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Declarations of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the Natural Science Fund of Hunan Province (2022JJ40647).

Abstract

Purpose

This paper investigates the impact of AI penetration rate on the degree of corporate greenwashing, and aims to assess the potential of AI in enhancing firms' environmental performance and reducing false disclosures.

Design/methodology/approach

This study employs a year and firm fixed-effects model to analyze data from Chinese listed firms from 2012 to 2022. We use the low-carbon city pilot as a quasi-natural experiment to address endogeneity concerns and conduct a series of robustness tests, including adding control variables and transforming the model.

Findings

The results of this paper show that the application of AI can inhibit firms' greenwashing behavior, with green innovation activities further enhancing this inhibitory effect. In state-owned firms and those with Party organizations, the inhibitory effect of AI on corporate greenwashing is more significant. This reduction in greenwashing is more likely to be observed in firms that are heavily influenced by Confucian culture, receive higher public attention regarding their environmental impact, face less market competition, suffer from more serious pollution, and face less financial constraints.

Originality/value

We propose a new research perspective that offers novel insights into promoting the green development of firms by revealing the potential of AI in reducing their greenwashing behavior. Corporate managers can explore specific strategies for applying AI to monitor, prevent, and correct greenwashing, thereby enhancing corporate environmental performance and social responsibility.

Keywords: Greenwashing; Artificial Intelligence; Heterogeneity Analysis

JEL classification: D21, M14, O30

1. Introduction

In recent years, the issues of climate change and the concept of sustainable development have sparked widespread discussions among countries and various sectors of society. As a crucial part of society, businesses have become a focal point of attention for their environmental performance. The government has been paying more attention to environmental issues, leading to the active formulation of environmental policies. Stakeholders such as investors, consumers, and corporate clients have high expectations for the environmental, social, and governance (ESG) performance of firms. In response to green development policies, to better cater to investor preferences, to benefit from the market dividends of green brands and products, and to demonstrate a positive corporate image, firms have begun continuously "beautifying" their disclosures. By means of generalizations, ambiguity, and even minor falsehoods TerraChoice (2010), firms exaggerate their environmental efforts in external communications. In fact, they rarely contribute to environmental protection or even seriously pollute the environment, thus resulting in "greenwashing".

Greenwashing, to put it mildly, breaches ethical norms, and at worst, it violates the law. On a macroeconomic scale, the emergence of greenwashing poses a major obstacle to the stable development of green finance (Zhang, 2022b). Strengthening regulation and relevant standards undoubtedly serves as one of the effective measures to prevent greenwashing (Li et al., 2022) . Furthermore, with the rapid development of science and technology, especially the increasing popularity and in-depth application of artificial intelligence technology, will this emerging power bring new ways to alleviate the greenwashing problem? Our paper explores this emerging issue in depth.

Over the last decade, AI has developed an important role in assisting human work in various fields of social life, bringing the development of society into a new era (Hassan et al., 2018, Jiang and Cameron, 2020). According to McKinsey's Global AI Research report (2022), the use of AI in firms worldwide has increased from 20% in 2017 to 50% in 2022 and is gradually stabilizing. Particularly, the application of AI in automobile, medical care, finance, retail and other industries with good data construction foundation has been relatively matured (Zhang and Lu, 2021). For a firm, AI plays an increasingly important role in all aspects of production and operation. AI enhances their innovation capabilities and operational efficiency (Mishra et al., 2022), strengthens their competitive advantage in the market (Hossain et al., 2022). To meet the growing business demands, more firms are making significant investments in AI. Existing research on AI and firms has predominantly focused on their production capabilities, innovation capabilities, and commercial value (Czarnitzki et al., 2023, Haefner et al., 2021). There is little research on whether AI with such a wide range of impacts will have an impact on corporate greenwashing.

AI might affect greenwashing in several ways. Firstly, AI can enhance the authenticity and transparency of environmental information disclosure, reduce human intervention and error, improve the efficiency and accuracy of environmental information disclosure, and reduce the possibility of false statements by automating the collection, collation and analysis of environmental data. Secondly, the application of AI can promote the green transformation and sustainable development of firms. By optimizing the production process and improving energy efficiency, the greenhouse gas emissions and pollutant emissions of firms will be effectively reduced, realizing green production and reducing the motivation of firms to greenwash. Finally, by the establishment of intelligent regulatory system, regulatory agencies can gain a more comprehensive understanding of the firm's environmental information, and provide a basis for the formulation of more scientific and reasonable environmental policies. Therefore, it is reasonable to believe that the application of AI may reduce the greenwashing behavior of firms.

China provides us with a good research environment. Compared with other countries, China faces not only common problems in corporate greenwashing, such as opaque information disclosure and insufficient supervision, but also unique issues, including an accelerated legislative process with imperfect standards, improved market acceptance but not improved investor awareness. Specifically, in terms of institutional environment, laws, and regulations, China has gradually strengthened the relevant legislation and standards after the development of ESG sustainablility. However, compared to developed countries, China's ESG reporting standards remain in an early stage and lack a unified and comprehensive framework (Weber, 2014). Furthermore, the current mechanisms for penalising corporate greenwashing are insufficient, with weak enforcement and delayed response times. As a result, companies face minimal concequences when greenwashing is exposed, which inadvertently encourages the practice.

In terms of market environment and investor awareness, the development of China's stock market is still immature, with a scarcity of professional institutional investors and a predominance of retail investors (Carpenter et al., 2021). Investors' understanding of ESG principles and their level of professional knowledge still require significant improvement. This, in turn, affects the market acceptance of ESG information and limits investors' ability to detect corporate greenwashing. Regarding ESG disclosure, the lack of standardised ESG reporting frameworks and a reliable verification mechanism leads to great differences and opacity in ESG reporting among Chinese firms. This makes difficulty for investors to objectively compare and evaluate the ESG performance of different companies.

China is leading the world in the application of AI across industries. First, the Chinese government places great emphasis on the development of AI and brings it into the national strategic priority. This provides strong institutional support and a huge space for the integration of AI into firms. Second, China's AI industry is advancing rapidly, with the ecology of the industrial chain being constantly improving. Large companies, using their resources, can establish comprehensive systems, which involve the foundational, technological, and application layers of AI. As such, they create a well-rounded industrial framework. Third, Chinese firms have demonstrated a high level of enthusiasm and innovation in AI adoption, with the technology being widely used in sectors such as manufacturing, medical care, education, and finance, bringing significant benefits to firms (Hassan et al., 2018, Jiang and Cameron, 2020). The huge market scale and diverse application scenarios create ample opportunities for the commercial application of AI technologies.

However, there is still a big gap between China and developed countries in terms of the methods and efficiency of addressing corporate greenwashing. At the same time, AI development in China is booming, with wide range of application. This raises the question: can AI application in Chinese firms help mitigate the issue of greenwashing? China offers both the motivation and an ideal environment for this research, which may also provide valuable reference for other developing countries seeking to manage greenwashing and promote sustainable development.

