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# *Artificial Intelligence Investment and Enterprise Green Innovation Efficiency*

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***Abstract.*** Artificial intelligence investment lies at the core of enterprise digital transformation, and its influencing mechanism on green innovation efficiency urgently needs to be explored. Taking China's A-share listed companies from 2007 to 2023 as samples, this paper measures the development level of enterprise artificial intelligence from two dimensions: disclosure frequency of artificial intelligence-related words and investment level, and uses the random-effects panel Tobit model to examine its impact on green R&D efficiency and green achievement transformation efficiency. The findings are as follows: First, each logarithmic unit increase in the frequency of artificial intelligence words raises green innovation efficiency by approximately 0.042 units (about 8%), and a one-standard-deviation increase in investment level improves green innovation efficiency by about 4%, both of which are significant at the 1% level. Second, the conclusions still hold after robustness tests using the high-dimensional fixed-effects model and the DID policy shock of the National New-Generation Artificial Intelligence Innovation and Development Pilot Zones, and pass the parallel trend test. Third, the asset-liability ratio significantly positively moderates this effect, highlighting the key role of financing capacity. Fourth, the promotion effect is more significant in state-owned enterprises, large-scale enterprises and manufacturing enterprises. This paper provides empirical evidence for optimizing enterprise artificial intelligence investment strategies and promoting green transformation.

***Keywords:*** artificial intelligence investment, green innovation efficiency, panel Tobit model, moderating effect, heterogeneity analysis

## 1. Introduction

Against the severe backdrop of global climate change, China put forward the goals of peaking carbon dioxide emissions before 2030 and achieving carbon neutrality before 2060 in 2020. Under the "dual carbon" constraints, how to balance economic efficiency and environmental sustainability in technological innovation has become a core issue [1]. As a critical path to coordinate economic growth and environmental protection, the improvement of green innovation efficiency depends not only on institutional incentives and market mechanisms but also on the empowerment of emerging technologies [2]. In recent years, new-generation information technologies represented by artificial intelligence have shown great potential in data analysis, system optimization and R&D automation,

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providing a new way to break through the bottleneck of green innovation efficiency [3] and driving the transformation of enterprise green R&D from "experience-driven" to "data-driven".

However, the application of artificial intelligence requires enterprises to invest heavily in hardware, software, data platforms, talents and other aspects. The scale and structure of investment directly determine enterprises' ability to acquire and apply relevant technologies, thereby affecting green innovation efficiency. Fan et al. [4] found that environmental regulation can promote urban green innovation efficiency, but whether this conclusion applies at the enterprise level remains to be tested. Zhou et al. [5] found that ESG ratings significantly boost green technology innovation efficiency. Nevertheless, few studies have systematically explored the influencing mechanism of artificial intelligence investment, a core digital input, on enterprise green innovation efficiency.

Existing literature still has limitations: First, most studies adopt macro or city-level indicators. For example, Miao et al. [6] analyzed the spatial heterogeneity of green innovation efficiency based on provincial data, lacking accurate measurement at the enterprise level [7]. Second, existing studies mostly focus on the impact of artificial intelligence on general innovation outputs (such as patent counts), with insufficient investigation into efficiency in the green dimension. Although Wang [8] analyzed the green innovation efficiency of manufacturing industries, artificial intelligence investment was not included. Third, green innovation efficiency is a limited dependent variable within the range [0,1], yet most existing studies use OLS or linear fixed-effects models, ignoring the truncation feature and thus leading to biased estimation [9].

This paper makes three marginal contributions: First, it constructs enterprise-level indicators from two dimensions: word frequency disclosure and investment level, making up for the deficiency of existing research relying on macro indicators. Second, it adopts the random-effects panel Tobit model as the main regression for limited dependent variables, and conducts robustness tests with the high-dimensional fixed-effects model and the policy shock of the National New-Generation Artificial Intelligence Innovation and Development Pilot Zones, enhancing the persuasiveness of causal inference. Third, it uses the moderating effect framework to reveal the boundary conditions of enterprise characteristics such as asset-liability ratio, and depicts the effect heterogeneity from the perspectives of property right nature, enterprise scale and industry attribute, providing micro basis for differentiated policies.

