2) of Table 4 shows that the interaction term coefficient between AI and HHI is -0.156, significant at the 5 % level. This indicates that the lower the market competition degree, the stronger AI's inhibitory effect on innovation. In highly competitive market environments, enterprises face greater innovation pressure, and even while promoting AI applications, they must maintain investment in traditional innovation activities to maintain competitive advantages. In contrast, in industries with higher monopoly degrees, enterprises may overly rely on efficiency improvements brought by AI while neglecting the importance of continuous innovation for enterprise long-term development.

Regarding financing constraints, Column (3) of Table 4 shows that the interaction term coefficient between AI and the SA index is -0.142, significant at the 5% level. This finding highly aligns with expectations from resource-based theory: enterprises with more severe financing constraints are more likely to experience crowding-out effects during AI project investment. Deeper analysis reveals that this phenomenon reflects enterprises' trade-offs under limited resources: on one hand, AI projects typically require large-scale upfront investment but show effects relatively quickly; on the other hand, traditional innovation activities have characteristics of long cycles and high uncertainty. Therefore, under tight funding conditions, enterprises may tend to allocate limited resources to AI projects to obtain more certain short-term returns.

The heterogeneity analysis of technology intensity provides another important perspective. As shown in Column (4) of Table 4, the interaction term coefficient between AI and TECH is 0.165, significant at the 1 % level. This indicates that in technology-intensive industries, AI's inhibitory effect on innovation significantly weakens. This result may reflect the deep interaction between industry characteristics and enterprise innovation strategies: technology-intensive enterprises typically have stronger innovation path dependence, with their core competitiveness highly dependent on continuous innovation input. Therefore, these enterprises are more cautious when promoting intelligent transformation, avoiding excessive reliance on AI that might damage their existing innovation advantages. Meanwhile, technology-intensive enterprises often possess stronger technology integration capabilities, better able to achieve complementary integration between AI and traditional innovation activities.

Finally, the moderating role of internal governance structure cannot be ignored. Column (5) of Table 4 shows that the interaction term coefficient between AI and MSH is 0.178, significant at the 1 % level. This result supports that management shareholding as an incentive mechanism can effectively mitigate agency problems in AI application processes. Specifically, when management holds more company shares, their decision-making horizon becomes longer-term, considering more the impact on enterprise long-term innovation capabilities when promoting AI projects. This interest alignment mechanism helps balance the relationship between short-term efficiency improvements and long-term innovation capability cultivation, thereby reducing AI's inhibitory effect on innovation.

These heterogeneity analysis results not only deepen theoretical understanding of AI's impact on enterprise innovation but also provide differentiated suggestions for different types of enterprises to optimize innovation resource allocation. The results show that enterprise characteristics significantly moderate AI's impact on innovation, and managers need to formulate corresponding innovation strategies based on their enterprise characteristics.

Particularly for groups easily affected by AI's inhibitory effects, such as non-state-owned enterprises, low-competition industry enterprises, and high financing constraint enterprises, greater vigilance is needed regarding the potential weakening of innovation capabilities from excessive reliance on AI.

Further Extensions

To explore the dynamic evolution characteristics of AI's impact on enterprise innovation, this paper introduces lagged terms of the core explanatory variable based on the baseline model. Specifically, lag variables from t-1 to t-3 periods (AI_L1, AI_L2, AI_L3) are set up while controlling for other factors that may affect innovation. Column (1) of Table 5 reports the regression results of dynamic effects. The research finds that AI's current period coefficient is -0.246, first-period lag coefficient is -0.284, second-period lag coefficient is -0.235, and third-period lag coefficient is -0.187, all significant at the 1 % level. From the coefficient change trend, AI's inhibitory effect on innovation is relatively weak in the initial implementation period, reaches its peak in the first year, and then gradually weakens, reflecting a learning and adaptation process in enterprises' AI application.

Table 5

Extension Analysis Results

Variable	(1) Dynamic	(2) Quality	(3) Value	(4) Break
AI	-0.246***	-0.156**	-0.168**	-0.142**
	(-3.28)	(-2.45)	(-2.52)	(-2.38)
AI_L1	-0.284***			
	(-3.42)			
AI_L2	-0.235***			
	(-3.15)			
AI_L3	-0.187***			
	(-2.96)			
YEAR	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	7,624	10,827	10,827	10,827
Adj_R^2	0.412	0.385	0.389	0.382

*Note: t-statistics in parentheses, ***, **, * indicate significance levels at 1 %, 5 %, 10 % respectively.*

Second, this paper examines AI's impact on innovations of different quality levels. Drawing on existing literature, the following indicators are used to measure innovation quality: (1) High citation patent ratio (HIGH_CITE), the proportion of invention patents with citation numbers ranking in the industry-year top 25 %; (2) Patent value (PAT_VALUE), measured by the logarithm of the product of patent maintenance time and citation numbers; (3) Breakthrough innovation (BREAK_INNO), the proportion of invention patents that cited at least one non-patent literature at application. Columns (2)-(4) of Table 5 report related regression results.

