WEP Warwick Evans Publishing

Transactions on Economics, Business and Management Research
ISSN: 2960-1789, eISSN: 2960-2254 | Volume 9
GBMS 2024

The Effect of Artificial Intelligence Technology on Corporate Greenwashing Level: Evidence from Chinese Listed Enterprises

Xiaotong Yang[1, #], Ziyan Ren[2, #], Yini Xie[3, *, #]

[1]School of International Finance and Trade, Shanghai International Studies University, Shanghai, China, 201620

[2]School of Management, Qufu Normal University, Rizhao, China, 276800

[3]School of Economics and Management, Beijing University of Chemical Technology, Beijing, China, 102299

* Corresponding Author Email: 13411986415@163.com

#These authors contributed equally.

Abstract. This study employs a fixed effects model to examine the impact of AI technology on corporate behavior based on data from Chinese A-share listed companies from 2012 to 2022. Findings show that artificial intelligence application can significantly reduce corporate greenwashing behavior, which remains robust after addressing endogeneity issues and conducting a series of robustness tests. Heterogeneity analysis reveals that property rights, industry, and regional factors influence AI's inhibition of greenwashing. This study highlights the crucial role of AI in corporate governance and emphasizes the importance of optimizing green finance regulation.

Keywords: Artificial Intelligence Technology; Greenwashing.

1. Introduction

In recent years, artificial intelligence (AI) has undergone a global surge and has become a pivotal driver for economic growth. As the world's second-largest economy, China is increasingly driving the advancement of artificial intelligence. The high penetration of AI is playing a crucial role in promoting high-quality and sustainable development of the real economy, and its impact on the behavior and decision-making of micro-enterprises has garnered widespread attention from academic and practical circles. On one hand, the implementation of artificial intelligence technology significantly enhances the eco-friendly production efficiency of enterprises(Xu et al.,2023)[1] On the other hand, it elevates the enterprise's capacity for green technology innovation(Vinuesa et al, 2020)[2]. Although there have been studies on the application of AI and green development in enterprises, there is a lack of literature focusing on the impact of AI on the level of greenwashing in enterprises. The misleading and inaccurate information disclosure associated with greenwashing hinders investors from making informed decisions, thereby impacting company value (Fatemi et al., 2018)[3]. The utilization of AI assists enterprises in providing more comprehensive and reliable information disclosure, thus mitigating unethical Environmental, Social and Governance(ESG) practices (Raza et al,2022)[4]. Therefore, based on the technology empowerment theory, this paper believes that the application of AI by enterprises can weaken corporates' incentives to greenwash and reduce the opportunities for greenwashing, so as to restrain the degree of enterprise greenwashing.

This study utilizes data from listed enterprises in China spanning the years 2012 to 2022 to empirically examine the influence of artificial intelligence technology application on greenwashing practices. The marginal contributions of this paper are as follows. Firstly, this paper focuses on the decision-making behavior of enterprises and enriches the relevant literature on the influence of artificial intelligence technology application on the degree of greenwashing. While existing literature extensively discusses the role of artificial intelligence technology in promoting green enterprise development, there is limited research on how its application affects the degree of greenwashing. The discussion in this paper not only fills this research gap but also provides a new idea and direction for future studies. Secondly, this paper further examines variations in the impact of artificial intelligence technology application on the degree of greenwashing among different types of enterprises and regions, offering guidance and suggestions for effectively utilizing artificial intelligence technology to reduce greenwashing and mitigate its harmful effects.

2. Literature review and hypothesis development

Both internal and external pressures influence enterprise greenwashing behavior. Internally, executive incentives and risk management strategies play pivotal roles, while externally, investor expectations and environmental regulations exert influence(Hongjun Xiao et al.,2013[5]; Shizhong Huang, 2022[6]). Moreover, information asymmetry and imperfect internal controls provide opportunities for greenwashing (Sumei Li,2024)[7]. This is where AI technology comes in. Based on the theory of technological empowerment, AI's data processing, risk prediction, and compliance-checking capabilities enable enterprises to make informed environmental decisions and enhance internal transparency (Shang et al.,2024)[8], thus lowering corporate greenwashing degree.