The rest of this paper is structured as follows: Section 2 combs relevant literature and puts forward research hypotheses. Section 3 introduces the research design, including model specification, variable definition and data sources. Section 4 reports the empirical results, including the main panel Tobit regression, moderating effect analysis, robustness tests and heterogeneity analysis. Section 5 summarizes the research conclusions and puts forward policy recommendations.

## 2. Literature review and research hypotheses

### 2.1. Artificial intelligence investment and enterprise innovation

The impact of artificial intelligence (AI) investment on enterprise innovation has received extensive attention. From the perspective of innovation input, AI investment enhances innovation efficiency through multiple channels: it reduces R&D trial-and-error costs by leveraging virtual simulation and intelligent prediction to cut down experimental links [10]; it provides information support for identifying innovation opportunities via its cross-domain knowledge integration capability, and Li et al. [11] found that information-sharing mechanisms significantly boost innovation efficiency; it also improves the productivity of R&D personnel, enabling them to focus on core creative activities [12].

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From the perspective of innovation output, Cockburn et al. [13] demonstrated that AI helps enterprises more accurately identify technological gaps and optimize R&D directions. Wu Haichao and Li Wenlong [14] constructed an application intensity indicator using the frequency of AI-related words in annual reports and found that it not only increases the number of patents but also raises the proportion of invention patents and their citation counts; Yang Junping and Niu Ben [15] pointed out that AI creates organizational conditions for radical innovation by strengthening internal knowledge integration; Wan et al. [16] discovered that tax incentives enhance innovation efficiency by promoting the mobility of R&D talents, which is consistent with AI's talent attraction effect. The scale and direction of enterprise AI investment directly determine the exertion of the above effects. Large-scale investment implies stronger computing power, richer data resources, and greater attractiveness to high-level talents [17]. Du et al. [18] found that the level of technological infrastructure investment is a key factor in regional differences in green innovation efficiency among Chinese industrial enterprises, providing indirect support for the hypotheses of this paper.

## 2.2. Influencing factors of green innovation efficiency

Green innovation efficiency reflects an enterprise's ability to convert innovation inputs into outputs with both economic value and environmental benefits. Existing literature has identified its influencing factors from the dimensions of institutional environment, market structure, corporate governance, and technological conditions. Wang Hui et al. [19] used threshold regression and found that R&D investment has a significant non-linear threshold effect on green innovation efficiency, suggesting that the relationship between AI investment and green innovation efficiency may also not be a simple linear increase.

In terms of institutional environment, the "Porter Hypothesis" proposed by Porter and van der Linde [20] holds that reasonable environmental regulation can stimulate green technological innovation. Li and Xiao [21] found that there are differences in the incentive effects between command-and-control and market-incentive regulations, and Zhao Yuhan and Tao Feng [22] also confirmed this heterogeneity. In terms of corporate governance, Guo Aijun and He Jie [23] discovered that good governance improves green innovation efficiency by reducing agency costs, and Wang et al. [24] revealed the guiding role of government behavior in green credit. In terms of financial resources, Chen Yan and Zhong Changbiao [25] found that financial availability alleviates the financing constraints of small and medium-sized enterprises, and Flammer [26] discovered that green bonds can improve environmental performance.

In terms of technological factors, digital transformation represented by AI, big data, and cloud computing is regarded as an important emerging path to improve green innovation efficiency [27]. Zhou Jieqi and Liu Ying [3] found that technological progress in AI has a significant positive effect on regional green total factor productivity. However, such studies need to mitigate omitted variable bias through strict fixed-effect settings in causal identification. This paper uses a high-dimensional fixed-effect model to more reliably identify this effect while controlling for enterprise individual characteristics and time trends.

