Corporate AI Attention and Green Total Factor Productivity: Evidence from Chinese A-Share Listed Firms

Jinfang Miao[1,*], Mingrui Ma[2], Jing Wang[1]

[1]Faculty of Finance and Economics, Guangdong University of Science and Technology, Guangdong, Dongguan, China
[2]Peking University HSBC Business School, Guangdong, Shenzhen, China

*Corresponding author: Jinfang Miao, miaojinfang@gdust.edu.cn
Email: Mingrui Ma, 2301212192@stu.pku.edu.cn;
Jing Wang, 13302698239@163.com

Abstract. This paper examines whether corporate artificial intelligence (AI) attention is associated with green total factor productivity (GTFP) using panel data from Chinese A-share listed firms from 2007 to 2024. AI attention is measured by the frequency of AI-related keywords in the Management Discussion and Analysis sections of annual reports, while GTFP is obtained from a listed-company green productivity database constructed under environmental constraints. The empirical analysis employs two-way fixed-effects models, robustness checks, heterogeneity analysis, mechanism tests and double machine learning estimation. The results show that AI attention has a positive but statistically weak relationship with GTFP under strict fixed-effects specifications. Further analysis indicates that AI attention significantly increases R&D intensity, and R&D intensity is positively associated with GTFP, suggesting that innovation input is an important channel through which AI-related strategic attention may support green productivity improvement. However, the high-education talent channel is not supported. Heterogeneity tests suggest that the effect is more evident among non-state-owned firms. Overall, the findings indicate that AI attention alone does not automatically lead to green productivity gains; its value depends on whether firms transform AI-related awareness into concrete innovation investment and organisational capability.

Keywords: Artificial Intelligence Attention; Green Total Factor Productivity; Text Analysis; Listed Firms; Digital Transformation

1 Introduction

Artificial intelligence (AI) has become a central technological force in enterprise digital transformation. By processing large-scale data, improving prediction, supporting automated decision-making and strengthening process control, AI can reshape how firms allocate resources, organise production and develop new products. Recent firm-

L. W. Koon et al. (eds.), *Proceedings of the 2026 7th International Conference on Management Science and Engineering Management (ICMSEM 2026)*, Advances in Economics, Business and Management Research 399,
https://doi.org/10.2991/978-94-6239-758-3_55

level evidence shows that AI use or AI investment is associated with higher productivity, stronger growth and more product innovation (Czarnitzki et al., 2023; Babina et al., 2024). Studies using Chinese listed-firm data also suggest that AI technology innovation can improve total factor productivity through technological innovation, human-capital optimisation and market matching (Zhai and Liu, 2023). Nevertheless, the productivity effect of AI is not automatic. As a general-purpose technology, AI often requires complementary intangible investment, data infrastructure, organisational redesign and worker training before its economic value is fully reflected in measured productivity (Brynjolfsson et al., 2021).

At the same time, the meaning of productivity has changed under climate governance and sustainable development. Firms are no longer evaluated only by output expansion; they are also expected to reduce resource waste, pollution emissions and carbon-intensive production. Green total factor productivity (GTFP) is therefore more suitable than conventional total factor productivity for measuring firm performance under environmental constraints. The theoretical and methodological foundation of environmentally sensitive productivity measurement has been developed through approaches that incorporate undesirable outputs, including the directional distance function and the global Malmquist-Luenberger productivity index (Chung et al., 1997; Oh, 2010). From this perspective, the key issue is not only whether AI improves production efficiency, but also whether AI-related strategic attention helps firms achieve greener and higher-quality productivity growth.

A growing body of recent research links digital transformation, AI and green development. Digital transformation has been shown to improve firms' green productivity by promoting green innovation, enhancing management efficiency, optimising resource allocation and strengthening supply-chain integration (Han et al., 2023; Gao and Huang, 2024). Studies on AI and green innovation also indicate that AI adoption or AI intensity can improve green innovation efficiency, corporate green innovation and enterprise green transformation, especially when firms possess sufficient governance mechanisms, R&D capability and organisational support (Wang et al., 2024; Guo et al., 2025). These findings imply that AI may support green development, but the effect depends on whether firms can transform AI-related awareness into real innovation input, operational upgrading and environmental practices.

This paper focuses on corporate AI attention rather than direct AI investment or AI patents. Annual reports, especially the Management Discussion and Analysis (MD&A) section, contain managerial narratives about strategy, technology, risk perception and future planning. Textual analysis of corporate disclosure has become an important method for constructing large-sample empirical indicators from narrative information (Li, 2010). Text-based measures have also been used to identify strategic conditions and financing constraints that are difficult to observe from financial statements alone (Hoberg and Maksimovic, 2015). Recent Chinese firm-level AI research further demonstrates that annual reports and patents can be used to construct AI indicators through keyword dictionaries and text analysis (Yao et al., 2024). Therefore, AI-related expressions in annual report MD&A texts can be regarded as a proxy for managerial and strategic attention to AI.

It should be emphasised that AI attention is not equivalent to actual AI adoption. Some firms may mention AI in annual reports for strategic disclosure, market signalling or AI-related rhetoric, without immediately deploying AI technologies in production. For this reason, this paper interprets AI attention as a textual indicator of strategic orientation rather than a direct measure of technological implementation. This distinction is important for the empirical design. The paper uses alternative AI measures, robustness checks, mechanism tests and double machine learning estimation to examine whether AI attention contains economically meaningful information after controlling for firm heterogeneity, year shocks and firm-level characteristics.