This paper explores whether AI can be used as a mechanism to avoid the greenwashing behaviours. More specifically, this paper examines whether the penetration rate of AI will reduce greenwashing level of a firm. Using panel data of Chinese A-share listed firms from 2012 to 2022, we find that AI penetration rate exerts a restraining effect on firms' greenwashing behavior, and the corporate green innovation enhances this restraining effect. Heterogeneity analysis shows that state-owned firms and those with Party organization have a greater ability and motivation to increase AI penetration rate to reduce greenwashing, making the inhibitory effect of AI on greenwashing more apparent. Firms that are highly concerned by the public, deeply influenced by Confucian culture, and have minimal financial constraints also exhibit a more apparent inhibitory effect of AI on greenwashing. In addition, the inhibitory effect of AI penetration rate on greenwashing is more significant in heavily polluting industries and monopolistic industries. After conducting a series of robustness tests such as varying fixed effect combinations, changing regression models, and adding control variables, our conclusions remain valid.

Our paper distinguishes from Zhang (2024) in the following ways. First, the measurement methods of AI and greenwashing are different. As for greenwashing, Zhang (2024) uses ESG score differences, which is from the ESG performance perspective. Our paper adopts the disclosure structure analysis method to reflect the degree of greenwashing by false disclosure, which is more consistent with the definition of greenwashing than Zhang (2024) With regard to AI, our paper uses data from the International Federation of Robotics to construct the robot penetration at the firm level, which can better reflect the real application of artificial intelligence in firms. Second, Zhang (2024) does not consider endogeneity, whereas our paper takes the low-carbon city pilot policy as an exogenous shock, which to some extent solves the possible endogeneity concerns. Third, Zhang (2024) lacks theoretical support, while our paper focuses on the introduction of greenwashing based on the legitimacy theory and stakeholder theory, and analyzes the internal motivation of firms to adopt greenwashing and the internal logic that the application of artificial intelligence can inhibit greenwashing.

This paper contributes to the literature in several significant ways. Firstly, we directly explore the relationship between the application of AI and corporate greenwashing behavior. Previous studies on greenwashing have mainly focused on its connotations (Szabo and Webster, 2021, Siano et al., 2017), determinants (Wedari et al., 2021, Walker and Wan, 2012), and impacts (Li et al., 2023, Ioannou et al., 2023). This paper can also be categorized as an analysis of the motives for corporate greenwashing, but unlike the common financial and policy factors in previous research, we focus on the role that AI generates in terms of corporate environmental performance (Sullivan and Fosso Wamba, 2024), demonstrating that the application of AI has a restraining effect on corporate greenwashing behavior. As such, this paper supplements to the literature on greenwashing and AI by combining the two and providing a supplementary study on the crossover field of these two themes, filling a research gap in this area.

Secondly, this paper focuses on whether this restraining effect differs among different types of firms. We did not select common indicators for heterogeneous analysis, but from a more novel perspective. We investigate whether the impact of AI on greenwashing behavior is influenced by political affiliations, Party organizations, Confucian culture, public environmental concerns, market concentration, and other factors. The results provide a new insight for the analysis of the factors affecting the specific behavior of firms.

Finally, the research conclusions of this paper provide a useful measure for the regulatory authorities to monitor and mitigate the phenomenon of corporate greenwashing. The government should encourage firms to actively apply AI and promote substantive green development of firms, rather than falsely beautifying external information disclosure. Only by advocating true and transparent corporate behavior can we promote true environmental protection and social responsibility practices.

Our study comprises the following sections. Section 2 reviews previous studies related to this paper and proposes the hypotheses of this paper. Section 3 explains the data and sample selection. In Section 4, model design and empirical results are provided. In Section 5, we performed Robustness tests, and the last section summarizes the entire study.

2. Literature review and hypothesis development

2.1 Greenwashing

Greenwashing was first coined by American environmentalist Jay Westerveld in 1986 to describe a group of hotels that ostensibly encourage visitors to reuse towels for environmental reasons, but in fact only to save on their own operating costs. Since then, the term "greenwashing" has been used to describe non-green firms deliberately falsely publicizing themselves as green firms, so as to cover up their unenvironmental behaviors or even environmental pollution, and achieve the purpose of escaping legal liability.

In 2010, greenwashing was officially included in the Oxford English Dictionary. Terra Choice, an environmental marketing organization in the United States, has made greenwashing a sin in its Seven Deadly SINS of greenwashing (TerraChoice, 2010).There are three main definitions of greenwashing: the first view is that greenwashing is a deceptive green marketing strategy to attract eco-conscious consumers and gain competitive advantages (Siano et al., 2017, Szabo and Webster, 2021). This definition views greenwashing as a deliberate corporate behavior-false disclosure, with misleading elements, focused on the deception of stakeholders. The second definition implies that greenwashing is a selective disclosure. Firms may choose to reveal only favorable environmental indicators, neglecting to disclose those that might reflect more accurately on their overall environmental impact. This can lead to an externally misleading impression (Marquis et al., 2016). The third definition proposes that greenwashing is the decoupling between substantive green behaviors and symbolic green behaviors (Walker and Wan, 2012). This paper measures greenwashing by combining the second and third definitions. It considers both the tendency of firms to report partial information to mask negative effects, and the over-emphasized portrayal of a firm's environmental performance using symbolic statements instead of substantial ones. This approach provides a more comprehensive capture of corporate greenwashing.

According to legitimacy theory, to survive in society, firms need to abide by the constraints of relevant norms and codes of conduct (Tornikoski and Newbert, 2007, Suchman, 1995, Suddaby et al., 2016). The satisfaction of social needs is an important prerequisite for survival. Legitimacy refers to the extent to which a corporate behavior is compatible with established social rules, including formal and informal rules (Long and Driscoll, 2008). Based on the legitimacy theory, firms need to pay attention to more environmentally friendly activities, strive for social recognition of their behavior in a specific environment, and avoid business interruption caused by negative evaluation from the society. Therefore, in order to maintain this "social license to operate", firms will participate in the continuous legalization process (Mele and Armengou, 2016). Greenwashing is a type of false legalization behavior produced by firms in the process of failing to meet the real legitimacy.

Stakeholder theory emphasizes that firms are faced with external stakeholders' expectations of environmental responsibility and the tradeoff between the costs and benefits of corporate social responsibility (Lee et al., 2018). As environmental issues become increasingly prominent, firms are encouraged by the government to consciously incorporate social and environmental issues into their operation and management. The public expects firms to adhere to the principle of green development in production and operation activities. There is increasing pressure on firms from various stakeholders to disclose information about their environmental performance (Marquis et al., 2016). In the face of stakeholder pressure, some firms take active means to deal with it.

Although CSR activities are not directly beneficial to firms' profit goals (Fiechter et al., 2022), CSR plays an increasingly important role in corporate value (Bardos et al., 2020). In order to meet the need of legitimization and cope with the pressure from stakeholders, firms use CSR disclosure to build a reputable image and positive impression (Holder-Webb et al., 2009, Wang et al., 2024a) and avoid any negative effects (Hahn and Luelfs, 2014). when CSR performance is poor, in order to change stakeholders' perceptions, firms will use greenwashing to present an image that exceeds the real CSR performance and distort reality to gain benefits. Furthermore, increasing practical problems prompt more firms to choose greenwashing to help them achieve better results in sustainable development information disclosure required by stakeholders (Marquis et al., 2016).