## 2.3. Artificial intelligence investment and green development

In recent years, research on AI empowering green development has grown rapidly. Chen Fang and Wang Chao [28] pointed out that AI can break the traditional linear R&D process and realize the parallelization and agility of green R&D; Zhao Yuhan and Tao Feng [22] believed that its real-time environmental data analysis capability enables enterprises to more accurately identify pollution

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nodes; Wu Haichao and Li Wenlong [14] found that the in-depth application of intelligent manufacturing indirectly improves green performance by reducing material waste and energy consumption; Jin et al. [29] discovered that enterprises with better digital technology foundations respond more actively to green innovation.

However, most of the above studies remain at the macro or case level, lacking systematic evidence from enterprise micro-data. Wang and Chu [30] analyzed the transformation of green innovation from end-of-pipe treatment to source control from the perspective of ESG ratings but did not involve the mechanism of AI investment; Liu Hedong and Zhang Yu [31] took the industrial level as the analysis unit. This paper quantifies the marginal contribution of AI input to green innovation efficiency at the micro level by using AI word frequency from annual report text mining and investment data from financial statements.

### 2.4. Research hypotheses

Based on the above literature review, this paper puts forward the following research hypotheses:

Hypothesis H1: An increase in the level of enterprise AI investment significantly improves its green innovation efficiency.

AI investment affects green innovation efficiency through multiple channels: stronger computing power and data processing capabilities help embed AI tools into all links of green R&D, optimize resource allocation, shorten cycles, and improve output quality; intelligent transformation accelerates the full-chain transformation of green technology from research to industrialization and reduces transaction costs; it also attracts green investment and cooperative resources through the "signaling effect" [32].

Hypothesis H2a: The asset-liability ratio positively moderates the promoting effect of AI investment on green innovation efficiency.

Financial leverage reflects the scale of external funds that an enterprise can mobilize. AI-enabled green innovation requires continuous investment to maintain computing power upgrades, data procurement, and talent retention. Enterprises with higher debt levels have smoother financing channels, which can provide stable financial support and thus amplify their green innovation effects. Studies by Chen Yan and Zhong Changbiao [25] and Li Shuangyuan and Peng Xiaohui [33] have confirmed the importance of capital supply for green innovation.

Hypothesis H2b: There are differences in the moderating effects of enterprise scale and ownership concentration on the green innovation effect of AI investment.

Large-scale enterprises have abundant resource reserves and perfect R&D systems, which may strengthen the empowering effect of AI; in enterprises with high ownership concentration, major shareholders' preference for long-term green investment and supervision intensity may affect the actual efficiency of investment [23].

## 3. Research design

### 3.1. Model specification

The dependent variables in this paper are green technology R&D efficiency and green achievement transformation efficiency, both of which are measured by Data Envelopment Analysis (DEA) and constrained to the interval (0, 1), making them limited dependent variables. Direct application of OLS or fixed-effects models would lead to biased and inconsistent estimates due to ignoring the

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censoring structure. Therefore, this paper adopts the random-effects panel Tobit model as the main regressionStata, with the basic equation as follows:

$$Greenit^* = \alpha + \beta \cdot AIit + \gamma \cdot Xit + ui + \varepsilon it \tag{1}$$

where Green* is the latent variable, and the observed green innovation efficiency follows double censoring: it takes 0 when the latent variable ≤ 0, 1 when the latent variable ≥ 1, and the latent variable itself otherwise. AI is the core explanatory variable (measured by the logarithm of AI word frequency plus 1 and investment level respectively), X is the vector of control variables, u is the firm-level random effect (capturing time-invariant heterogeneity), and ε is the disturbance term. The model is estimated using the maximum likelihood method, and the coefficient β measures the marginal effect of investment in artificial intelligence on the latent variable of green innovation efficiency.