From a motivational perspective, AI weakens enterprises' motivation for greenwashing and fosters genuine progress in environmental protection. Firstly, AI encourages enterprises to adopt sustainable practices by improving operational efficiency and reducing expenses. In resource management, AI algorithms enable enterprises to allocate and utilize resources efficiently (Lu et al.,2023)[9]. In production, AI can help develop eco-friendly and energy-efficient products, reduce energy consumption and waste(Xu et al.,2023[1]), and improve supply chain sustainability(Wong et al.,2022)[10]. Secondly, in environmental monitoring, AI integrates big data analytics to monitor pollutant emissions, and boost enterprises' response to environmental issues (Karthika et al.,2023)[11]. As a result, through the application of AI technology, enterprises can enhance their actual environmental performance.

From an opportunity perspective, AI reduces opportunities for enterprises to translate greenwashing motivation into actions. Firstly, AI addresses the issue of information asymmetry in the green market by providing comprehensive and objective information (Huaijin Qi et al., 2022)[12], thus improving moral hazard and adverse selection issues. Secondly, based on the agency theory and upper echelons theory, managers' short-termism and profit-seeking mentality can significantly influence corporate decisions (Hambrick & Mason, 1984)[13]. AI can enhance monitoring efficiency and increase transparency in corporate operations, thereby limiting managers' manipulation of environmental information (Sumei Li et al.,2024[7]). Moreover, AI facilitates instant communication between enterprises and stakeholders, which fosters information integration and creates external supervisory pressure to deter corporate greenwashing (Haifang Wang et al.,2022)[14].

H1: The application of artificial intelligence technology in enterprises can inhibit corporate greenwashing level.

3. Research design

3.1. Sample selection

In this paper, the data of A-share listed companies from 2012-2022 are selected as the initial research sample, and the data are processed as follows to ensure the accuracy of the research: first, the financial industry companies are excluded; second, the samples in ST and *ST status in the current year are excluded; third, the samples with missing relevant variables are excluded; and fourth, this paper shrinks all continuous variables at 1% and 99% levels. After the above treatment, 8157 observations are finally obtained. The corporate drift green data used in this paper comes from Bloomberg and Huazheng ESG rating agencies, and the AI data comes from annual reports of listed companies and is manually processed; the relevant data at the corporate level comes from the CSMAR Database and the data at the macro level comes from the National Statistical Yearbook.

3.2. Main variables

3.2.1. Corporate greenwashing

Referring to the research of Zhang(2023)[15], the degree of greenwashing is quantified by the variance between standardized ESG disclosure scores and ESG performance scores, as shown in formula (1). Within the formula, $ESGD_{i,t}$ and $ESGP_{i,t}$ represent the enterprise′s ESG disclosure score and ESG performance score respectively, while $\overline{ESGD}$ and $\overline{ESGP}$ denote the average values of these scores, and σ_{ESGD} and σ_{ESGP} signify their standard deviations. The term GWL_{it} indicates the extent of greenwashing by the enterprise, with a higher value indicating more severe greenwashing.

$$\mathrm{GWL}_{it} = \left(\frac{ESGD_{i,t} - \overline{ESGD}}{\sigma_{ESGD}}\right) - \left(\frac{ESGP_{i,t} - \overline{ESGP}}{\sigma_{ESGP}}\right) \tag{1}$$

3.2.2. Artificial intelligence

Following Jiaquan Yao et al. (2024)[16], we utilize Python to conduct statistical analysis on the frequency of keywords related to artificial intelligence technology in annual enterprise reports. The natural logarithm of the total word frequency of artificial intelligence technology plus 1 is taken as the enterprise's artificial intelligence technology index(lnAI).

3.2.3. Control variables

Following Kim and Lyon (2015)[17], The control variables selected in this paper include: Size is the natural logarithm of total enterprise assets; Lev is the ratio of total liabilities to total assets of a business; ROA is the ratio of net profit to total assets at the end of the year; Growth is the growth rate of operating revenue; Tobin Q is the ratio of market value to replacement cost of the asset; Dual reflects whether the Chairman and CEO are held by the same person; Top5 is the proportion of top five shareholders; ListAge is the natural logarithm of listed years with one added; Mshare is the ratio of shares held by management to total number. Specific variables are described in Table.1.