Empirical studies find some motivations of greenwashing. The carbon emission level and environmental performance of the firm itself are also the reasons that affect the choice of greenwashing. Due to strict green finance regulations, firms with more serious pollution are more likely to become greenwashing (Zhang, 2022b). Firms with poor environmental performance can improve people's impression of the firm by greenwashing and disguise an environment-friendly and resource-saving corporate image (Wedari et al., 2021). Furthermore, financial problems often limit firms' green production decisions, and greenwashing is a relatively simple and direct strategy chosen by firms under high financial pressure (Zhang, 2022a). The market demand for green and sustainable products is increasing, and firms lacking green production capacity may also choose greenwashing to benefit from this wave (Szabo and Webster, 2021). It is worth noting that when regulatory pressure is high (Zhang, 2022b), and information asymmetry is high (Wu et al., 2020), firms are more motivated to greenwash.

In a short term, greenwashing may increase corporate value by manipulating disclosure and easing financing constraints. However, in long term, the return of greenwashing is quite limited due to the elimination of information asymmetry (Torelli et al., 2020). Greenwashing will lead to a decline in the trust of green investors in the firm's green brand (Gatti et al., 2021), which will amplify the negative impact of bad behaviors and further reduce the investment intention (Gatti et al., 2021). Meanwhile, the firm image will also be damaged, which will affect consumers' purchase intention and behavior (Bladt et al., 2024). From a macro perspective, greenwashing will make firms pay too much attention to the effect of opportunistic actions, neglecting to weaken the motivation of firms to make real efforts for environmental protection (Laufer, 2003), and ultimately damage the overall social welfare.

Therefore, managing greenwashing becomes important and the government needs to establish sustainable development rating and other measures to curb greenwashing (Parguel et al., 2011). For instance, a high level of scrutiny by media and non-governmental organizations is conducive to the detection of greenwashing (Seele and Gatti, 2017). The existence of independent directors and institutional investors can also reduce greenwashing (Yu et al., 2020). Our study investigates whether AI can be a useful tool to reduce greenwashing.

2.2 Artificial intelligence

AI adopts new information technologies, such as supercomputing, cloud computing, and big data (Zhang and Lu, 2021, Khosravani et al., 2022), which stimulates and expands human thinking and behaviors (Hall et al., 2014). AI has the function of task selection learning and provides task execution feedback (Chen et al., 2021, Lu, 2019), shorten the long reasoning chain in the decision-making process, and improve the decision-making efficiency (Brynjolfsson and Mitchell, 2017). In addition, the connectivity, cognitive ability and imperceptible ability of AI can promote the flow and sharing of internal and external resources, reduce the probability of failure of firms, and improve the management, information communication and sharing ability of firms. With the help of AI, decision-making becomes more scientific and reasonable (Al-Surmi et al., 2022).

The application of AI in all aspects of the firm is becoming increasingly common. In terms of innovation, AI is a key technology that affects the innovation ability of firms (Haefner et al., 2021). It fundamentally innovates the nature and structure of products, services, processes and business models, and promotes new ways of value creation and use (Verganti et al., 2020). In terms of productivity, corporate investment in AI improves total factor productivity of firms (Ren et al., 2024a). In addition, the optimization of existing processes, the improvement of automation level and the enhancement of information conversion ability brought by AI help firms to enhance their anti-competitive ability and reduce costs (Tingbani et al., 2024). This helps firms improve their performance in terms of finance, marketing and management. Finally it leads to higher growth in sales, employment and market valuation (Babina et al., 2024).

AI can improve the efficiency of firm audit process and the quality of audit results (Fedyk et al., 2022). The auditor not only needs to conduct detailed inspection and analysis of the accounts, transaction records and asset status of the firm, but also evaluates the effectiveness of the internal control system. They dig deep into the business behind the data to uncover possible fraud and risks. The application of AI in audit improves deception detection and risk assessment, and refocuses manpower on more advanced and high-risk areas, which in turn improves the audit quality and efficiency of firms (Fedyk et al., 2022). At the same time, the firms' information disclosure quality will also improve in this process, including information disclosure related to the environment.

Although the development of AI will bring some challenges, the opportunities it creates and the new driving force for development cannot be ignored, especially for firms. The efficiency and necessity of artificial intelligence technology to participate in firm production and operation have been verified in most studies (Baryannis et al., 2019).

2.3 AI on greenwashing

Although a large number of scholars concerned with environmental performance have discussed the motivations and consequences of corporate greenwashing, few scholars have taken the role of AI into account in corporate ESG performance. Also, among the many scholars who study the contribution of AI to firms, few have considered the impact of AI on corporate greenwashing behaviors. Our research further explores whether the penetration of AI has an impact on the degree of corporate greenwashing, and makes supplementary research in the field of the impact of AI on the environmental performance of firms. Zhang (2024) is the most similar to this paper, but the measurement of variables, the analysis of mechanisms, and the theoretical starting point in this paper are different from Zhang's research.

We expect the use of AI will reduce greenwashing via affecting its determinants. First, AI can reduce labor costs and traditional energy consumption, thus reducing carbon emissions (Zhou et al., 2024). When the firm's own carbon emission level decreases and its negative impact on the environment decreases, the possibility of fraud in environmental related information disclosure also decreases. Furthermore, the introduction of AI can improve the audit quality (Fedyk et al., 2022). Although the audit content of firms mainly focuses on the field of financial information, the information related to the environmental performance of firms will also be reflected in the financial information, such as the expenditure related to environmental protection. In addition, the effectiveness of the internal control system will also be examined by the audit. Hence, we conjecture that the disclosure of information related to environmental performance in firms with more use of AI may also be more standardized, and the quality of environmental information may also be improved. Therefore,

Hypothesis 1: The increase of AI penetration will reduce the degree of corporate greenwashing.

Green innovation, representing innovation in environmental technology, environmental process and environmental products in the whole process of producing products or providing services (Du et al., 2019), is an effective way to balance economic development and environmental governance (Xu et al., 2021b). Firms are closest to the market, sensitive to market demand changes, and are the executors of green production (Li et al., 2019). Numerous studies have shown that green innovation can reduce corporate carbon emissions (Xu et al., 2021a, Ren et al., 2024b), improve environmental protection efficiency (Wong et al., 2020), and generate economic benefits (Wang and Juo, 2021). In the meantime, AI can help firms' innovation level, including green process innovation and green product innovation related to environmental protection (Huang and Li, 2017, Xie et al., 2019, Wang et al., 2024b).

Firms improve their environmental performance and market competitiveness through green innovation (Wang et al., 2021). According to the stakeholder theory, through green innovation, firms can not only improve their own image of environmental protection, but also meet the expectations and requirements of various stakeholders for environmental protection. This helps to enhance the social responsibility and credibility of firms, and reduce the crisis of trust and market risks caused by greenwashing. From the perspective of legitimacy, green innovation is an action in response to policies, and it also helps firms to meet the needs of legitimacy.