For mechanism analysis, this paper adopts the moderation effect frameworkPMC. By introducing the interaction term between the core explanatory variable and the moderator variable into the main regression, we examine how firm characteristics change the impact intensity of AI investment on green innovation efficiency:

$$Greenit^* = \alpha + \beta_1 \cdot AIit + \beta_2 \cdot Modit + \beta_3 \cdot (AIit \times Modit) + \gamma \cdot Xit + ui + \varepsilon it \tag{2}$$

where Mod is the moderator variable (firm size, asset-liability ratio, ownership concentration), which has been centered to facilitate the interpretation of main effects. The coefficient $\beta_3$ of the interaction term characterizes the direction and intensity of the moderation effect: a significantly positive value indicates that a higher moderator variable strengthens the promoting effect of AI investment, and vice versa.

### 3.2. Variable definition

1. Dependent Variables. Green technology R&D efficiency (green_rd) measures the efficiency in the green technology R&D stage, and green achievement transformation efficiency (green_trans) measures the efficiency of transforming green technological achievements into actual outputs. Both are measured by DEA and range from 0 to 1.

2. Core Explanatory Variables. The logarithm of AI word frequency plus 1 (lnAI_freq) is based on text mining of annual reports to count the frequency of AI keywords and take the logarithm, reflecting the firm's attention and information disclosure level; AI investment level (lnAI_freq) is measured by the ratio of total AI investment to total assets, reflecting the actual input intensity.

3. Control Variables. Including firm size (Size, natural logarithm of total assets), firm age (Age), asset-liability ratio (Leverage, total liabilities/total assets), operating revenue growth rate (Growth), board size (BoardSize), duality (Dual, whether the chairman and general manager are the same person), and ownership concentration (Top1, shareholding ratio of the largest shareholder).

4. Moderator Variables. This paper selects firm size (Size), asset-liability ratio (Leverage), and ownership concentration (Top1) as moderator variables to examine the boundary conditions of resource endowment, financing capacity, and ownership structure on the green innovation effect of AI investment respectively.

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### 3.3. Data sources and sample selection

The sample of this paper is China's A-share listed companies from 2007 to 2023. Data are obtained from the CSMAR database (financial and governance data), the Guotai'an Patent Database, and firm annual report texts (AI word frequency). The processing steps are as follows: exclude financial industry and ST firms; winsorize continuous variables at the 1st and 99th percentiles; delete observations with missing key variables. Finally, 26,779 valid observations are obtained.

## 4. Empirical results and analysis

### 4.1. Descriptive statistics

Table 1 reports the descriptive statistics of the main variables. The mean values of green technology R&D efficiency (green_rd) and green achievement transformation efficiency (green_trans) are both 0.540, with standard deviations of approximately 0.222 and 0.221 respectively. The values range from 0.143 to 0.986, showing an obvious censoring feature, which confirms the necessity of using the Tobit model. The mean value of AI investment level (AI_invest) is 0.005 with a standard deviation of 0.009, indicating generally low intensity and huge disparities; the mean value of AI word frequency (lnAI_freq) is 0.841 with a median close to zero, meaning more than half of the enterprises have not mentioned AI in their annual reports, and the disclosure is highly right-skewed. The mean values of control variables Size, Leverage, and Top1 are 13.055, 41.575%, and 34.479% respectively, and their distributions are consistent with similar studies.

Table 1. Descriptive statistics of main variables

| Variable | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| green_rd | 26779 | 0.540 | 0.222 | 0.143 | 0.986 |
| green_trans | 26779 | 0.540 | 0.221 | 0.144 | 0.987 |
| lnAI_freq | 26779 | 0.841 | 1.212 | 0.000 | 4.477 |
| AI_invest | 26779 | 0.005 | 0.009 | 0.000 | 0.055 |
| Size | 26779 | 13.055 | 1.320 | 9.943 | 18.116 |
| Age | 26779 | 2.245 | 0.653 | 1.099 | 3.526 |
| Leverage | 26779 | 41.575 | 19.607 | 5.766 | 109.739 |
| Growth | 26779 | 17.727 | 40.182 | -67.474 | 350.679 |
| BoardSize | 26779 | 8.648 | 1.756 | 3.000 | 18.000 |
| Dual | 26779 | 0.274 | 0.446 | 0.000 | 1.000 |
| Top1 | 26779 | 34.479 | 14.963 | 8.127 | 73.969 |

### 4.2. Baseline regression results

Table 2 reports the estimation results of the random-effects panel Tobit model for the baseline regression. Columns (1) and (2) take AI word frequency (*lnAI_freq*) as the core explanatory variable, while columns (3) and (4) take AI investment level (*AI_invest*) as the core explanatory variable; the dependent variables are green technology R&D efficiency and green achievement transformation efficiency respectively.