Table 1. Variable definitions

Variable Name	Variable Symbol	Definitions of Variables
Greenwashing level	GWL	The difference between standardized ESG disclosure scores and standardized ESG performance scores.
Artificial intelligence	lnAI	The natural logarithm of the total word frequency of artificial intelligence technology plus 1.
Corporate size	Size	The natural logarithm of corporate total assets at the end of the period.
Financial leverage	Lev	Corporate total liabilities / total assets.
Return on assets	ROA	Year-end net profit / total assets.
Corporate growth	Growth	Growth rate of operating income.
Tobin Q	Tobin Q	Market value/replacement cost of assets
Dual function	Dual	Whether the Chairman and the CEO are held by the same person
Ownership concentration	Top5	Number of top five shareholders / total number of shares
Corporate age	ListAge	The natural logarithm of corporate listed years plus 1.
Management shareholding ratio	Mshare	Number of management shareholdings / total number of shares

3.3. Model design

The research model of this study is presented below:

$$\mathrm{GWL}_{i,t} = \alpha_0 + \alpha_1 \mathrm{lnAI}_{i,t} + \sum\mu \mathrm{Controls}_i + \mathrm{Industry}_t + \mathrm{Year}_i + \varepsilon_{i.t} \tag{2}$$

Where, $\mathrm{GWL}_{i,t}$ is the explained variable, $\mathrm{lnAI}_{i,t}$ is the core explanatory variable. α_1 is the coefficient of main interest in this study. If α_1 is significantly less than 0, it indicates that with the increase in the artificial intelligence technology application, corporate greenwashing degree will be inhibited. $\mathrm{Controls}_i$ represent the set of control variables. Fixed effects for year and industry are employed to eliminate the impact of unobservable factors. $\varepsilon_{i.t}$ is the random error term.

4. Empirical test and analysis

4.1. Descriptive Statistics

Table.2 presents the descriptive statistics for all variables. The mean value of GWL is -0.466, with a standard deviation of 1.269, suggesting that the average greenwashing degree of enterprises is relatively low and varies significantly across different entities. The mean value of lnAI is 0.813, with a standard deviation of 1.157, indicating substantial room for development in the application of enterprise AI and notable disparities in AI technology levels among different enterprises.

Table 2. Descriptive statistics

Variable	N	Mean	S.D	Min	Max
GWL	8157	-0.466	1.269	-5.546	5.691
lnAI	8157	0.813	1.157	0	6.122
Size	8157	23.36	1.276	19.63	26.45
Lev	8157	0.479	0.191	0.0350	0.908
ROA	8157	0.0680	0.0670	-0.365	0.287
Growth	8157	0.157	0.371	-0.658	4.024
TobinQ	8157	1.935	1.405	0.802	15.61
Dual	8157	0.203	0.403	0	1
Top5	8157	55.26	16.29	18.75	89.21
ListAge	8157	2.538	0.653	0	3.401
Mshare	8157	6.454	14.14	0	70.17

4.2. Regression analysis.

Following Huang Rongbing et al[18], we conducted regression analysis with controlled year and industry fixed effects gradually, resulting in benchmark regression results shown in Table.3. The regression coefficients in columns (1) ~ (3) indicate that the relationship between corporate artificial intelligence technology and greenwashing level is significantly negative at a 1% level, suggesting that continuous improvement of enterprise artificial intelligence technology can reduce the greenwashing degree of enterprises, thus supporting H_1.