The research finds, as shown in Column (2) of Table 5, that AI's impact coefficient on high citation patent ratio is -0.156, with both significance level and impact intensity smaller than its impact on total patent applications (-0.246 in baseline regression). Similarly, from Columns (3) and (4), AI's negative impacts on patent value and breakthrough innovation are also relatively small, at -0.168 and -0.142 respectively. These results indicate that although AI application generally inhibits enterprise innovation activities, its impact on high-quality innovation is relatively limited. Possible explanations are: on one hand, enterprises prioritize input to core innovation projects under resource constraints; on the other hand, AI's auxiliary functions may play certain complementary roles in high-quality innovation processes.

Through these extension analyses, this paper not only reveals the temporal evolution pattern of AI's impact on enterprise innovation but also discovers its differentiated impact on innovations of different quality levels. These findings enrich existing research and provide new insights for enterprises to balance efficiency improvement and innovation capability cultivation during digital transformation. Particularly, the dynamic effect analysis results indicate that enterprises need to fully recognize the potential innovation inhibitory effects in the initial period of AI application and optimize resource allocation mechanisms through continuous learning and experience accumulation. Meanwhile, the discovery of differentiated impacts suggests that enterprises should establish hierarchical innovation management systems when promoting intelligent transformation to ensure core innovation capabilities remain unaffected.

Potential Mechanism Exploration

Based on the theoretical analysis and research hypotheses from previous sections, this section deeply examines the mechanisms through which AI influences enterprise innovation. Enterprises face complex resource allocation trade-offs during intelligent transformation processes, and large-scale investment in AI projects may affect enterprise innovation activities through multiple channels. This paper focuses on two key transmission paths: innovation talent input intensity and professional technical equipment configuration, systematically examining how AI application shapes enterprise innovation behavior by influencing enterprise factor input structure.

AI's impact on enterprise innovation talent input reflects the complex interaction between technological progress and human capital accumulation. On one hand, AI systems possess powerful data processing and pattern recognition capabilities, potentially replacing traditional R&D personnel's work in certain fields. This substitution effect may cause enterprises to reduce R&D talent input while promoting intelligence. As shown in Column (1) of Table 6, AI's regression coefficient on RDRATIO is -0.074, significantly negative at the 1 % level, indicating that AI application indeed reduces enterprise R&D talent input intensity. Furthermore, Column (2) results show that after controlling for RDRATIO, AI's negative impact on innovation significantly weakens, RDRATIO's coefficient is significantly positive, and Sobel test also supports the existence of mediating effects.

Table 6

Mechanism Test Results

Variable	(1) RDRATIO	(2) LN_PAT	(3) FARATIO	(4) LN_PAT
AI	-0.074***	-0.182***	-0.064***	-0.196***
	(-3.24)	(-2.96)	(-3.38)	(-3.04)
RDRATIO		0.865***		
		(4.86)		
FARATIO				0.782***
				(4.52)
YEAR	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	10,827	10,827	10,827	10,827
Adj_R^2	0.342	0.406	0.338	0.398

*Note: t-statistics in parentheses, ***, **, * indicate significance levels at 1 %, 5 %, 10 % respectively.*

However, this reduction in talent input may bring deep-level negative impacts. Innovation activity is essentially a complex process requiring creative thinking and professional judgment, and purely relying on algorithms and data cannot completely replace the role of human R&D personnel. Particularly in fields such as frontier technology development and interdisciplinary innovation, R&D personnel's experience accumulation and intuitive judgment often play crucial roles. Enterprises' excessive reliance on AI while reducing R&D talent may lead to structural weakening of innovation capabilities. This impact is reflected not only in the decline of innovation quantity but may also damage enterprises' ability to grasp innovation directions and evaluate innovation value.

Professional technical equipment configuration is an important material foundation supporting enterprise innovation activities, and AI's impact on this factor reflects digital transformation's profound reshaping of enterprise asset structure. As shown in Column (3) of Table 6, AI's impact coefficient on FARATIO is significantly negative, indicating that AI application reduces enterprise professional equipment input intensity. This phenomenon reflects multiple logics: First, AI systems themselves require large funding investment, potentially crowding out resources for purchasing professional R&D equipment under budget constraints; Second, AI's popularization accelerates technology update iteration speed, making enterprises more cautious about specialized equipment investment; Third, some traditional R&D equipment functions may be partially replaced by intelligent systems, reducing enterprises' necessity to configure professional equipment. However, the reorientation of this equipment investment strategy also brings potential risks. Professional technical equipment often carries enterprises' years of accumulated process experience and technical know-how, being an important carrier for maintaining core competitiveness. Excessive reliance on general-purpose AI systems while neglecting professional equipment input may cause enterprises to lose technical advantages in certain segments. Particularly in innovation activities requiring precision processing, professional testing, and other special capabilities, professional equipment's supporting role is difficult to completely replace with AI. The empirical results in Column (4) also verify the mediating role of professional equipment configuration in AI's impact on enterprise innovation.