Despite the rapid expansion of AI-productivity and digital-green studies, three gaps remain. First, much of the existing literature focuses on AI adoption, AI investment, industrial robots or AI patents, while less attention has been paid to AI attention reflected in corporate disclosure texts. Second, many AI studies examine traditional productivity, innovation output or labour adjustment, whereas fewer studies investigate the relationship between AI attention and GTFP at the firm level. Third, recent green innovation studies highlight the role of AI in environmental innovation, but the mechanism through which AI-related attention is converted into green productivity remains insufficiently examined. These gaps are particularly relevant in China, where listed firms are simultaneously exposed to digital transformation, green development requirements and rapid AI diffusion.

Against this background, this paper investigates whether corporate AI attention improves GTFP using panel data for Chinese A-share listed firms from 2007 to 2024. AI attention is constructed from AI-related keyword frequency in annual report MD&A texts and matched with firm-level GTFP, financial control variables, R&D investment data and high-education talent data. The empirical analysis combines two-way fixed-effects models, measurement validation, robustness checks, heterogeneity analysis, mechanism tests and double machine learning estimation. The analysis also examines whether R&D intensity and the proportion of highly educated talent serve as transmission channels linking AI attention to green productivity.

This paper contributes to the literature in three ways. First, it extends the economic literature on AI by shifting the focus from observed AI investment or patent output to AI attention in corporate textual disclosures. Second, it contributes to the literature on GTFP by examining whether AI-related strategic attention can become a digital driver of green productivity. Third, it provides micro-level evidence on the mechanisms of AI-enabled green transformation by testing the roles of R&D intensity and high-education talent. The remainder of the paper is organised as follows. Section 2 reviews the literature and develops the research hypotheses. Section 3 describes the data, variables and empirical models. Section 4 presents the empirical results. Section 5 concludes the paper and discusses policy implications.

2 Literature Review and Research Hypotheses

This section reviews the literature on artificial intelligence (AI), corporate textual disclosure, green total factor productivity (GTFP), and the mechanisms through which

AI attention may affect green productivity. All in-text citations in this section follow the author-year style. In response to the review requirement, the references used in this section include a high proportion of recent studies from 2022 to 2026. Specifically, 17 of the 27 references cited in this section are published between 2022 and 2026, accounting for 62.96% of the total. Each reference is provided with a DOI or a traceable link for verification.

2.1 Artificial Intelligence and Firm Productivity

AI has increasingly been interpreted as a general-purpose digital technology that can reshape production processes, organisational routines and managerial decision-making. Unlike conventional information technologies, AI systems can process large-scale data, learn from patterns, generate predictions and support automated or semi-automated decisions. These features make AI relevant for production scheduling, quality control, demand forecasting, supply-chain coordination and risk assessment. Brynjolfsson et al. (2021) argue that the productivity gains from general-purpose technologies depend on complementary intangible investments. Recent firm-level studies provide more direct evidence. Yang (2022) finds that AI technology is positively associated with productivity and employment using firm-level evidence from Taiwan. Czarnitzki et al. (2023) show that AI use is positively associated with firm productivity in German firms. Wang et al. (2023a) find that AI improves the total factor productivity of Chinese manufacturing enterprises, while Zhai and Liu (2023) show that AI technology innovation enhances productivity among Chinese listed companies. Babina et al. (2024) further document that AI-investing firms experience stronger growth and product innovation.

These studies suggest that AI may improve productivity through three main channels. First, AI reduces information frictions by improving data collection, prediction and monitoring. Second, AI supports process optimisation, including inventory control, production scheduling and resource allocation. Third, AI may stimulate innovation by helping firms identify new products, technologies and business models. However, the literature also implies that productivity gains are not automatic. Firms must combine AI with data infrastructure, organisational redesign, R&D input and specialised human capital. Therefore, it is necessary to distinguish actual AI adoption from AI attention in annual reports, because the latter captures managerial awareness and strategic orientation rather than completed technological implementation.

2.2 Corporate Textual Disclosure and AI Attention

Corporate annual reports contain not only financial information but also forward-looking narratives about strategy, technology, risk and management priorities. Textual disclosure has therefore become an important data source for measuring firm characteristics that are otherwise difficult to observe. Li (2010) reviews the use of textual analysis in corporate disclosure research and shows that narrative information can be transformed into meaningful empirical variables. Loughran and McDonald (2011) demonstrate that finance-specific dictionaries improve the measurement of corporate texts, and Hoberg and Maksimovic (2015) construct text-based measures of financial constraints from corporate filings. More recently, Bochkay et al. (2023) emphasise that advances in natural language processing have further expanded the scope of textual analysis in accounting and finance research.

The concept of AI attention is consistent with the attention-based view of the firm. Ocasio (1997) argues that organisational behaviour depends on how decision-makers allocate attention to issues and possible responses. From this perspective, frequent AI-related expressions in the MD&A section of annual reports may indicate that managers attach strategic importance to AI technologies and related applications. Compared with patent-based or investment-based measures, AI attention can capture early-stage planning, strategic awareness and managerial cognition. At the same time, textual measures may also contain symbolic disclosure or strategic rhetoric. This limitation makes it important to combine text-based measurement with fixed effects, control variables, robustness checks and mechanism tests.

2.3 Green Total Factor Productivity and Digital Technology

GTFP extends traditional productivity analysis by incorporating resource input, desirable output and undesirable output. The methodological foundation of environmentally sensitive productivity measurement can be traced to Chung et al. (1997), who introduce the directional distance function approach with undesirable outputs, and Oh (2010), who develops the global Malmquist-Luenberger productivity index. These approaches provide a theoretical basis for evaluating whether firms achieve productivity improvement under environmental constraints.