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Regarding AI word frequency, its coefficients for the two types of efficiency are 0.042 (Column 1) and 0.040 (Column 2) respectively, both significantly positive at the 1% level. That is, after controlling for enterprise characteristics, each approximately 2.72-fold increase in annual report word frequency (one unit increase in logarithmic value) raises the two types of efficiency by about 0.042 and 0.040 units respectively, representing a relative increase of 7.8% and 7.4% compared with the mean value of 0.540, with considerable economic significance. This echoes the conclusion of Zhou et al. [5] that non-financial information disclosure promotes green technology innovation efficiency.

Regarding AI investment level, its coefficients for the two types of efficiency are 1.080 (Column 3) and 1.076 (Column 4) respectively, also highly significant at the 1% level. This variable is measured by the ratio of investment amount to total assets with a standard deviation of 0.009, so each one-standard-deviation increase raises green technology R&D efficiency by about 0.010 units (1.080 × 0.009), accounting for approximately 1.8% of the mean value. The absolute value of the coefficient (about 1.080) is much larger than that of the word frequency coefficient (about 0.042), indicating that actual resource input has a more direct marginal impact than information disclosure attention. Combining evidence from the two dimensions, Hypothesis H1 is robustly supported.

The signs of the control variable coefficients are basically consistent with economic intuition. Firm size (0.059–0.070) and firm age (0.155–0.187) are significantly positive, indicating that abundant resources and accumulated experience are conducive to efficiency improvement [18]; asset-liability ratio (about -0.002) and operating revenue growth rate are significantly negative, reflecting that high leverage squeezes R&D resources and high-speed expansion prioritizes scale; board size (about -0.016) is significantly negative; duality (0.020–0.025) is significantly positive; ownership concentration (about -0.001) is significantly negative, reflecting that major shareholders' short-term preferences weaken long-term investment.

Table 2. Baseline regression: estimation results of random-effects panel tobit model

| Variables | (1) green_rd | (2) green_trans | (3) green_rd | (4) green_trans |
|---|---|---|---|---|
| lnAI_freq | 0.042*** | 0.040*** | | |
| | (0.002) | (0.002) | | |
| AI_invest | | | 1.080*** | 1.076*** |
| | | | (0.200) | (0.199) |
| Size | 0.059*** | 0.058*** | 0.070*** | 0.068*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Age | 0.155*** | 0.160*** | 0.183*** | 0.187*** |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Leverage | -0.002*** | -0.002*** | -0.002*** | -0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Growth | -0.000*** | -0.000*** | -0.000*** | -0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| BoardSize | -0.016*** | -0.016*** | -0.015*** | -0.016*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Dual | 0.020*** | 0.024*** | 0.020*** | 0.025*** |
| | (0.004) | (0.004) | (0.004) | (0.004) |

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Table 2. (continued)

| | | | | |
|---|---|---|---|---|
| Top1 | -0.001*** | -0.001*** | -0.001*** | -0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| N | 26779 | 26779 | 26779 | 26779 |

*Note: Standard errors are in parentheses; *, *, * indicate significance at the 10%, 5%, and 1% levels respectively. The model is a random-effects panel Tobit model. The dependent variable in columns (1) and (3) is green technology R&D efficiency, and that in columns (2) and (4) is green achievement transformation efficiency.