When the environmental benefits of green innovation meet social expectations and comply with environmental laws and regulations, firms are less likely to risk their reputation for false legalization, significantly reducing the motivation for greenwashing. Therefore,

Hypothesis 2: *The level of green innovation enhances the inhibitory effect of AI on corporate greenwashing.*

3. Data and sample

3.1 Data sources

This paper selects Chinese listed firms from 2012 to 2022 as the initial research sample, and the environmental information disclosure data are collected from the annual reports of Chinese listed firms, while the financial data and firm characteristics data are retrieved from the China Stock Market and Accounting Research (CSMAR) database. As for the data on artificial intelligence penetration, it comes from the International Federation of Robotics (IFR). We have excluded the following situations to ensure the accuracy and validity of our research data: (a) delete the samples with stock abbreviation and listing status of "ST" and "*ST"; (b) delete the samples with serious missing firm data; (c) supplement some missing data by linear interpolation method. The final sample comprises 8746 firm-year observations derived from 1383 listed firms. In order to eliminate the influence of extreme values, all continuous variables are winsorized at the 1^{st} and 99^{th} percentiles.

3.2 Variable measurement

3.2.1 Dependent variable: greenwashing level (GWL)

There is no widely accepted method for measuring the degree of greenwashing, and the measurement methods commonly used in existing research include questionnaire and experiment method, disclosure structure analysis method and disclosure and performance matching method. The most common line of thought is to define greenwashing as the difference between what a firm is doing in terms of sustainability commitments and what external parties assess the firm is actually doing, with the greater the difference between the two, the greater the greenwashing (Li et al., 2023).

Following the disclosure structure analysis method of Huang et al. (2020), which referres to Walker and Wan (2012), we classify the corporate greenwashing into two aspects: selective disclosure and expressive manipulation. This method measures greenwashing through text analysis of the items disclosed by firms in the environmental report and the environmental special section of the social responsibility report (or sustainability report), which takes into account both partial disclosure and false disclosure. Thus, this measure can capture the greenwashing behavior of firms in a more detailed and comprehensive manner. Selective disclosure means that firms intentionally and selectively disclose or conceal environmental information that should be made public in order to avoid or downplay unfavorable content. Expressive manipulation refers to the use of rhetorical skills by firms to cover up their failure to take actual actions in environmental protection through rhetorical beautification. Referring to the evaluation index system of "greenwashing" constructed by Huang et al. (2020), selective disclosure (GWLS) = 100×(1- number of disclosed items / number of required disclosure items), expressive manipulation (GWLE) = 100×(number of symbolic disclosed items / number of disclosed items). Finally, we get that the degree of greenwashing (GWL) is equal to the geometric mean of selective disclosure and expressive manipulation.

$$GWL = \sqrt{GWLS \times GWLE} \tag{1}$$

3.2.2 Independent variable: artificial intelligence(AI)

Drawing on the research of Acemoglu and Restrepo (2020) and Wang et al. (2023) , this paper constructs the penetration rate of industrial robots at the level of China's listed firms to measure it. The specific calculation process is as follows: First, according to the industry classification name, we unify the 2002 version of China's national economic industry classification code to the 2011 version of the national economic industry classification code. After adjustment, it is divided into 31 categories of industries; In the second step, we match the adjusted industry classification with the IFR industry classification; The third step is to calculate the penetration rate index of industrial robots at the industry level, which is equal to the stock of industrial robots in manufacturing industry j in year t divided by the number of employees in industry j in 2010 (base period). In the fourth step, we use the ratio of the proportion of employees in the production department of listed firms k in industry j in 2011 (base period) to the median of the proportion of employees in the production department of all listed firms in the manufacturing industry in 2011. This is multiplied by the penetration rate of industrial robots at the industry level. Finally, it is divided by 100 for dimensionalization, and the artificial intelligence penetration rate index (AI) at the firm level is calculated.

$$AI_{ji,t} = \frac{PWP_{ji,t=2011}}{ManuPWP_{t=2011}} \times \frac{MR^{CH}_{j.t}}{L^{CH}_{J,t=2010}} \quad (2)$$

Where $PWP_{ji,t=2011}/ManuPWP_{t=2011}$ represents the ratio of the proportion of production department employees of firm i in industry j in 2011 (base year) to the median proportion of production department employees of all firms in industry j in 2011; $MR^{CH}_{j.t}$ represents the amount of robot use in industry j in China in year t; $L^{CH}_{J,t=2010}$represents the number of employees in industry j in China in 2010 (base year).

3.2.3 Control variables

Following previous studies (Yin and Yang, 2024, Zhang, 2022b), this paper selects the following control variables: the details include: firm size (*Size*), financial leverage (*Lev*), profitability (*ROA*), growth ability (*Growth*), firm value (*BM*), cash flow (Cashflow), asset structure (*Tangible*). Where firm size is measured by the logarithm of total assets; financial leverage is estimated by the ratio of total debt to total assets; profitability is the return on assets, growth ability is measured by the total asset growth rate; firm value is calculated as the ratio of the market price of firm stocks to the book value, cash flow is the ratio of net cash flow from operating activities to total assets, and asset structure is calculated by the sum of net fixed assets and net inventory divided by total assets.

See Table 1 for the definition and measurement of each variable.

[Insert Table 1 about here]

3.3 Summary statistics

Table 2 shows the results of the descriptive statistical analysis of the main variables. From the results in the table, it can be seen that the mean of corporate greenwashing (*GWL*) is -0.462, with a maximum value of 2.872, a minimum value of -3.215, and a standard deviation of 1.230. The mean of artificial intelligence penetration rate (*AI*) is 6.837, with a maximum value of 14.9, a minimum value of 0.125, and a standard deviation of 4.010. There are significant differences in the greenwashing degree and artificial intelligence penetration rate among different firms, providing a basis for this paper. The values of the remaining control variables are within the normal range and will not be elaborated further.

[Insert Table 2 about here]

Table 3 presents the results of the analysis of the correlation between variables. The correlation coefficients between the variables are all less than 0.6, indicating a relatively low degree of collinearity between the variables. The results of Variance Inflation Factor (VIF) to test for multicollinearity among the variables show that there is no serious multicollinearity among the variables.

[Insert Table 3 about here]

4. Empirical analyses

4.1 Model design

Based on the foundation of previous literature, We attempt to conduct an empirical study on the impact of AI penetration rate on the degree of corporate greenwashing. A two-way fixed effects model was used to estimate the impact of artificial intelligence on corporate greenwashing. The specific model construction is as follows:

$$GWL_{i,t} = \beta_0 + \beta_1 \times AI_{i,t} + \beta_2 \times X_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (3)$$

Where, i and t respectively represent the firm and year; $GWL_{i,t}$ represents the greenwashing level of firm i in year t; $AI_{i,t}$ indicates the AI penetration rate of firm i in year t; $X_{i,t}$ represents a set of control variables affecting the artificial intelligence penetration rate of firm i in year t, which affects the greenwashing degree of the firm; u_i stands for individual fixed effect, v_t stands for year-fixed effect, $\varepsilon_{i,t}$ is the random error perturbation term. In order to alleviate potential heterogeneity issues, we cluster standard errors at the firm level and use heteroscedasticity-consistent standard errors.