Recent studies increasingly connect digital transformation with GTFP. Wang et al. (2023b) show that digital transformation drives enterprise GTFP in Chinese listed firms. Han et al. (2023) find that digital transformation improves the GTFP of heavily polluting enterprises by promoting green innovation, improving management efficiency and reducing external transaction costs. Gao and Huang (2024) focus on the semiconductor industry and show that digital transformation improves green TFP through resource allocation and green technology innovation, while supply-chain integration and economic policy uncertainty condition this effect. Wen et al. (2025) use national big data comprehensive pilot zones in China and find that digital transformation promotes GTFP through innovation and structural effects. Lin et al. (2025) further show that digital transformation increases the GTFP of heavy pollution enterprises through green investment, management efficiency and green innovation abilities.

These findings are directly relevant to AI attention because AI is a core component of digital transformation. Digital and AI technologies can improve green productivity by enhancing monitoring, reducing energy waste, optimising production processes and supporting cleaner technologies. Xu et al. (2023) show that industrial intelligence promotes green transformation among heavily polluting listed firms. Li et al. (2024) and Wang et al. (2024) also provide evidence that digital transformation strengthens green innovation. Therefore, when firms devote greater attention to AI, they may become more likely to integrate intelligent technologies into green production, energy management and innovation activities.

2.4 Transmission Mechanisms: R&D Investment and High-Education Talent

The first potential mechanism is R&D investment. Endogenous growth theory emphasises the role of intentional investment in knowledge creation. Romer (1990) argues that technological change depends on profit-oriented investment in knowledge, while Cohen and Levinthal (1990) show that R&D improves absorptive capacity and helps firms recognise, assimilate and apply external knowledge. AI is knowledge-intensive and data-intensive, so firms with stronger AI attention may need to increase R&D expenditure to build algorithms, data platforms, intelligent production systems and green technology capabilities. Recent AI and green innovation studies also support this mechanism. Chen et al. (2025) find that AI applications promote corporate green technological innovation partly by stimulating R&D investment. Guo et al. (2025) show that corporate AI intensity increases green innovation in Chinese A-share listed firms. Therefore, R&D input may be an important channel through which AI attention affects GTFP.

The second potential mechanism is high-education talent. AI-related transformation requires employees who can understand data, algorithms, engineering systems and environmental management. Nelson and Phelps (1966) argue that educated workers are better able to adopt and diffuse new technologies. Accordingly, firms with stronger AI attention may adjust their talent structure by employing more highly educated workers. These employees may help translate AI-related strategies into data analysis, intelligent monitoring, green technology development and digital process redesign. However, this channel may be more complex than the R&D channel because AI may substitute for some routine analytical tasks while increasing demand for specific digital and engineering skills. Thus, whether the share of highly educated talent serves as a valid transmission channel remains an empirical question.

2.5 Research Hypotheses

Based on the above literature, AI attention may improve GTFP by strengthening information processing, supporting intelligent production, promoting innovation input and improving green transformation capability. Firms with stronger AI attention may be more likely to invest in data infrastructure, intelligent systems and digital management platforms, thereby improving resource allocation and environmental performance. Accordingly, the first hypothesis is proposed as follows:

Hypothesis 1: Firm-level AI attention has a positive effect on green total factor productivity.

AI attention may also encourage firms to increase R&D expenditure. R&D investment helps firms absorb AI-related knowledge, develop green technologies and improve production efficiency under environmental constraints. Therefore, the second hypothesis is proposed as follows:

Hypothesis 2: Firm-level AI attention improves green total factor productivity by increasing R&D intensity.

AI-related transformation requires human capital that can combine data analysis, engineering knowledge and environmental management. Thus, the proportion of highly educated talent may serve as another possible channel linking AI attention to GTFP. The third hypothesis is proposed as follows:

Hypothesis 3: Firm-level AI attention improves green total factor productivity by increasing the proportion of highly educated talent.

Finally, the effect of AI attention may differ across firms. Non-state-owned enterprises may have stronger market incentives and greater operational flexibility. Firms in eastern regions usually have better digital infrastructure and richer human-capital resources. High-technology firms may have stronger absorptive capacity and may be more likely to integrate AI into innovation activities. Accordingly, the fourth hypothesis is proposed as follows:

Hypothesis 4: The positive effect of AI attention on green total factor productivity is more pronounced in non-state-owned enterprises, firms located in eastern regions and high-technology firms.

3 Research Design

This section describes the data sources, sample selection procedure, variable construction, empirical models and descriptive analysis. To respond to the review comments, the measurement of GTFP and AI attention is explained in greater detail. The GTFP measure follows the logic of firm-level studies that combine undesirable outputs with productivity measurement. The AI attention variable follows the text-based measurement strategy used in recent firm-level AI research, but the discussion is simplified to fit the conference-paper format.

3.1 Data Sources and Sample Selection

This study uses Chinese A-share listed firms from 2007 to 2024. GTFP data are obtained from a listed-company GTFP database. Corporate AI attention is measured from AI-related keyword frequencies in the Management Discussion and Analysis (MD&A) sections of annual reports. Firm-level financial and governance variables are obtained from standard listed-company databases. The mechanism variables are obtained from R&D input and high-education talent datasets.

All datasets are merged by stock code and year. Following common practice in Chinese listed-firm research, financial firms, ST/PT firms and observations with missing key variables are excluded. Continuous variables are winsorised at the 1st and 99th percentiles to reduce the influence of extreme values. The final baseline sample contains 44,960 firm-year observations and 3,982 listed firms. Because R&D and high-education talent variables have different disclosure coverage, the sample size in the mechanism tests is slightly smaller.