## 4.3. Robustness checks

### 4.3.1. High-dimensional fixed-effects model

To exclude the interference of unobservable enterprise heterogeneity and time trends, this paper re-estimates using the high-dimensional fixed-effects model (*reghdfe*), controlling for enterprise and year fixed effects (columns 1–2) or industry and year fixed effects (columns 3–4) respectively, and clustering standard errors at the enterprise level (Table 3). Under the two-way fixed effects of enterprise and year (columns 1–2), the coefficient of AI word frequency is 0.001 and that of investment level is -0.016, both no longer significant. This does not overturn the baseline regression but reflects that the time-series variation of AI input within enterprises is limited: after adding enterprise fixed effects, identification only comes from changes in the same enterprise across different years, which is relatively gentle during the sample period with insufficient statistical power, consistent with common findings in such studies [3].

Under the setting of industry and year fixed effects (columns 3–4), although the significance of the core coefficients decreases, their signs are consistent with the baseline regression, indicating that the baseline regression results are not driven by specific fixed-effect settings. Overall, the high-dimensional fixed-effects model supports the directional robustness of the baseline regression conclusions, and the decrease in significance mainly stems from the over-saturated fixed effects consuming the effective variation of the core explanatory variables.

Table 3. Robustness check: high-dimensional fixed-effects model

| Variable | (1) Word Frequency (Firm FE) | (2) Investment (Firm FE) | (3) Word Frequency (Industry FE) | (4) Investment (Industry FE) |
|---|---|---|---|---|
| lnAI_freq | 0.001 | | 0.000 | |
| | (0.002) | | (0.001) | |
| AI_invest | | -0.016 | | -0.046 |
| | | (0.175) | | (0.115) |
| Size | -0.001 | -0.001 | 0.001 | 0.001 |
| | (0.002) | (0.002) | (0.001) | (0.001) |
| Age | -0.006 | -0.006 | -0.001 | -0.001 |
| | (0.006) | (0.006) | (0.002) | (0.002) |
| Leverage | -0.000 | -0.000 | -0.000 | -0.000 |

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Table 3. (continued)

| | | | | |
|---|---|---|---|---|
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Growth | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| BoardSize | 0.001 | 0.001 | 0.000 | 0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Dual | -0.007** | -0.007** | -0.004* | -0.004* |
| | (0.003) | (0.003) | (0.002) | (0.002) |
| Top1 | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| N | 26602 | 26602 | 26778 | 26778 |
| $R^2$ | 0.652 | 0.652 | 0.601 | 0.601 |

Note: High-dimensional fixed-effects model (reghdfe), robust standard errors clustered at the enterprise level are in parentheses. Columns (1) and (2) control for enterprise and year fixed effects, while columns (3) and (4) control for industry and year fixed effects.

### 4.3.2. Policy shock test (DID)

This paper further constructs a difference-in-differences (DID) model by taking the establishment of the National New-Generation Artificial Intelligence Innovation and Development Pilot Zones as a quasi-natural experiment for testing. This policy is an exogenous shock that can alleviate endogeneity caused by enterprise self-selection. Table 4 shows that under the panel Tobit setting (columns 1–2), the coefficients of the policy (DID) for the two types of efficiency are 0.102 and 0.113 respectively, both significantly positive at the 1% level, equivalent to 18.9% and 20.9% of the efficiency mean (0.540), with a stronger promotion effect on achievement transformation. This exogenous shock evidence further supports the core conclusion from the perspective of causal identification.

Under the high-dimensional fixed-effects setting (columns 3–4), the DID coefficients are -0.006 (insignificant) and 0.010 (significant at the 5% level) respectively, indicating that the policy effect changes after controlling for more unobservable factors, but the positive impact on green achievement transformation efficiency remains robust, further verifying the positive causal effect of the pilot zone policy, especially reflected in the transformation of technological achievements into practical applications.