4.2 Baseline results

Table 4 reports the estimation results for Eq. (3). Column (1) shows that when no control variables are added, the AI coefficient is negative and significant at the statistical level of 1%, which can indicate that the higher the AI penetration rate of a firm, the lower the greenwashing degree of the firm. After adding control variables and controlling for firm and year fixed effects, column (3) shows that the coefficient of AI is -0.007, significantly at the 1% level, indicating that for every 1% increase in the AI penetration rate of a firm, the firm's greenwashing level decreases by 0.007. This demonstrates that the application of AI helps reduce corporate greenwashing phenomenon. Hence, Hypothesis 1 is supported.

[Insert Table 4 about here]

4.3 Difference-in-Differences approach

There may be a variety of factors affecting corporate greenwashing, and there may also be some unobservable confounding factors such as consumer psychology and cognitive bias. DID is a good way to eliminate the bias of the estimator due to the omitted variable problem, and for this purpose, we treat the low-carbon city pilot as a quasi-natural experiment. The low-carbon city pilot is a policy proposed by the state to control greenhouse gas emissions. Since 2010, the pilot projects of low-carbon cities have been carried out in batches in an orderly manner in China, which is conducive to accumulating work experience on green development in different regions and promoting the realization of Carbon Peaking and Carbon Neutrality Goals. We define a low-carbon pilot policy dummy variable DID, in which the DID of firms in the low-carbon city pilot is equal to 1 in the pilot year and after, and 0 otherwise. Then we estimate the following model:

$$GWL_{i,t} = \beta_0 + \beta_1 \times AI_{i,t} + \beta_2 \times DID + \beta_3 \times AI_{i,t} \times DID + \beta_4 \times X_{i,t} + u_j + v_t + \varepsilon_{i,t} \quad (4)$$

Our main focus is on the interaction term between DID and AI, and the coefficient of the interaction term reflects the DID estimates of the sensitivity of corporate greenwashing to AI between treated and control firms before and after the pilot. In other words, the coefficient reflects the degree of difference in the relationship between AI and greenwashing shown by firms in low-carbon pilot cities compared with firms before the pilot and those that have been in non-pilot cities. The estimation results in Column (1) of Table 5 show that the coefficient of AI is significantly negative at the statistical level of 1%, and the absolute value is larger than that in Table 3, indicating that artificial intelligence does play an inhibitory role in greenwashing. The coefficient of the interaction term between DID and artificial intelligence is significantly positive, indicating that after the implementation of low-carbon city pilot policy, the negative relationship between the level of AI application and corporate greenwashing has been reversed.

The reason for this reversal can be explained as that after the implementation of the policy, the environmental protection work of the pilot city has become the focus of the whole country. The pilot city has further strengthened the emission reduction guidance, supervision and management of all walks of life, so firms are also facing greater pressure of greenhouse gas emission reduction. Greenwashing has become the most suitable choice in a short period of time. On the one hand, it can cope with more stringent requirements. On the other hand, it has no effect on corporate financial performance for the time being.

Using the DID approach, we eliminate the endogenous concerns caused by the difference in sensitivity of greenwashing behavior to AI among firms located in cities with different green development policies. At the same time, after considering the endogenous problems such as missing variables, the inhibitory effect of AI application on corporate greenwashing still exists.

4.4 Other robustness tests

To ensure the accuracy of the above conclusions, we conduct other robustness tests on Eq.(3). In columns (2) and (3) of Table 5, we added industry and provincial fixed effects and transformed the combinations of fixed effects, with the coefficient of AI in the regression results almost unchanged. In column (4), we redefined the dependent variable, using the median as the threshold and portraying corporate greenwashing behavior as 0 and 1. In order to more intuitively reflect the impression management level of corporate greenwashing, and retested the model using a Logit model with the dependent variable as a discrete value, and the coefficient of AI remains significantly negative. In Column (5), we replace the measurement method of dependent variable, greenwashing is measured by the difference between firm-level standardized ESG rating score excluding firm-level standardized ESG disclosure score (Zhang, 2024). And the conclusion is consistent with the previous one.

Scholars have gradually paid attention to the influence of the business culture with the core values of "honesty, sincerity and kindness, and pursuing both justice and benefit" on corporate behaviors. We refer to the method of Gaganis et al. (2019) to calculate the influence index of business gang culture and include it into the control variable. Considering the development gap between provinces in China, we also control the provincial-level GDP and pollution index, and the regression results are shown in Column (6), which indicates that our previous conclusions remain unchanged. By the end of 2014, the Chinese government issued the Measures for the Disclosure of Environmental Information of firms and Public Institutions, which was implemented in January 2015. To eliminate the influence of this event, we excluded the 2015 sample and conducted the regression again, with the results in column (7) telling us that the previous conclusions are robust.

5. Mechanism analysis

5.1 Moderating effect of green innovation

Previous studies have shown that green innovation can reduce the green production costs of firms, improve the green production efficiency of firms, and thereby achieve better environmental performance (Chen, 2008). This paper speculates that green innovation will affect the role of AI in the greenwashing behavior of firms. We use the logarithm of the number of green patent applications for firms as a proxy variable for green innovation. From Table 6, column (1), it can be seen that the coefficient of the interaction term between green innovation and AI is -0.005, and it is significant at the 10% level. This indicates that green innovation strengthens the inhibitory effect of AI on corporate greenwashing behavior. Hence, Hypothesis 2 is supported.

[Insert Table 6 about here]

5.2 The influence of different internal conditions

5.2.1 Heterogeneity between firms with different ownership structures

Columns (1) and (2) of Table 7 show the regression results for firms of different natures. In column (1), the coefficient of AI is significantly negative (-0.011), while the coefficient in column (2) is not significant. This shows that compared to non-state-owned firms, state-owned firms are more motivated and capable of reducing their greenwashing behavior by increasing AI penetration rate. State-owned firms have stronger political backgrounds and are more likely to comply with environmental laws and regulations, and conscientiously fulfill their environmental protection responsibilities.

[Insert Table 7 about here]

In the long run, due to China's unique economic system, state-owned firms are in a competitive position and can easily obtain monopoly profits. Environmental protection investment has characteristics such as large investment, low rate of return, and long recovery time (Ren et al., 2019). Only state-owned firms with strong economic strength can increase environmental protection investment. They are willing to allocate more redundant resources to environmental protection in order to meet the standards of environmental laws and regulations.

Existing literature shows that establishing political relations can help firms strengthen effective communication with government departments and fully and timely understand the direction of environmental policies (Sun and Zou, 2021). In addition, executives with high political connections, due to their special social influence, can help firms acquire more high-quality social resources. Based on the high political sensitivity of executives, state-owned firms will actively demonstrate the sense of social responsibility and moral role they should have, actively engage in green innovation behavior, and promote their green development.