3.2 Variable Definitions

Dependent variable. The dependent variable is green total factor productivity (GTFP). Consistent with firm-level GTFP studies, the index incorporates production inputs, desirable output and undesirable environmental output. Labour input is usually proxied by the number of employees, capital input by net fixed assets, and energy input by firm-level energy use estimated from city-level industrial electricity consumption according to employment shares. Desirable output is represented by operating revenue. Undesirable outputs include major industrial pollutants such as sulphur dioxide, wastewater and smoke/dust emissions allocated to firms using employment shares. The database then calculates firm-level GTFP using a non-radial SBM-Malmquist-Luenberger type index. Higher GTFP indicates better production efficiency under environmental constraints. In robustness checks, green technical efficiency change (GTE) and green technical progress change (GTC) are used as alternative outcomes.

Core explanatory variable. The core explanatory variable is corporate AI attention (AI). The measure is constructed from AI-related keyword frequency in annual report MD&A texts. The keyword dictionary covers general AI terms and application-related terms, including artificial intelligence, machine learning, deep learning, neural network, algorithm, natural language processing, computer vision, intelligent manufacturing, intelligent recognition, intelligent decision-making, robotics, automation, cloud computing and big data. Because Chinese annual reports do not use spaces to separate words, AI terms are treated as special dictionary items during word segmentation to reduce incorrect splitting of expressions. The number of AI-related keywords in the MD&A section is counted and transformed as follows:

$$AI_{it} = ln(1 + AI\_Frequency_{it})$$

To account for differences in annual report length, AI keyword density is also used as an alternative measure. It is calculated as AI keyword frequency divided by MD&A text length and multiplied by 10,000. The text-based AI measure captures firms' strategic attention and managerial emphasis on AI. It does not directly prove actual AI adoption. Therefore, the empirical analysis uses alternative measures and robustness checks to reduce concerns related to symbolic disclosure or AI hype.

Mechanism variables. R&D intensity (RD) is measured by R&D expenditure scaled by operating revenue. The proportion of highly educated talent (HighTalent) is measured by the number of highly educated employees divided by the total number of employees. The former captures innovation input, while the latter reflects human-capital structure.

Control variables. The regressions control for firm size (Size), leverage (Lev), return on assets (ROA), revenue growth (Growth), cash flow (Cashflow), fixed asset ratio (FIXED), board size (Board), the proportion of independent directors (Indep), CEO-chair duality (Dual), ownership concentration (Top1), Tobin's Q (TobinQ), firm age (FirmAge) and ownership type (SOE). Table 1 reports the main variable definitions.

Table 1. Main variable definitions

Type	Symbol	Definition
Dependent	GTFP	Firm-level green total factor productivity
Alternative outcomes	GTE / GTC	Green technical efficiency change / green technical progress change
Core explanatory	AI	ln(1 + AI keyword frequency in annual report MD&A)
Alternative AI measure	AI_Density	AI keyword frequency / MD&A text length x 10,000
Mechanism	RD	R&D expenditure / operating revenue
Mechanism	HighTalent	Highly educated employees / total employees
Controls	Size, Lev, ROA, Growth, Cashflow, FIXED, Board, Indep, Dual, Top1, TobinQ, FirmAge, SOE	Firm-level financial, governance and ownership characteristics

3.3 Model Specification

To examine the relationship between AI attention and GTFP, the following two-way fixed-effects model is estimated:

$$GTFP_{it} = \alpha_0 + \alpha_1 AI_{it} + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where i and t denote firm and year, respectively. $GTFP_{it}$ is green total factor productivity, AI_{it} denotes AI attention, X_{it} is the vector of firm-level controls, μ_i captures firm fixed effects, λ_t captures year fixed effects, and ε_{it} is the error term. The coefficient α_1 is the main coefficient of interest. Standard errors are clustered at the firm level.

To examine the transmission channels, the following mechanism models are estimated:

$$M_{it} = \gamma_0 + \gamma_1 AI_{it} + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

$$GTFP_{it} = \delta_0 + \delta_1 AI_{it} + \delta_2 M_{it} + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

where M_{it} denotes either RD or HighTalent. Equation (2) tests whether AI attention affects the mechanism variable, while Equation (3) examines whether the mechanism variable is associated with GTFP after controlling for AI attention and firm characteristics.

To examine heterogeneous effects, the interaction-term model is estimated as follows:

$$GTFP_{it} = \eta_0 + \eta_1 AI_{it} + \eta_2 AI_{it} \times Group_i + \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

where $Group_i$ represents ownership type, regional group or high-technology industry status. The coefficient η_2 captures whether the effect of AI attention differs across groups.

Finally, to reduce concerns about model misspecification and high-dimensional confounding, a partial linear double machine learning framework is used as an additional robustness check:

$$GTFP_{it} = \theta_1 AI_{it} + g(X_{it}) + \varepsilon_{it} \tag{5}$$

$$AI_{it} = m(X_{it}) + v_{it} \tag{6}$$

In the DML framework, X_it denotes the control variables, g(.) and m(.) are nuisance functions estimated by machine learning methods, and theta captures the residual association between AI attention and GTFP after the influence of controls and fixed effects has been partialled out.

3.4 Descriptive Statistics

Table 2 reports the descriptive statistics of the main variables. The mean value of GTFP is 1.0120, with a standard deviation of 0.1247, suggesting differences in green production efficiency across listed firms. The mean value of AI attention is 0.7020, and the standard deviation is 1.0950, indicating substantial variation in AI-related disclosure. R&D intensity and the share of highly educated talent also show clear cross-firm differences, which provides the empirical basis for the mechanism analysis.