Table 3. Regression analysis

VARIABLES	(1) GWL	(2) GWL	(3) GWL
lnAI	-0.065***	-0.085***	-0.065***
	(-5.217)	(-6.598)	(-3.781)
Size	0.148***	0.126***	0.125***
	(10.290)	(8.466)	(7.929)
Lev	-0.529***	-0.446***	-0.516***
	(-5.738)	(-4.776)	(-5.078)
ROA	-0.771***	-0.657***	-0.700***
	(-3.105)	(-2.623)	(-2.699)
Growth	0.181***	0.178***	0.182***
	(4.634)	(4.494)	(4.569)
TobinQ	0.057***	0.051***	0.057***
	(4.911)	(4.195)	(4.480)
Dual	0.159***	0.146***	0.166***
	(4.445)	(4.091)	(4.581)
Top5	0.006***	0.006***	0.005***
	(6.531)	(6.512)	(5.231)
ListAge	-0.109***	-0.148***	-0.178***
	(-4.209)	(-5.511)	(-6.392)
Mshare	0.005***	0.004***	0.004***
	(4.146)	(3.309)	(3.576)
Constant	-3.833***	-3.241***	-3.076***
	(-12.387)	(-9.845)	(-8.780)
Year	No	Yes	Yes
Industry	No	No	Yes
Observations	8,157	8,157	8,157
R-squared	0.044	0.048	0.067

***p<0.01,**p<0.05,*p<0.10

4.3. Robustness test

4.3.1. Lagging explanatory variables and control variables by 1 to 3 periods

Considering the lagged effect of AI technology application on the degree of greenwashing, we lag both the core explanatory variables and control variables by 1 to 3 periods. The results shown in columns (1) to (3) of Table.4 exhibit no significant differences compared to the baseline regression.

4.3.2. Adding provincial-level fixed effects

Considering that enterprises located in the same province may be subject to the same macro factors, provincial fixed effects are added to eliminate this effect. Results shown in column (4) of Table.4 indicate the robustness of the baseline regression.

4.3.3. Changing the sample period

Considering that in 2016, China passed the Environmental Protection Tax Law, which increases the pressure on enterprises to actively participate in environmental protection, and contributes to the reduction of greenwashing degree. To exclude this impact, we shorten the sample period to 2016-2022. The results in column (5) of Table.4 still demonstrate robustness.

Table 4. Robust test1-3

VARIABLES	(1) GWL1	(2) GWL2	(3) GWL3	(4) GWL	(5) GWL
lnAI	-0.081***	-0.108***	-0.121***	-0.066***	-0.072***
	(-4.187)	(-4.903)	(-4.841)	(-3.796)	(-3.834)
Constant	-3.933***	-4.242***	-4.694***	-2.783***	-4.168***
	(-9.998)	(-9.582)	(-9.527)	(-7.683)	(-10.055)
Controls	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Province	No	No	No	Yes	No
Observations	6533	5384	4423	8154	5646
R-squared	0.072	0.079	0.091	0.115	0.078

***p<0.01,**p<0.05,*p<0.10

5. Endogeneity analysis

Given that the measure of AI technology application relies on the disclosure of annual reports, observations for non-listed or non-disclosing enterprises can't be obtained, which may introduce a self-selection bias.

Drawing upon Wu and Tian's research(2022)[19], we employ the Heckman two-stage model to address endogeneity issues. The results are shown in Table.5. In the first stage, we use ifAI as the dependent variable. The average level of AI application (lnAI_mean) serves as the exclusion restriction variable, and Probit regression is conducted. In the second phase, the inverse Milliken ratio (imr) is inserted. The results in column (2) still demonstrate robustness.

Table 5. Heckman two-stage model

VARIABLES	(1) ifAI	(2) GWL
lnAI		-0.087***
		(-3.681)
lnAI_mean	1.924***	
	(51.486)	
imr		-0.039*
		(-1.695)
Constant	-4.525***	-3.030***
	(-10.507)	(-8.631)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
Observations	8,157	8,147
R-squared	0.503	0.067

***p<0.01,**p<0.05,*p<0.10

6. Heterogeneity analysis

6.1. Analysis of firm heterogeneity

Compared to non-SOEs, SOEs usually have access to more financial support and are required to take more social responsibility in environmental protection. Therefore, SOEs are more capable and motivated to adopt high-cost AI technologies. The regression results in columns (1) and (2) of Table.6 show that lnAI is significantly negative in the sample of state-owned enterprises, which indicates that applying AI technology can effectively reduce the degree of greenwash in state-owned enterprises.

