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The Impact of Digital Transformation on Corporate Bleaching Green Behavior

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Abstract: Utilizing data from Chinese A-share listed companies between 2013 and 2022, this study investigates the governance effect of digital transformation on corporate environmental information misrepresentation and its underlying mechanisms. The empirical findings reveal that (1) digital transformation significantly inhibits corporate greenwash behavior; (2) Organizational dynamic capabilities act as a partial mediator between digital transformation and greenwashing behavior, with digital advancements curbing information distortion by strengthening knowledge integration, innovation mechanisms, and external environmental responsiveness; (3) the heterogeneity analysis reveals that the inhibition effect is more pronounced for non-state-owned enterprises and enterprises in the eastern region, which indicates that the degree of marketization and the institutional environment are the important boundary conditions. The study reveals the non-economic benefits of digital transformation in environmental governance, and provides theoretical and practical basis for policy makers to promote green transformation of enterprises.

Keywords: digital transformation, drifting green behavior, dynamic capabilities, heterogeneity analysis, environmental governance

1. Introduction

In the face of the current intensifying global climate crisis, the deterioration of the ecological environment has aroused widespread international concern. In this situation, corporate environmental commitments have proliferated in an attempt to demonstrate their social responsibility and commitment to sustainable development. However, according to GDP 2022 data, 38% of enterprises have inaccurate environmental disclosure. This means that there is a serious disconnect between the environmental statements of a large number of companies and their actual actions, which not only misleads investors and consumers, but also hinders the realization of global environmental governance goals.

At the same time, the International Data Corporation (IDC) released the "Global Digital Transformation Expenditure Guide", which shows that the global digital transformation investment scale exceeded 2.1 trillion U.S. dollars in 2023, and is expected to reach 4.4 trillion U.S. dollars in 2028, with a five-year compound growth rate of 15.4% from 2023 to 2028. For China, digital transformation expenditures are anticipated to reach $733 billion by 2028, accounting for about 16.7% of global spending, with a five-year compound growth rate of about 15.6%, a rate higher than the overall global growth rate. In the face of such a large scale of expenditure, digital transformation is no longer an optional strategy for enterprises, but the core of the strategy for the survival and development of enterprises. Enterprises expect to leverage digital technologies to improve operational efficiency, optimize resource allocation, and strengthen market competitiveness, thereby attracting greater stakeholder attention and profitability.

However, a paradoxical phenomenon is quickly emerging between corporate commitment and digital development. On the one hand, digital transformation brings new opportunities for environmental governance. Technologies such as big data, artificial intelligence and the Internet of Things (IoT) can realize the accurate collection and real-time analysis of environmental data, helping enterprises to identify and solve environmental problems in a timely manner and promote green production and sustainable development. On the other hand, some enterprises, however, use digital technology for false propaganda, taking advantage of the convenience and dissemination power of digital media to exaggerate their own environmental protection effectiveness and cover up environmental violations, and more and more members of the public are beginning to question the authenticity of their environmental governance data. Literature related to this paper includes the following two aspects:

First, the impact of corporate digital transformation. Most of the academic research on enterprise digital transformation focuses on economic benefits. Some scholars have found that digital transformation can significantly improve the enterprise's stock liquidity and financial stability [1], but also optimize the enterprise cost structure, enhance the cost control ability [2]; other studies explore the relationship between digital transformation and organizational innovation, suggesting a positive correlation with enhancing organizational innovation metrics [3]. However, these investigations seldom adopt an environmental governance lens, overlooking how digital transformation influences corporate environmental accountability and sustainability practices.

The second is the reason for the research on greenwash behavior. Existing research mainly centers on institutional pressure. Some scholars have pointed out that institutional factors such as government regulation and industry norms have prompted enterprises to take surface environmental protection measures to cope with external pressures [4], and further explored the mechanism of the institutional environment's influence on enterprises' greenwash behavior [5], and the characteristics of greenwash behavior at different stages of institutional pressure [6]. Although these studies provide important references for understanding greenwash behavior, no unified conclusion has been drawn on the role of technology drivers in it. As an emerging influencing factor, the complex relationship between technology and corporate greenwash behavior still needs to be deeply explored.

By combing through the above literature, it can be found that the existing enterprise digitalization-related research focuses on economic benefits, but less on non-economic benefits, and does not take into account the impact of the fulfillment of corporate environmental responsibility. Furthermore, while research on corporate greenwashing often focuses on its root causes, few examine how ongoing digital shifts influence such practices. Aiming at the above shortcomings, this paper selects the economic data of A-share listed companies, uses ESG scores to construct bleaching green indexes to measure corporate bleaching green behavior, and uses text extraction analysis to construct corporate digital transformation indexes to further explore whether digital transformation has an inhibitory effect on corporate bleaching green behavior.