Conclusions and Recommendations

Main Research Conclusions

Based on data from Chinese A-share listed companies from 2013–2023, this paper uses text analysis methods to construct an enterprise AI application intensity index and systematically examines AI's impact on enterprise innovation behavior and its mechanisms. The research finds the following important conclusions:

First, at the overall level, AI application has a significant inhibitory effect on enterprise innovation. Empirical results show that for every standard deviation increase in AI application intensity, enterprise innovation level decreases by an average of 4.94 %. This impact remains robust after controlling for potential endogeneity problems, revealing the innovation resource allocation challenges enterprises face during digital transformation.

Second, AI's impact on enterprise innovation shows significant boundary condition effects. Specifically, in state-owned enterprises, high market competition industries, low financing constraint enterprises, technology-intensive industries, and high management shareholding enterprises, AI's inhibitory effect significantly weakens. These heterogeneous characteristics reflect the important roles of enterprises' institutional environment, market structure, resource endowment, and governance mechanisms in moderating the relationship between AI and innovation.

Third, mechanism analysis reveals that AI inhibits innovation activities by influencing enterprises' innovation factor input structure. On one hand, AI application reduces enterprises' R&D talent input intensity, and excessive reliance on intelligent systems while neglecting talent cultivation may damage enterprises' long-term innovation capabilities; on the other hand, AI investment crowds out professional technical equipment configuration resources, causing enterprises' technical advantages in certain key innovation areas to be weakened. These findings directly support the concept of an "innovation paradox" presented in our title: as enterprises invest heavily in AI technologies with the intention of gaining competitive advantages, they inadvertently undermine their long-term innovation capabilities through resource allocation distortion. This paradox emerges because resources directed toward AI implementation and maintenance compete with investments in traditional innovation inputs like specialized R&D talent and technical equipment. The short-term efficiency gains from AI may thus come at the expense of sustained innovation capacity, particularly when enterprises fail to recognize and manage this trade-off explicitly.

Finally, further analysis finds that AI's impact on enterprise innovation has dynamic and differentiated characteristics. From a temporal dimension, this inhibitory effect is most significant in enterprises' initial AI application period, then gradually weakens with the accumulation of learning experience. From an innovation quality perspective, although AI reduces enterprises' overall patent application numbers, its impact on high-quality innovation is relatively limited, reflecting enterprises' project prioritization choices under resource constraints.

Management Recommendations

Based on the above research conclusions, this paper proposes the following management implications and policy recommendations.

For enterprise managers, first, they need to establish scientific AI investment evaluation mechanisms to accurately assess intelligent projects' impact on enterprise innovation resource allocation. They should be vigilant about innovation capability weakening risks from excessive reliance on AI, maintaining reasonable R&D talent reserves and professional equipment input while promoting digital transformation. Specific strategies might include: (1) implementing stage-gate decision processes for AI investments that explicitly evaluate potential displacement effects on innovation resources; (2) establishing protected innovation budgets that remain insulated from AI implementation cost overruns; (3) developing integrated talent management plans that balance AI expertise with traditional R&D capabilities; and (4) creating organizational structures that facilitate knowledge sharing between AI teams and innovation departments. Additionally, enterprises might consider complementary AI-innovation strategies, such as using AI tools specifically designed to enhance R&D productivity rather than replace innovation activities. Second, they should formulate differentiated innovation strategies based on enterprise characteristics. Enterprises with relatively scarce innovation resources need to be more cautious in evaluating AI investment scale and pace to avoid too great an impact on traditional innovation activities. Finally, they should value AI application's learning curve effect, optimizing the coordinated allocation of AI and innovation resources through continuous experience accumulation.

For policy makers, first, they should improve support policy design to help enterprises better balance intelligent transformation and innovation capability enhancement. They can consider establishing special funds to support enterprises in maintaining necessary innovation input while promoting AI application. Second, they should pay attention to the differentiated challenges faced by different types of enterprises in digital transformation. Particularly for groups easily affected by AI's inhibitory effects, such as private enterprises and enterprises in low-competition industries, more targeted policy support should be provided. Finally, they should strengthen innovation factor market construction, reducing enterprises' costs in acquiring R&D talent and professional equipment, helping enterprises maintain diversified innovation input structures.

Limitations and Future Research Directions

Despite the valuable insights this study provides on the relationship between AI application and corporate innovation, several limitations warrant acknowledgment and offer opportunities for future research. First, our measurement of AI application intensity relies on text analysis of annual reports, which may not perfectly capture the actual implementation quality and depth of AI systems within enterprises. Second, while we address endogeneity through instrumental variable approaches, the Bartik-type instrument may not fully satisfy exclusion restrictions if industry-level AI trends affect innovation through channels beyond firm-level AI adoption. Third, our sample is limited to Chinese A-share listed companies during 2013–2023, potentially restricting generalizability to different institutional contexts or time periods. Future research could extend this work through several promising avenues: developing more direct measures of AI implementation quality through surveys or field studies; exploring potential non-monotonic relationships and threshold effects between AI intensity and innovation outcomes; conducting cross-country comparative analyses to examine how different institutional environments moderate the observed effects; investigating specific organizational structures and governance mechanisms that successfully balance AI implementation with sustained innovation capabilities; and examining longer-term dynamic interactions between AI adoption and innovation as technologies mature and organizations adapt their resource allocation strategies.

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