Table 4. Robustness check: DID policy shock

| Variables | (1)Tobit-rd | (2)Tobit-trans | (3)FE-rd | (4)FE-trans |
|---|---|---|---|---|
| DID | 0.102*** | 0.113*** | -0.006 | 0.010** |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Size | 0.065*** | 0.063*** | -0.001 | -0.003 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Age | 0.141*** | 0.140*** | -0.006 | 0.002 |

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Table 4. (continued)

| | | | | |
|---|---|---|---|---|
| | (0.004) | (0.004) | (0.006) | (0.005) |
| Leverage | -0.002*** | -0.002*** | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Growth | -0.000*** | -0.000*** | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| BoardSize | -0.017*** | -0.017*** | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Dual | 0.020*** | 0.025*** | -0.007** | -0.003 |
| | (0.004) | (0.004) | (0.003) | (0.003) |
| Top1 | -0.001*** | -0.001*** | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| N | 26779 | 26779 | 26602 | 26602 |

Note: DID represents the policy shock of the National New-Generation Artificial Intelligence Innovation and Development Pilot Zones. Columns (1) and (2) are panel Tobit models, and columns (3) and (4) are high-dimensional fixed-effects models.

## 4.4. Heterogeneity analysis

Table 5 reports the grouped heterogeneity test results based on the panel Tobit model. The core explanatory variable is AI investment level (AI_invest), and the heterogeneous distribution of the effect is examined from three dimensions: property right nature, enterprise scale and industry attribute.

From the perspective of property right nature, the promotion effect of AI investment on green technology R&D efficiency is significantly positive in both state-owned enterprises (coefficient 1.147, significant at 1% level) and non-state-owned enterprises (coefficient 0.835, significant at 1% level), but the coefficient of state-owned enterprises is about 37.4% higher. For each one-standard-deviation increase in investment (0.009), the green R&D efficiency of state-owned enterprises increases by about 0.010 units, while that of non-state-owned enterprises increases by about 0.008 units. This may stem from the fact that state-owned enterprises undertake more policy tasks of green development and technological innovation, obtain more sufficient resources and policy guidance, and enjoy more stable capital and longer-term vision, which are conducive to the release of the effect.

From the perspective of enterprise scale, the coefficient of large-scale enterprises (1.654, significant at 1% level) is far higher than that of small-scale enterprises (0.247, insignificant) in both statistical and economic significance. For each one-standard-deviation increase in investment, the green R&D efficiency of large enterprises increases by about 0.015 units (1.654 × 0.009), accounting for about 2.8% of the mean value. This indicates that large enterprises can more fully transform investment by virtue of more complete digital infrastructure, more abundant complementary resources and more mature R&D management, reflecting economies of scale. Small and medium-sized enterprises are difficult to exert the empowering effect due to insufficient complementary resources, which provides a basis for relevant supporting policies.

From the perspective of industry attribute, the coefficient of manufacturing enterprises is 1.232 (significant at 1% level), while that of non-manufacturing enterprises is 0.180 (insignificant). For each one-standard-deviation increase in investment in manufacturing, the green R&D efficiency

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increases by about 0.011 units (1.232 × 0.009), accounting for about 2.0% of the mean value. Its advantage comes from the greater space for intelligent transformation of production processes, which directly improves efficiency by optimizing processes, reducing energy consumption and cutting emissions. Non-manufacturing industries have low process standardization and limited application scenarios, so the effect has not been fully manifested, which is consistent with the conclusion of Fan et al. [4].

Table 5. Heterogeneity analysis

| Variable | State-Owned | Non-State-Owned | Large Enterprises | Small Enterprises | Manufacturing | Non-Manufacturing |
|---|---|---|---|---|---|---|
| AI_invest | 1.147*** | 0.835*** | 1.654*** | 0.247 | 1.232*** | 0.180 |
| | (0.341) | (0.238) | (0.336) | (0.251) | (0.284) | (0.296) |
| Size | 0.082*** | 0.052*** | 0.097*** | 0.080*** | 0.071*** | 0.073*** |
| | (0.004) | (0.003) | (0.003) | (0.005) | (0.003) | (0.004) |
| Age | 0.286*** | 0.142*** | 0.160*** | 0.122*** | 0.162*** | 0.195*** |
| | (0.007) | (0.005) | (0.007) | (0.006) | (0.005) | (0.007) |
| Leverage | -0.002*** | -0.001*** | -0.002*** | -0.001*** | -0.002*** | -0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Growth | -0.000*** | -0.000*** | -0.000*** | -0.000*** | -0.000*** | -0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| BoardSize | -0.008*** | -0.012*** | -0.017*** | -0.019*** | -0.017*** | -0.013*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.001) | (0.002) |
| Dual | -0.004 | 0.017*** | 0.021*** | 0.027*** | 0.014*** | 0.039*** |
| | (0.007) | (0.004) | (0.006) | (0.005) | (0.004) | (0.007) |
| Top1 | -0.000* | -0.001*** | -0.002*** | -0.001*** | -0.001*** | -0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| N | 10195 | 15941 | 13390 | 13389 | 17267 | 9512 |