Compared to existing work, this paper makes three key contributions: (1) Theoretically, it expands the discourse on digital transformation's non-economic impacts by analyzing its role in curbing greenwashing, thereby enriching environmental governance scholarship; (2) Practically, it evaluates how digital transformation enhances dynamic capabilities—specifically absorptive, innovative, and adaptive capacities—to reshape corporate environmental management systems and reduce greenwashing incentives; (3) Policy-wise, it provides actionable recommendations to guide governments in designing evidence-based regulations and assist firms in leveraging digital tools for sustainable growth, fostering synergies between economic and environmental goals.

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2. Theoretical Analysis and Research Hypotheses

2.1. Digital Transformation and Bleaching Green Behavior

Existing studies generally agree that the essence of corporate greenwash is the "inconsistency" between environmental commitments and actual actions [4]. Such behavior often arises from information asymmetry and failure of external monitoring. This paper argues that digital transformation can be used as a technological tool to curb corporate greenwash through three core paths: enhancing information transparency, strengthening stakeholder monitoring, and improving the efficiency of environmental governance. First, digital transformation can crack the "black box of information", rapidly improve information transparency, and reduce the possibility of corporate data forgery. The application of digital technology (e.g., blockchain, big data) can realize the real-time collection, tamper-proof storage and multi-dimensional disclosure of environmental data [7]. For example, Internet of Things (IoT) devices can automatically record pollutant emission data, and blockchain technology ensures data traceability [8]. Such technological features directly compress the space for firms to manipulate environmental information. Studies have shown that the quality of environmental information disclosure by enterprises adopting digital technology improves by about 27% [9], and the probability of false statements drops significantly. Second, digital transformation can help build a diversified shared governance network and strengthen the supervision among business stakeholders. Digital channels such as social media and online commenting platforms significantly reduce the monitoring costs of the public, media and NGOs [10]. For example, the public monitors environmental performance in real time through corporate carbon emission data API interfaces [11], and environmental NGOs use web crawler technology to identify corporate propaganda contradictions. According to empirical data, after the digital transformation of enterprises to a certain degree, the level of corporate risk-taking will also increase with it [12], which indicates that external monitoring pressure forms an effective constraint on enterprises, which in turn inhibits greenwash behavior. Third, digital transformation can promote the internal enterprise from passive response to active management, thus realizing the optimization and improvement of environmental governance efficiency. Artificial intelligence algorithms can optimize environmental decision-making processes, such as predicting environmental risks through machine learning and simulating cleaner production options with digital twin technology. This makes companies more inclined to avoid risks through substantial environmental investments rather than relying on false propaganda. Based on this, the study formulates its initial hypothesis:

H1: Digital transformation contributes to reducing deceptive environmental practices in corporate operations.

2.2. The Mediating Role of Dynamic Capabilities

Dynamic capabilities theory emphasizes that enterprises need to "Integrate, Build, and Reconfigure" resources to maintain competitive advantage in a rapidly changing environment [13]. Digital transformation not only provides technological tools, but also influences environmental behavioral choices by reshaping the dynamic capabilities of enterprises. First, digital transformation inhibits greenwash by enhancing the absorptive capacity of firms, accelerating the internalization of environmentally relevant knowledge, and reducing symbolic disclosure due to unclear concepts. Digital technology enhances the efficiency of enterprises' identification and digestion of external green technologies through tools such as knowledge graphs and collaborative filtering algorithms [14]. For example, the industrial internet platform constructed by Sany Heavy Industry, real-time docking global environmental technology patent library, its green technology absorption efficiency increased by 40%. Second, cloud computing and simulation technology can enhance the innovation

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ability of enterprises and significantly reduce the marginal cost of green innovation. For example, Geely Automobile utilizes digital twin technology to develop new energy vehicles, shortening the R&D cycle from 24 months to 14 months and reducing trial-and-error costs by 62%. Measurement results show that for every 1 unit increase in enterprise digitalization investment, green patent applications increase by 12.48%-13.84% [15]. Third, the big data monitoring system enables enterprises to rapidly improve their adaptive capacity and capture policy changes. Haier has shortened its ESG compliance response time from 30 days to 7 days through the environmental regulations intelligent parsing system. Statistics show that the environmental policy adaptation index of highly digitalized enterprises is higher than the industry average [16]. Building on this foundation, the study posits the second hypothesis:

H2: Digital transformation enhances firms' dynamic capabilities, which in turn inhibits firms' greenwash behavior.

3. Research Design

3.1. Sample Selection

In this study, the data of Chinese A-share listed companies spanning from 2013 to 2022 are chosen as the initial sample. These data are then processed in the following ways: 1) exclude the data of companies listed in irregular trading, including ST, ST*, and listed companies of PT nature; 2) given the unique characteristics of the financial industry, data from financial sector companies are removed; 3) exclude the data with serious missing key data; 4) subject continuous variables to a bilateral shrinkage of 1 percent to eliminate the impact of data extremes and ensure that the values and frequencies of the sample distribution are in a controllable range. The final sample size of regression observations is 13,646. The raw data regarding green behavior are sourced from the Bloomberg database and the Wind database. Data related to digital transformation are obtained from the annual reports of enterprises available on the official websites of the Shenzhen Stock Exchange and the Shanghai Stock Exchange. As for the remaining raw data, they are retrieved from the Cathay Pacific (CSMAR) database.