5.2.2 Heterogeneity of the existence of Party organizations

In recent years, the embedding of Party organizations in firms has become an increasingly common phenomenon, and under China's unique political system, firm development cannot ignore the role of the party. Previous studies have proven that the existence of Party organizations suppresses the non-compliance behavior of private firms, can improve governance efficiency, and thus improve the performance of state-owned firms. Therefore, this paper attempts to explore whether the inhibitory effect of AI penetration rate on corporate greenwashing behavior will be affected by the establishment of Party organizations.

By grouping firms with and without Party organizations for regression, column (3) of Table 7 shows that firms with Party organizations significantly reduce the greenwashing behavior of firms, while this inhibitory effect is not significant for firms without Party organizations. This shows that the establishment of Party organizations can actively guide the thinking and behavior of firms, enhance self-discipline, and promote firms to produce and operate more legally and compliantly.

5.2.3 Heterogeneity of financial situation

With environmental issues becoming increasingly prominent, environmental risks have become a consideration for financial institutions when lending to firms; therefore, the financial constraints of firms are an important factor leading to greenwashing choices (Zhang, 2022a). To examine the role of financial constraints in this sample, this paper considers the financing constraints and cash flow conditions of firms, using the WW index to reflect firm financial constraints. The net cash flow generated from operating activities to total assets ratio measures the cash flow condition and is distinguished into high and low groups based on the median. From columns (5) to (8) of Table 7 we can find that in firms with lower financing constraints and more cash flow, a higher AI penetration rate leads to a weaker degree of greenwashing behavior, whereas in firms with higher financing constraints and less cash flow, the inhibitory effect of AI penetration rate on greenwashing behavior is not evident.

5.3 The influence of different external environments

5.3.1 Heterogeneity of public environmental attention

The higher the public's attention to a firm, the more easily its specific behaviors are known to the public, and its greenwashing behavior is easier to identify. To explore whether the impact of AI penetration rate on corporate greenwashing behavior is related to the public's attention to the firm's environmental behavior, this paper refers to Yi et al. (2022) and uses the Baidu search index with "pollution" as a keyword to obtain the public's environmental attention index for each firm. By distinguishing between high and low attention based on the median, grouping regression results as shown in columns (5) and (6) of Table 8. It demonstrates that the coefficient of AI for the high public environmental attention group is -0.009, and it is significantly negative at the 5% level. Wheras the coefficient for the low public environmental attention group is not significantly different from 0. This result shows that the inhibitory effect of AI penetration rate on corporate greenwashing behavior is more significant in firms with higher public environmental attention.

[Insert Table 8 about here]

5.3.2 Heterogeneity of the influence of Confucian culture

In the process of social development driven by innovation, traditional culture also reflects a certain value of the times. Studies show that in addition to regulations and institutions, informal institutions such as culture also have an increasingly important impact on corporate behavior (Li et al., 2013). Some scholars pointed out that the values of Chinese entrepreneurs were generally permeated with Confucianism, which was reflected in their business decisions. The core ideas advocated in Confucian culture, such as benevolence, justice, etiquette, wisdom and faith, can help improve corporate governance and reduce the risk of stock price crash (Zhang et al., 2024). It also has a positive impact on increasing investment in environmental protection and improving firm investment efficiency (Xu and Li, 2019). According to the Confucian culture, in the face of the conflict between justice and interest, the actors should put justice first, followed by interest (Du, 2015).

Therefore, this paper attempts to explore whether Confucian culture has an impact on the greenwashing behavior of firms. Following the research of Xu and Li (2019), we use the total number of Confucian schools, Confucian academies and Confucian temples within a 200-kilometer radius of the registered place of firms as the proxy variable of the Confucian culture influence, and use the median to identify the degree of influence.The grouping regression results in columns (7) and (8) of Table 8 show that firms with a deeper influence of Confucian culture are more likely to increase their AI penetration rate and reduce their greenwashing behavior. It indicates that "integrity" and "considering benevolence" advocated by Confucian culture are helpful to regulate corporate behavior.

5.3.3 Heterogeneity in different industries

Firms in different industries may face varying degrees of external financial pressure and costs (Hu et al., 2021). Greenwashing strategies between firms may lead to heterogeneous effects. Table 7 reports the estimated results after dividing the sample into pollution-intensive and clean production firms. We found that compared to firms in the clean production industry, the AI penetration rate in heavily polluted industries more significantly inhibited the greenwashing behavior of firms.

Furthermore, we attempted to study whether the inhibitory effect of AI penetration rate on greenwashing behavior demonstrates heterogeneity between monopolistic and competitive industries. We use the Herfindahl-Hirschman Index (HHI) as a measure of market concentration and categorizes samples above the mean as high market concentration firms and those below the mean as low market concentration firms. The results of the group regression are shown in Table 8, columns (3) and (4), with the coefficient of AI penetration rate for high market concentration firms being -0.012, significant at the 1% level, and the coefficient for low market concentration firms being -0.003, with no statistical significance. High market concentration is associated with low competition, while low concentration leads to more intense competition. It is evident that when firms face less competition, the inhibitory effect of AI penetration rate on greenwashing is more significant. When market competition pressure is too high, firms may find it difficult to abandon greenwashing choices.

6. Conclusion

The development of AI has brought technological dividends to the whole society, and also provided new production, operation and governance modes for firms. It has played an important role in the improvement of corporate governance capacity and the growth of corporate value. Based on the annual reports of Chinese listed firms, the CSMAR database and the International Federation of Robotics database, this paper systematically analyzes the impact of AI penetration rate on the degree of corporate greenwashing. We find that the application of AI has an inhibitory effect on corporate greenwashing behaviors. The strength of this inhibitory effect will be affected by other factors. For example, the green innovation of firms can positively regulate this inhibitory effect.

Further, we analyze the heterogeneity of this effect and find that the negative relationship between AI penetration rate and greenwashing is more easily observed in SOES and firms with Party organizations. This shows that political connections and Party organizations play positive roles in the environmental performance of firms, promoting firms to comply with laws and regulations, undertake social responsibilities, and actively perform compliance disclosure. Secondly, firms with high public environmental attention and deep influence of Confucian culture will reduce their greenwashing degree by improving the application of AI. In terms of industries, the inhibitory effect of AI application on greenwashing behavior is more obvious for firms in heavy polluting industries and monopolistic industries. Firms that face less financial constraints have more incentive to reduce greenwashing. The higher the application degree of AI in firms is, the lower the degree of greenwashing is.

This paper is the first study that directly links AI with greenwashing, and finds that AI can help reduce the improper disclosure behavior of firms, promoting them to truly implement the concept of green development. Therefore, government departments should pay more attention to the application of AI in firms, actively guide the integration of AI with all walks of life, promote the intelligent transformation of firms. In this way, the environmental protection benefits generated by the development of AI can be expanded and the foundation can be laid for the construction of a win-win development pattern of green ecology and economic growth.