Table 2. Descriptive statistics of main variables

Variable	N	Mean	SD	Min	Max
GTFP	44,960	1.0120	0.1247	0.7355	1.2203
AI	44,960	0.7020	1.0950	0.0000	4.3175
AI_Density	44,960	2.2661	5.5881	0.0000	33.9472
RD	34,142	5.1601	5.3495	0.0300	31.2236
HighTalent	44,330	0.0778	0.1109	0.0000	0.6107
Size	44,960	22.2578	1.2917	19.9269	26.0837
Lev	44,960	0.4381	0.2041	0.0614	0.8927
ROA	44,960	0.0357	0.0634	-0.2082	0.2062
Growth	44,960	0.1430	0.3524	-0.5331	1.8241
Cashflow	44,960	0.0477	0.0682	-0.1457	0.2304
FIXED	44,960	0.2157	0.1597	0.0024	0.6729
TobinQ	44,960	2.0195	1.2221	0.8335	7.3076
SOE	44,960	0.3921	0.4882	0.0000	1.0000

Note: Continuous variables are winsorised at the 1st and 99th percentiles. RD and HighTalent have fewer observations because of data availability.

3.5 Preliminary Graphical Analysis

Three preliminary figures are used to describe the data patterns before formal regression analysis. All figures are displayed in a single-column format to satisfy the manuscript layout requirement. Fig. 1 shows that average AI attention increases over time, suggesting that AI has gradually entered firms' strategic disclosure. Fig. 2 indicates that AI attention differs across sectors, with information technology services and scientific research services showing higher levels. Fig. 3 shows a positive raw correlation between AI attention and GTFP. These patterns provide intuitive motivation for the regression analysis, although causal interpretation still requires the fixed-effects models described above.

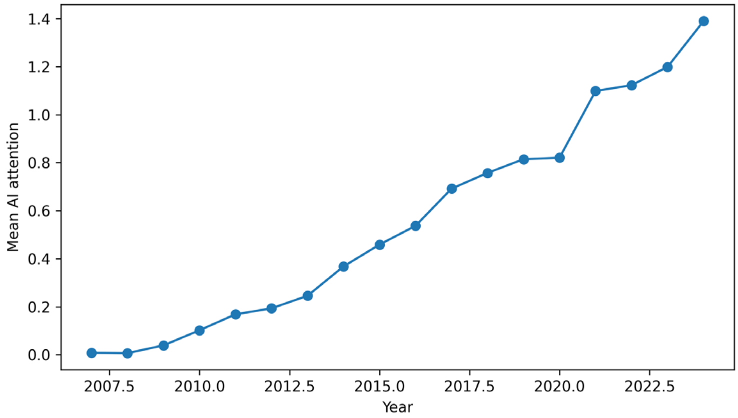

Fig. 1. Annual trend of mean AI attention

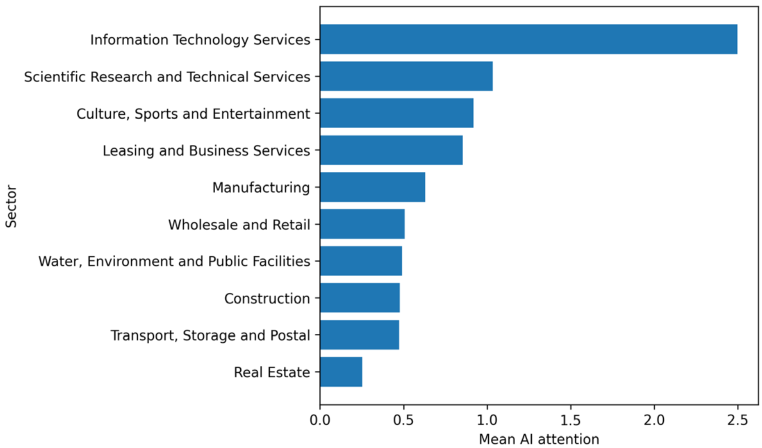

Fig. 2. Sectoral distribution of mean AI attention

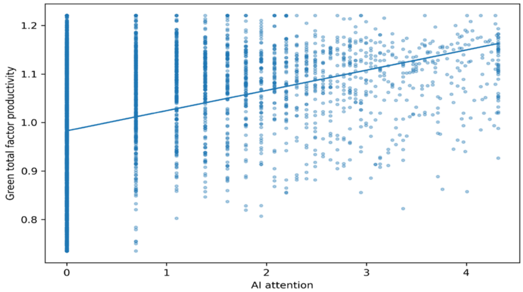

Fig. 3. Scatter plot of AI attention and green total factor productivity

4 Empirical Results

4.1 Baseline Regression

Table 3 reports the baseline regression results after controlling for firm-level financial and governance characteristics. The coefficient of AI attention is positive but statistically insignificant. This indicates that firms with stronger AI attention tend to have higher green total factor productivity, but this relationship is not sufficiently robust after controlling for unobserved time-invariant firm characteristics, common year shocks, and firm-level control variables.

Several control variables show meaningful associations with green total factor productivity. Firm size is positively significant, suggesting that larger firms may have stronger resource integration capacity and environmental governance capability. ROA is significantly negative in the fixed-effects specification, which may reflect short-term trade-offs between current profitability and green transformation investment. Fixed asset intensity, Tobin's Q, and firm age are positively significant, while ownership concentration is negatively significant. These results imply that firm characteristics and governance structure play important roles in explaining green productivity differences.