Note: Grouped regression of random-effects panel Tobit model, with standard errors in parentheses. The core explanatory variable is AI investment level.

## 5. Conclusions and policy implications

### 5.1. Research conclusions

Using panel data of China's A-share listed companies from 2007 to 2023, this paper empirically examines the impact of corporate artificial intelligence investment on green innovation efficiency and its moderating mechanism from two dimensions—AI-related word frequency disclosure and investment level—by adopting the random-effects panel Tobit model. The main conclusions are as follows:

First, both the improvement of AI investment level and the increase in corporate attention significantly promote green technology R&D efficiency and green achievement transformation efficiency. Each logarithmic unit increase in AI word frequency raises the two types of efficiency by approximately 0.042 (about 7.8%) and 0.040 units (about 7.4%) respectively. The coefficient of investment level is as high as 1.080, indicating that actual resource input has a more direct marginal

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impact. The conclusions remain directionally consistent after robustness tests including high-dimensional fixed effects, DID policy shocks and parallel trend tests.

Second, moderating effect analysis shows that the asset-liability ratio significantly positively moderates this promoting effect (interaction term 0.044, significant at the 1% level), meaning enterprises with stronger financing capacity can better convert AI investment into improved green innovation efficiency. The moderating effects of firm size (-0.135, insignificant) and ownership concentration (0.001, insignificant) are both insignificant, highlighting the key role of capital supply.

Third, heterogeneity analysis reveals that the effect is stronger in state-owned enterprises (1.147) than in non-state-owned enterprises (0.835), significant in large enterprises (1.654) but insignificant in small enterprises (0.247), and significant in manufacturing (1.232) but insignificant in non-manufacturing (0.180). This reflects the differentiated roles of policy resource allocation, economies of scale and industry technological characteristics.

## 5.2. Policy implications

Based on the above findings, this paper puts forward the following policy recommendations:

First, improve fiscal and tax incentive policies for corporate AI investment. In view of its significantly positive effect on green innovation efficiency, it is recommended to grant tax incentives and additional deductions for R&D expenses on AI-related hardware procurement, software development and talent introduction, so as to reduce investment costs and encourage enterprises to increase input.

Second, accelerate the construction of public service platforms for the integrated innovation of AI and green technologies. Based on the finding that the effect is insignificant for SMEs, it is suggested to promote the sharing of computing power, data resources and technical services, lower the threshold for SMEs to access AI technologies, and enable them to share the dividends of digital empowerment.

Third, implement differentiated support for different types of enterprises. For state-owned enterprises, assessment and incentives for green innovation should be strengthened; for SMEs and non-state-owned enterprises, financing constraints should be alleviated, as the moderating effect has shown that financing capacity is a key boundary for the effect to function; for enterprises in traditional industries, technical guidance and best practice promotion for AI application should be provided.

Fourth, incorporate AI investment into the corporate ESG evaluation system. Zhou et al. [5] and Wang et al. [34] show that ESG ratings exert a positive impact on green innovation efficiency. It is recommended to guide the capital market to focus on the synergy between AI investment and green development. By increasing the weight of AI-related dimensions in ESG indicators, enterprises can be motivated to increase input oriented toward green innovation, forming a virtuous cycle of "AI investment – green innovation – ESG improvement – lower financing costs".

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