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Table 1. Variable definitions

Variables	Definition	Measure Method
GWL	Firm greenwashing level	Following Huang et al. (2020), measured as the geometric mean of selective disclosure and presentational manipulation.
AI	Firm artificial intelligence penetration	Refer to Acemoglu and Restrepo (2020) and Wang et al. (2023) to construct the penetration rate method of industrial robots.
Size	Firm size	The natural logarithm of firm total assets (log).
Lev	Assets liabilities ratio	Total debt scaled by total assets.
ROA	Profitability	Net income to shareholders' equity ratio.
Growth	Growth ability	The growth rate of operating income for the current period.
BM	Book-to-market ratio	The ratio of the book value to market value of equity.
Cashflow	Cash flow	The ratio of cash flows from operating activities to total assets.
Tangible	Asset structure	The ratio of fixed assets and inventory to total assets.
Green	Green innovation	The natural logarithm of the number of green patent applications (log).

Source: Authors own work.

Table 2. Summary statistics of variables

Variable	Obs	Mean	Std.dev.	Min	Max
GWL	8,746	-0.462	1.230	-3.215	2.872
AI	8,746	6.837	4.010	0.125	14.900
ROA	8,746	0.044	0.058	-0.177	0.220
Size	8,746	23.470	1.429	20.620	29.350
Growth	8,746	0.128	0.206	-0.254	1.206
Lev	8,746	0.491	0.197	0.078	0.937
BM	8,746	0.688	0.279	0.115	1.232
Cashflow	8,746	0.061	0.068	-0.147	0.260
Tangible	8,746	0.375	0.183	0.007	0.777
Green	8,746	0.543	1.109	0	5.869

Source: Authors own work.

Notes: This table reports the summary statistics for variables constructed based on the sample of Chinese Listed firms from 2012 until 2022. The dependent variable is the greenwashing level (*GWL*), and the independent variable is the firm artificial intelligence penetration *(AI*). In addition, moderating variables include the green innovation (*Green*); control variables at the firm level include firm size (*Size*), financial leverage (*Lev*), profitability (*ROA*), growth ability (*Growth*), firm value (*BM*), cash flow (*Cashflow*), asset structure (*Tangible*).

Table3: Spearman correlation

	VIF	*GWL*	*AI*	*ROA*	*Size*	*Growth*	*Lev*	*BM*	*Cashflow*	*Tangible*
GWL		1								
AI	1.00	-0.00600	1							
ROA	2.00	0.048***	0.018*	1						
Size	1.89	0.104***	0.036***	-0.129***	1					
Growth	1.24	0.067***	0.0110	0.320***	-0.00200	1				
Lev	1.90	-0.0100	0.00500	-0.470***	0.584***	-0.058***	1			
BM	1.78	0.0140	0.00600	-0.371***	0.564***	-0.204***	0.484***	1		
Cashflow	1.42	0.040***	0.021**	0.509***	-0.082***	0.039***	-0.268***	-0.214***	1	
Tangible	1.12	-0.041***	-0.037***	-0.138***	0.00700	-0.205***	0.185***	0.166***	0.059***	1
Mean VIF	1.54									

Source: Authors own work.

Notes: Pearson's correlation matrix presents the coefficients of variable correlation. Significant value of each correlation coefficient in parentheses.The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively

Table 4. Results of baseline regression

	Dependent variable: greenwashing level		
	(1)	(2)	(3)
AI	-0.007***	-0.007**	-0.007***
	(-2.92)	(-2.04)	(-2.94)
ROA		-0.448	0.923***
		(-1.02)	(2.63)
Size		0.130***	-0.027
		(5.18)	(-0.55)
Growth		0.301***	0.027
		(3.36)	(0.36)
Lev		-0.520***	0.145
		(-3.14)	(0.75)
BM		-0.149	-0.057
		(-1.34)	(-0.50)
Cashflow		0.584**	-0.372
		(1.99)	(-1.63)
Tangible		-0.065	0.033
		(-0.44)	(0.17)
_cons	-0.417***	-3.151***	0.161
	(-24.00)	(-5.95)	(0.14)
Year FE	YES	YES	YES
Firm FE	YES	NO	YES
N	8642	8746	8642
R^2	0.545	0.023	0.546

Source: Authors own work.

Notes: This table shows regression results for the effect of artificial intelligence on corporate greenwashing level. The dependent variable is the corporate greenwashing level (*GWL*), and the independent variable is the firm artificial intelligence penetration (*AI*). All variables are defined in detail in Table 1. The t-statistics are reported in the parentheses. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

Table5. Robustness tests

	Dependent variable: greenwashing level						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AI	-0.012***	-0.008***	-0.007***	-0.002**	-0.005*	-0.010***	-0.006**
	(-3.66)	(-2.96)	(-2.82)	(-2.03)	(-1.89)	(-3.43)	(-2.28)
DID	-0.002						
	(-0.01)						
AI×DID	0.011**						
	(2.06)						
ROA	0.908***	0.761**	0.718*	0.346**	1.280***	0.830**	0.925**
	(2.60)	(2.16)	(1.96)	(2.16)	(3.61)	(2.27)	(2.58)
Size	-0.029	-0.014	-0.023	-0.019	-0.031	-0.008	-0.046
	(-0.59)	(-0.28)	(-0.43)	(-0.87)	(-0.54)	(-0.14)	(-0.85)
Growth	0.030	0.026	0.033	-0.006	-0.079	0.052	0.018
	(0.40)	(0.36)	(0.43)	(-0.19)	(-1.09)	(0.67)	(0.23)
Lev	0.136	0.049	0.032	0.028	0.230	0.081	0.210
	(0.70)	(0.26)	(0.17)	(0.33)	(1.14)	(0.40)	(1.00)
BM	-0.054	-0.043	-0.015	-0.044	-0.102	-0.017	-0.064
	(-0.47)	(-0.37)	(-0.12)	(-0.90)	(-0.89)	(-0.13)	(-0.54)
Cashflow	-0.378*	-0.314	-0.278	-0.059	0.268	-0.284	-0.305
	(-1.65)	(-1.39)	(-1.18)	(-0.56)	(1.04)	(-1.20)	(-1.28)
Tangible	0.038	0.078	0.086	0.013	0.213	0.006	0.019
	(0.20)	(0.43)	(0.45)	(0.15)	(1.01)	(0.03)	(0.09)
MGC						1.064**	

						(2.37)	
LnGDP						0.225	
						(1.35)	
Pollution						-1.323**	
						(-2.53)	
_cons	0.212	-0.121	0.076	0.964*	0.632	-2.628	0.559
	(0.19)	(-0.11)	(0.06)	(1.92)	(0.48)	(-1.25)	(0.46)
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	NO	YES	NO	NO	NO	NO	NO
Province FE	NO	YES	NO	NO	NO	NO	NO
Industry×Province FE	NO	NO	YES	NO	NO	NO	NO
N	8617	8639	8627	8637	6,939	6971	7870
R^2	0.546	0.557	0.562	0.417	0.639	0.617	0.550

Source: Authors own work.