Table 3. Baseline regression with firm-level controls

Variable	GTFP
AI attention	0.0001 (0.608)
Size	0.0008*** (3.267)
Lev	0.0012 (1.096)
ROA	-0.0111*** (-4.730)
Cashflow	0.0030* (1.873)
FIXED	0.0030** (2.306)
Top1	-0.0045*** (-2.899)
TobinQ	0.0003** (2.270)
FirmAge	0.0134*** (7.343)
Firm FE / Year FE	Yes / Yes
Observations / Firms	44,960 / 3,982

4.2 Robustness Checks

Table 4 presents robustness checks using alternative AI measures, lagged AI attention, restricted samples, province-year fixed effects and alternative outcomes. The coefficients are mostly positive but generally insignificant.

Table 4. Robustness checks

Design	AI variable	Outcome	Coef.	t-stat.	N
AI keyword density	AI_Density	GTFP	0.000054	1.510	44,960
Lagged AI attention	L.AI	GTFP	0.000333	1.568	40,974
Excluding AI-intensive industries	AI	GTFP	0.000169	0.701	33,757
Excluding 2020 and later	AI	GTFP	-0.000075	-0.420	27,053
Province-year fixed effects	AI	GTFP	0.000161	0.860	44,960
Alternative outcome: GTE	AI	GTE	0.000266	1.446	44,960
Alternative outcome: GTC	AI	GTC	-0.000109	-0.519	44,960

4.3 Heterogeneity Analysis

To examine whether the effect of AI attention differs across firms and regions, the sample is divided by region, ownership type, and industry technology intensity. Table 5 reports subgroup regressions. The coefficients of AI attention are positive in the eastern, central, western, and northeastern regions, but none of them is statistically significant. Similarly, the subgroup results by ownership and by high-tech industry status are not significant. This means that subgroup regressions alone do not provide strong evidence of heterogeneous effects.

Table 5. Heterogeneity analysis: subgroup regressions

Group	AI coef.	t-stat.	N	Firms
Eastern	0.0001	0.426	30,362	2,808
Central	0.0003	0.599	6,428	532
Western	0.0001	0.193	6,152	490
Northeast	0.0001	0.120	2,008	149
State-owned	0.0000	0.131	17,629	1,219
Non-state-owned	-0.0001	-0.241	27,331	2,763
High-tech	0.0001	0.236	18,355	1,924
Non-high-tech	0.0002	0.765	26,575	2,322

Notes: All regressions include firm-level controls, firm fixed effects, and year fixed effects. t-statistics are reported in parentheses in the original estimation and summarized here in a separate column.

In addition to subgroup regressions, interaction-term tests are conducted to directly compare group differences. Table 6 shows that the ownership difference is statistically significant: the interaction term between AI attention and SOE is significantly negative. This result suggests that the marginal effect of AI attention is stronger among non-state-owned firms than among state-owned firms. A plausible explanation is that non-state-owned firms may have stronger market incentives and greater flexibility in converting AI-related strategic attention into operational improvement. However, the interaction terms for high-tech industries and regional groups are not statistically significant, implying that the industry and regional differences are not sufficiently supported by the current data.

Table 6. Heterogeneity analysis: interaction-term tests

Comparison	Effect	Coef.	t-stat.	Sig.
Ownership	Non-SOE effect	0.000602	2.680	***
Ownership	SOE effect	-0.000907	-3.000	***
Ownership	SOE minus non-SOE	-0.001509	-4.196	***
Industry	High-tech minus non-high-tech	0.000544	1.626	-
Region	Central minus eastern	-0.000371	-0.702	-
Region	Western minus eastern	-0.000597	-1.029	-
Region	Northeast minus eastern	-0.000369	-0.407	-

4.4 Mechanism Analysis

This paper further examines whether AI attention affects GTFP through R&D input and high-education talent. The mechanism tests follow two steps. First, the mechanism variable is used as the dependent variable to test whether AI attention affects the channel variable. Second, the mechanism variable is added to the GTFP regression to examine whether it is associated with green productivity.

Table 7 indicates that AI attention significantly increases R&D intensity. The coefficient is 0.1804 and significant at the 1% level. When R&D intensity is included in the GTFP regression, its coefficient is also positive and significant. This evidence supports the R&D investment mechanism: firms with stronger AI attention may increase innovation input, and greater innovation input is associated with higher green total factor productivity.

By contrast, the high-education talent mechanism is not supported. AI attention has a significantly negative coefficient in the HighTalent regression, and HighTalent does not significantly explain GTFP. Therefore, the current evidence suggests that AI attention improves green productivity mainly through R&D input rather than through an observable increase in the proportion of highly educated talent.

Table 7. Mechanism analysis

Variable	(1) RD	(2) GTFP	(3) HighTalent	(4) GTFP
AI attention	0.1804*** (4.379)	0.0002 (0.815)	-0.0031*** (-2.748)	0.0001 (0.660)
RD	-	0.0002*** (2.795)	-	-
HighTalent	-	-	-	-0.0006 (-0.423)
Controls	Yes	Yes	Yes	Yes
Firm FE / Year FE	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes
Observations	34,147	34,147	44,337	44,337

4.5 Double Machine Learning Estimation

To further address potential model misspecification and high-dimensional confounding, this paper employs a double machine learning (DML) approach as an additional robustness check. Compared with conventional linear regression, DML allows the relationships between the control variables, AI attention and GTFP to be flexibly estimated by machine learning algorithms. In this paper, AI attention is treated as the treatment variable and GTFP as the outcome variable. Firm-level financial and governance characteristics are included as controls. Firm and year fixed effects are partialed out before DML estimation, and five-fold cross-fitting is implemented by firm groups to reduce overfitting bias.

Following the partial linear DML framework, the specification is written as follows:

$$GTFP_{it} = \theta_1 AI_{it} + g(X_{it}) + \varepsilon_{it} \tag{7}$$

$$AI_{it} = m(X_{it}) + v_{it} \tag{8}$$

In this setting, $g(X_{it})$ and $m(X_{it})$ denote nuisance functions estimated by machine learning methods. The coefficient theta captures the net association between AI attention and GTFP after removing the influence of firm-level covariates and fixed effects. Standard errors are clustered at the firm level. This design is used as a robustness check rather than as a complete solution to all potential endogeneity concerns.