6.2. Analysis of industry heterogeneity

The high-tech industry possesses robust technical capabilities and demonstrates a high level of transparency in disclosing environmental practices, which means that the potential impact of AI technology on reducing greenwashing may not be readily apparent. The regression coefficients of lnAI in non-high-tech industries are more significant than those in high-tech industries. The empirical P-value of the difference in regression coefficients between groups obtained by the Bootstrap method 1000 times is 0.054, which indicates that the implementation of AI technology has a more significant impact on mitigating greenwashing in non-high-tech industries.

Table 6. Firm and Industry Heterogeneity Regression Results

VARIABLES	(1) State-owned business GWL	(2) Non-state enterprise GWL	(3) High-tech industries GWL	(4) Non-high-tech industries GWL
lnAI	-0.136***	-0.021	-0.043*	-0.098***
	(-5.158)	(-0.880)	(-1.959)	(-3.531)
Constant	-3.894***	-3.667***	-3.642***	-2.682***
	(-7.883)	(-6.260)	(-6.423)	(-5.948)
Controls	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Observations	4,294	3,677	3,704	4,453
R-squared	0.099	0.089	0.075	0.065
Experience P-value	0.000***		0.054*	

***p<0.01,**p<0.05,*p<0.10

6.3. Analysis of regional heterogeneity

Regions with a high government intervention, innovation levels, and R&D intensity tend to invest more resources in improving technological infrastructure and incentivizing enterprises to apply AI technology. Specifically, referring to Jiao's (2019)[20]study, the share of government fiscal expenditure in regional GDP measures the degree of government intervention. Referring to Zhang's (2016)[21]study, the number of invention patent applications received in each region measures the level of innovation. According to Fan's (2024)[22]study, the internal expenditure of R&D funds as a share of regional GDP measures the R&D intensity. The regression results in Table.7 show that lnAI is significantly negative in regions with high government intervention, innovation levels, and R&D intensity, which indicates that that AI technology applications can effectively reduce the degree of enterprise greenwash in regions with high government intervention, innovation levels, and R&D intensity.

Table 7. Regression results for regional heterogeneities

VARIABLES	(1) Regions with high levels of government intervention GWL	(2) Regions with low levels of government intervention GWL	(3) Regions with high levels of innovation GWL	(4) Regions with low levels of innovation GWL	(5) Regions with high R&D intensity GWL	(6) Regions with low R&D intensity GWL
lnAI	-0.066***	0.084	-0.066***	0.206	-0.065***	-0.043
	(-3.865)	(0.433)	(-3.863)	(0.942)	(-3.794)	(-0.205)
Constant	-3.007***	-1.255	-3.015***	-119.562**	-3.111***	-58.382
	(-8.548)	(-0.028)	(-8.564)	(-2.452)	(-8.840)	(-1.109)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,094	61	8,087	69	8,093	63
R-squared	0.067	0.703	0.068	0.613	0.067	0.458

***p<0.01,**p<0.05,*p<0.10

7. Conclusions

This paper selects Chinese A-share listed companies as a sample from 2012-2022 to empirically verify the influence of enterprise AI technology applications on the degree of greenwashing. Our findings can be summarized as follows. First, AI technology application significantly inhibits the degree of corporate greenwash, and the conclusion still holds after the discussion of endogeneity issues and a series of robustness tests. Second, the application of AI technology has a more significant inhibiting effect on the degree of greenwash of state-owned, high-tech enterprises and enterprises located in regions with high government intervention, high innovation level, and greater R&D intensity.

The insights of this paper lie in the following. Firstly, considering the positive effects of AI technology in reducing the degree of greenwash in enterprises, government departments should set up a special fund to encourage more SMEs to introduce AI technologies and talents to enhance their technological level and innovation ability. Second, considering the significant inhibiting effect of government intervention on the degree of greenwash, government departments must strengthen capital investment and supervision of environmental regulation, and improve the ecological compensation mechanism to promote the realization of the dual objectives of enterprise development and environmental protection. Third, the government should expand the popularization of basic knowledge of environmental protection, deepen social awareness of the dangers of environmental pollution, improve the moral quality of the public, and establish a sound system of non-governmental ecological protection organizations to enhance the degree of public participation in environmental protection.

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