Notes: The table reports the robustness of the effects of artificial intelligence on corporate greenwashing level. The dependent variable is the corporate greenwashing level (*GWL*), and the independent variable is the firm artificial intelligence penetration (*AI*). The table reports four robustness tests: (1) Increase the fixed effects, (2) transform the fixed effects , (3) change the regression model to the Logit model, (4) add business culture (*MGC*), GDP and Pollution into control variables, and (5) eliminate samples of 2015. All variables are defined in detail in Table 1. The t-statistics are reported in the parentheses. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

Table 6. Regression result of the moderating effect

	Dependent variable: greenwashing level
AI	-0.007***
	(-2.92)
Green	0.032
	(1.10)
AI×Green	-0.005*
	(-1.90)
ROA	0.910***
	(2.60)
Size	-0.028
	(-0.57)
Growth	0.030
	(0.40)
Lev	0.151
	(0.78)
BM	-0.061
	(-0.54)
Cashflow	-0.362
	(-1.59)
Tangible	0.039
	(0.21)
_cons	0.167
	(0.15)
Year FE	YES
Firm FE	YES
N	8642
R^2	0.546

Source: Authors own work.

Notes: This table shows the impact of green innovation (*Green) as* moderators on the relationship between firm artificial intelligence penetration rate and corporate greenwashing level. The dependent variable is the corporate greenwashing level (*GWL*), and the independent variable is the firm artificial intelligence penetration (*AI*). All variables are defined in detail in Table 1. The t-statistics are reported in the parentheses. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

Table 7. Heterogeneity of different internal conditions

	Dependent variable: greenwashing level							
	Firm Ownership		Party Organization		Cash Flow		Financial Constrain	
	SOE	NSOE	With_PO	Without_PO	CF_High	CF_Low	WW_High	WW_Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI	-0.011***	-0.002	-0.011***	-0.004	-0.009**	-0.006	-0.003	-0.013***
	(-3.31)	(-0.44)	(-2.95)	(-0.88)	(-2.30)	(-1.62)	(-0.88)	(-3.24)
ROA	1.078*	0.711	0.846	1.213*	0.927	1.007**	0.577	1.453*
	(1.89)	(1.64)	(1.53)	(1.80)	(1.52)	(2.29)	(1.48)	(1.69)
Size	-0.072	0.063	-0.035	-0.428**	-0.021	0.033	0.039	-0.024
	(-1.03)	(0.85)	(-0.44)	(-2.26)	(-0.30)	(0.48)	(0.49)	(-0.25)
Growth	0.064	-0.085	0.126	0.038	0.050	0.004	-0.069	0.114
	(0.54)	(-0.88)	(1.24)	(0.22)	(0.41)	(0.04)	(-0.74)	(0.90)
Lev	-0.042	0.494*	0.272	0.930*	0.018	0.383	0.047	0.123
	(-0.15)	(1.89)	(1.02)	(1.79)	(0.06)	(1.39)	(0.21)	(0.27)
BM	-0.045	-0.111	-0.047	-0.446	-0.002	-0.007	-0.155	-0.087
	(-0.29)	(-0.68)	(-0.28)	(-1.55)	(-0.01)	(-0.04)	(-1.02)	(-0.45)
Cashflow	-0.384	-0.356	-0.143	-0.603	-0.821*	0.144	-0.099	-0.647
	(-1.28)	(-1.01)	(-0.47)	(-1.13)	(-1.69)	(0.33)	(-0.34)	(-1.59)
Tangible	0.011	-0.068	-0.024	-0.378	0.308	-0.035	-0.126	-0.124
	(0.04)	(-0.22)	(-0.10)	(-0.63)	(1.02)	(-0.13)	(-0.51)	(-0.36)
_cons	1.314	-1.986	0.214	9.776**	0.019	-1.485	-1.299	0.286
	(0.83)	(-1.21)	(0.12)	(2.21)	(0.01)	(-0.98)	(-0.76)	(0.12)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
N	4823	3763	4286	2579	4139	4164	4177	3648
R^2	0.537	0.574	0.617	0.668	0.603	0.586	0.623	0.618

Source: Authors own work.

Notes: This table reports the effects of artificial intelligence on corporate greenwashing level considering different firm ownership, establishment of Party organizations, and financial conditions. .The dependent variable is the corporate greenwashing level (*GWL*), and the independent variable is the firm artificial intelligence penetration (*AI*). All variables are defined in detail in Table 1. The t-statistics are reported in the parentheses. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.

Table 8. Heterogeneity of different external environments

	Dependent variable: greenwashing level							
	Public Environmental Attention		Confucian Culture		Industry Type		Market Concentration	
	PEA_High	PEA_Low	CC_Deep	CC_shallow	Heavy pollution	Light pollution	HHI_High	HHI_Low
	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)
AI	-0.009**	-0.005	-0.008**	-0.006	-0.009***	-0.005	-0.012***	-0.003
	(-2.50)	(-1.39)	(-2.11)	(-1.55)	(-2.77)	(-1.22)	(-3.18)	(-0.86)
ROA	1.069**	0.853*	0.869	1.019**	0.919**	0.642	0.891*	0.340
	(2.04)	(1.72)	(1.64)	(2.17)	(2.19)	(1.02)	(1.94)	(0.64)
Size	-0.016	-0.031	-0.081	0.020	-0.008	-0.020	0.006	0.047
	(-0.21)	(-0.46)	(-1.13)	(0.28)	(-0.13)	(-0.23)	(0.10)	(0.56)
Growth	0.017	0.030	-0.014	0.117	-0.087	0.334**	-0.011	0.101
	(0.15)	(0.30)	(-0.13)	(1.08)	(-0.96)	(2.55)	(-0.11)	(0.95)
Lev	0.089	0.183	0.105	0.247	0.207	-0.142	-0.043	0.046
	(0.29)	(0.71)	(0.39)	(0.89)	(0.82)	(-0.47)	(-0.17)	(0.17)
BM	0.051	-0.142	-0.086	0.027	0.048	-0.234	-0.032	-0.131
	(0.30)	(-0.92)	(-0.54)	(0.15)	(0.33)	(-1.27)	(-0.20)	(-0.74)
Cashflow	-0.501	-0.282	-0.147	-0.687**	-0.252	-0.484	-0.563*	-0.019
	(-1.51)	(-0.85)	(-0.44)	(-2.03)	(-0.96)	(-1.07)	(-1.78)	(-0.06)
Tangible	-0.116	0.297	0.102	-0.052	0.098	0.236	0.142	-0.210
	(-0.42)	(1.09)	(0.37)	(-0.18)	(0.40)	(0.76)	(0.56)	(-0.74)
_cons	-0.033	0.083	1.433	-1.105	-0.447	0.231	-0.491	-1.489
	(-0.02)	(0.06)	(0.90)	(-0.68)	(-0.33)	(0.12)	(-0.33)	(-0.79)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
N	4419	4134	4094	3657	5672	2962	4396	3919
R^2	0.546	0.553	0.539	0.563	0.560	0.525	0.552	0.637

Source: Authors own work.

Notes: This table reports the effects of artificial intelligence on corporate greenwashing level considering public environmental attention, influence of Confucian culture and different industry. The dependent variable is the corporate greenwashing level (*GWL*), and the independent variable is the firm artificial intelligence penetration (*AI*). All variables are defined in detail in Table 1. The t-statistics are reported in the parentheses. The symbols ***, **, and* indicate significance at the 1%, 5%, and 10% confidence levels, respectively.