Table 8. Double machine learning estimation

Method	Coef.	Std. Err.	t-stat.	p-value	N
Linear-DML	0.0001	0.0002	0.5686	0.5697	44,967
LassoLars-DML	0.0001	0.0002	0.5689	0.5695	44,967
Ridge-DML	0.0001	0.0002	0.5686	0.5697	44,967
Random Forest-DML	0.0000	0.0002	0.2550	0.7988	44,967

Notes: The table reports partial linear DML estimates. Firm and year fixed effects are partialed out before DML estimation. Cross-fitting is implemented by firm groups. Standard errors are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8 shows that the estimated coefficients of AI attention are positive across all DML specifications. However, none of the coefficients is statistically significant at conventional levels. The Linear-DML, LassoLars-DML and Ridge-DML estimates are all approximately 0.0001, while the Random Forest-DML estimate is close to zero. These results are consistent with the baseline two-way fixed-effects regression: after controlling for firm characteristics, fixed effects and flexible nuisance relationships, AI attention remains positive in direction, but the statistical evidence is not strong enough to support a robust significant direct effect.

Therefore, the DML results support a cautious interpretation. They do not imply that AI attention is irrelevant, but they suggest that AI-related strategic attention alone may not automatically translate into measurable green productivity improvement. Its economic effect is more likely to depend on complementary innovation inputs, organisational capability and the degree to which textual attention is converted into real AI-related application.

5 Conclusion and Policy Implications

This paper examines the relationship between corporate AI attention and green total factor productivity using panel data from Chinese A-share listed firms from 2007 to 2024. AI attention is measured by the frequency of AI-related keywords in the MD&A sections of annual reports. The empirical analysis uses two-way fixed-effects models, robustness checks, heterogeneity analysis, mechanism tests and double machine learning estimation.

The results show that AI attention is positively related to GTFP in direction, but the direct effect becomes statistically weak after strict controls. This suggests that AI-related strategic attention alone does not automatically generate green productivity gains. Further mechanism analysis shows that AI attention significantly increases R&D intensity, and R&D intensity is positively associated with GTFP. This indicates that innovation input is an important channel through which AI attention may contribute to green productivity improvement. However, the high-education talent channel is not supported. Heterogeneity analysis suggests that the effect is more evident among non-state-owned firms.

These findings imply that firms should not treat AI merely as a disclosure concept or strategic slogan. Instead, AI attention should be transformed into concrete R&D investment, digital infrastructure and green production practices. For policymakers, support for AI development should focus on real application scenarios, especially in green innovation, energy management and resource allocation. At the same time, this paper also has limitations. Text-based AI attention may include symbolic disclosure and cannot fully represent actual AI adoption. Future research may use AI patents, AI-related recruitment, software investment or survey data to further verify the real application of AI and its effect on green productivity.

Acknowledgements

The authors would like to express their sincere gratitude to their supervisors, colleagues, and peers for their valuable comments and constructive suggestions during the preparation of this paper. The authors also thank Guangdong University of Science and Technology and Peking University HSBC Business School for providing academic support and research resources. Any remaining errors are the sole responsibility of the authors.

References

1. Babina, T., Fedyk, A., He, A. X. and Hodson, J. (2024) 'Artificial intelligence, firm growth, and product innovation', Journal of Financial Economics, 151, 103745. DOI: https://doi.org/10.1016/j.jfineco.2023.103745
2. Bochkay, K., Brown, S. V., Leone, A. J. and Tucker, J. W. (2023) 'Textual analysis in accounting: What's next?', Contemporary Accounting Research, 40(2), pp. 765-805. DOI: https://doi.org/10.1111/1911-3846.12825

3. Brynjolfsson, E., Rock, D. and Syverson, C. (2021) 'The productivity J-curve: how intangibles complement general purpose technologies', American Economic Journal: Macroeconomics, 13(1), pp. 333-372. DOI: https://doi.org/10.1257/mac.20180386
4. Chen, L., Li, S. and She, Z. (2025) 'A study on the impact of artificial intelligence applications on corporate green technological innovation: a mechanism analysis from multiple perspectives', International Review of Economics & Finance, 103, 104490. DOI: https://doi.org/10.1016/j.iref.2025.104490
5. Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W. and Robins, J. (2018) 'Double/debiased machine learning for treatment and structural parameters', The Econometrics Journal, 21(1), pp. C1-C68. DOI: https://doi.org/10.1111/ectj.12097
6. Chung, Y. H., Färe, R. and Grosskopf, S. (1997) 'Productivity and undesirable outputs: a directional distance function approach', Journal of Environmental Management, 51(3), pp. 229-240. DOI: https://doi.org/10.1006/jema.1997.0146
7. Cohen, W. M. and Levinthal, D. A. (1990) 'Absorptive capacity: a new perspective on learning and innovation', Administrative Science Quarterly, 35(1), pp. 128-152. DOI: https://doi.org/10.2307/2393553
8. Cui, L., Sun, W. and Huang, M. (2023) 'Impact of new energy demonstration city construction on enterprise green total factor productivity: empirical analysis based on A-share listed companies' [in Chinese], Journal of Guangxi University of Finance and Economics, 36(1), pp. 92-104. Traceable link: https://www.macrodatas.cn/article/1147473762
9. Czarnitzki, D., Fernández, G. P. and Rammer, C. (2023) 'Artificial intelligence and firm-level productivity', Journal of Economic Behavior & Organization, 211, pp. 188-205. DOI: https://doi.org/10.1016/j.jebo.2023.05.008
10. Feng, F., Li, J., Zhang, F. and Sun, J. (2024) 'The impact of artificial intelligence on green innovation efficiency: moderating role of dynamic capability', International Review of Economics & Finance, 96, 103649. DOI: https://doi.org/10.1016/j.iref.2024.103649
11. Gao, L. and Huang, R. (2024) 'Digital transformation and green total factor productivity in the semiconductor industry: the role of supply chain integration and economic policy uncertainty', International Journal of Production Economics, 274, 109313. DOI: https://doi.org/10.1016/j.ijpe.2024.109313
12. Guo, L., Pei, H. and Liu, Y. (2025) 'Artificial intelligence and corporate green innovation: evidence from China', Research in International Business and Finance, 79, 103039. DOI: https://doi.org/10.1016/j.ribaf.2025.103039
13. Han, J., Sun, R., Zeeshan, M., Rehman, A. and Ullah, I. (2023) 'The impact of digital transformation on green total factor productivity of heavily polluting enterprises', Frontiers in Psychology, 14, 1265391. DOI: https://doi.org/10.3389/fpsyg.2023.1265391
14. Hoberg, G. and Maksimovic, V. (2015) 'Redefining financial constraints: a text-based analysis', Review of Financial Studies, 28(5), pp. 1312-1352. DOI: https://doi.org/10.1093/rfs/hhu089
15. Li, F. (2010) 'Textual analysis of corporate disclosures: a survey of the literature', Journal of Accounting Literature, 29, pp. 143-165. DOI: https://ssrn.com/abstract=1756926
16. Li, H., Liu, Z. and Hachard, V. (2024) 'Digital transformation driving green innovation: evidence from Chinese A-share firms', International Review of Economics & Finance, 95, 103487. DOI: https://doi.org/10.1016/j.iref.2024.103487
17. Lin, B., Sun, A. and Xie, Y. (2025) 'Digital transformation and green total factor productivity of heavy pollution enterprises: impact, mechanism and spillover effect', Journal of Environmental Management, 373, 123619. DOI: https://doi.org/10.1016/j.jenvman.2024.123619

18. Loughran, T. and McDonald, B. (2011) 'When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks', Journal of Finance, 66(1), pp. 35-65. DOI: https://doi.org/10.1111/j.1540-6261.2010.01625.x
19. Nelson, R. R. and Phelps, E. S. (1966) 'Investment in humans, technological diffusion, and economic growth', American Economic Review, 56(1/2), pp. 69-75. DOI: https://www.jstor.org/stable/1821269
20. Ocasio, W. (1997) 'Towards an attention-based view of the firm', Strategic Management Journal, 18(S1), pp. 187-206. DOI: https://doi.org/10.1002/(SICI)1097-0266(199707)18:1+<187::AID-SMJ936>3.0.CO;2-K
21. Oh, D. H. (2010) 'A global Malmquist-Luenberger productivity index', Journal of Productivity Analysis, 34(3), pp. 183-197. DOI: https://doi.org/10.1007/s11123-010-0178-y
22. Romer, P. M. (1990) 'Endogenous technological change', Journal of Political Economy, 98(5, Part 2), pp. S71-S102. DOI: https://doi.org/10.1086/261725
23. Wang, J., Liu, Y., Wang, W. and Wu, H. (2023) 'How does digital transformation drive green total factor productivity? Evidence from Chinese listed enterprises', Journal of Cleaner Production, 406, 136954. DOI: https://doi.org/10.1016/j.jclepro.2023.136954
24. Wang, K. L., Sun, T. T. and Xu, R. Y. (2023) 'The impact of artificial intelligence on total factor productivity: empirical evidence from China's manufacturing enterprises', Economic Change and Restructuring, 56(2), pp. 1113-1146. DOI: https://doi.org/10.1007/s10644-022-09467-4
25. Wang, X., Li, C. and Zhang, H. (2024) 'Digital transformation and green innovation: firm-level evidence from China', Frontiers in Environmental Science, 12, 1389255. DOI: https://doi.org/10.3389/fenvs.2024.1389255
26. Wen, J., Hai, H., Zhang, Y., Chen, Z. and Li, L. (2025) 'Does digital transformation impact green total factor productivity? Evidence from national big data comprehensive pilot zones in China', Economic Analysis and Policy, 86, pp. 2207-2221. DOI: https://doi.org/10.1016/j.eap.2025.05.058
27. Xu, Y., Yang, C., Ge, W., Liu, G., Yang, X. and Ran, Q. (2023) 'Can industrial intelligence promote green transformation? New insights from heavily polluting listed enterprises in China', Journal of Cleaner Production, 421, 138550. DOI: https://doi.org/10.1016/j.jclepro.2023.138550
28. Yang, C. H. (2022) 'How artificial intelligence technology affects productivity and employment: firm-level evidence from Taiwan', Research Policy, 51(6), 104536. DOI: https://doi.org/10.1016/j.respol.2022.104536
29. Yao, J., Zhang, K., Guo, L. and Feng, X. (2024) 'How does artificial intelligence improve firm productivity? Evidence from labour skill structure adjustment' [in Chinese], Management World, 40(2), pp. 101-116+133+117-122. DOI: https://doi.org/10.19744/j.cnki.11-1235/f.2024.0018
30. Zhai, S. and Liu, Z. (2023) 'Artificial intelligence technology innovation and firm productivity: evidence from China', Finance Research Letters, 58, 104437. DOI: https://doi.org/10.1016/j.frl.2023.104437