3.2. Model Setup

To empirically validate Hypothesis H1 and assess the influence of digital transformation on corporate greenwashing activities, the following regression framework is formulated:

$$GWL_{i,t} = \alpha + \beta \mathrm{EDT}_{i,t} + \gamma Controls_{i,t} + \mu_{Nnindcd} + \lambda_{Year} + \varepsilon_{i,t} \tag{1}$$

In the baseline regression model, $GWL_{i,t}$ denotes the bleaching green behavior of enterprise i in year t, $\mathrm{EDT}_{i,t}$ captures the digital adoption metrics of firm i in year t, $Controls_{i,t}$ represents the control variables, and this paper The analysis employs a dual fixed-effects specification to account for industry fixed effects ($\mu_{Nnindcd}$) and year fixed effects (λ_{Year}), and $\varepsilon_{i,t}$ is the random error term.

3.3. Variable Settings

3.3.1. Explained Variable

Greenwash behavior (GWL). In this paper, we refer to the method of Hu [17] and consider the characteristics of Chinese listed companies, firstly, we obtain the annual reports of the companies from 2013 to 2022, and use Python to count the word frequency of the "Management Discussion and Analysis" (MD&A) part of the annual reports to construct a dataset of terms related to greenness and environment, which includes the characteristic words and sentences such as "green", "environmental

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protection", "low carbon", and "environment". Including "green", "environmental protection", "low carbon", "environment" and other characteristic words and sentences. If the frequency of green publicity words of enterprise i in year t is higher than the median of its SEC secondary industry, then $Oral_{i,t} = 1$, otherwise it is 0. Secondly, if enterprise i is subject to environmental administrative penalty in year t, then $Actual_{i,t} = 1$, otherwise it is 0. In summary, the definition of $DGW_{i,t}$ is constructed as follows:

$$DGW_{i,t} = \begin{cases} 1, if\ Oral_{i,t}=1\ and\ Actual_{i,t}=1 \\ 0, \qquad o.w. \end{cases} \tag{2}$$

Meanwhile, following Zhang [18] on the robustness test to measure the firm's peer relative bleaching green behavior score, construct the firm i's year t bleaching green behavior ($GWL_{i,t}$) indicator defined as follows:

$$GWL_{i,t} = \frac{ER\_Disclose_{i,t} - \overline{ER\_Disclose_t}}{\sigma_{Disclose}} - \frac{ER\_Perform_{i,t} - \overline{ER\_Perform_t}}{\sigma_{Perform}} \tag{3}$$

Where $ER\_Disclose_{i,t}$ is the disclosure rating of enterprise i in year t, measured by Bloomberg Environmental Disclosure Score; $ER\_Perform_{i,t}$ is the actual rating of enterprise i in year t, measured by CSI Environmental Disclosure Score; which is normalized by subtracting the average value of the same industry, to obtain the indicator of bleaching green behavior of enterprise i in year t ($GWL_{i,t}$). The larger the value of this indicator, the stronger the tendency of greenwashing behavior.

3.3.2. Explanatory Variable

Digital Transformation (EDT). Drawing on the methodology of Wu et al. (2021) [1], this study employs textual keyword frequency analysis of annual reports. Specifically, automated data extraction tools in Python are utilized to collect relevant keywords from annual disclosures of A-share listed firms on the Shanghai and Shenzhen exchanges between 2013 and 2022 (detailed in Table 1). The total keyword occurrences per annual report ($Count_{i,t}$) are quantified. To address right-skewed distribution in the data, the digital transformation metric for enterprise i in year t ($\mathrm{EDT}_{i,t}$) is constructed as follows:

$$\mathrm{EDT}_{i,t} = \ln\left(1 + Count_{i,t}\right) \tag{4}$$

Table 1: Digital transformation keywords

technical field	Keyword examples
artificial intelligence (AI)	Machine learning, face recognition, natural language processing, etc.
blockchain	Smart contracts, distributed ledgers, consensus mechanisms, etc.
Digital technology applications	Smart Factory, Digital Transformation, Industrial Internet, etc.

3.3.3. Control Variable

In this paper, some of the characteristic variables are selected to further control for the potential factors affecting firms' greenwash behavior: firm age (Age), profitability of total assets (ROA), financial leverage (Lev), operating cashflow (Cashflow), proportion of independent directors (Director), proportion of executives' shareholdings (Exeholdings), Tobin Q. (Tobin Q) . The specific variables are calculated as follows in Table 2:

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Table 2: Variable definitions

Variable category	Variable abbreviation	variable name	calculation method
explanatory variable	GWL	Corporate Greenwashing Behavior	Standard deviation of ESG ratings of CSI and Bloomberg rating agencies
explanatory variable	EDT	Digital Transformation Index	Total word frequency about digital transformation taken in logarithms
intermediary variable	DC	dynamic capability	Standardized mean of absorptive capacity, innovative capacity and adaptive capacity
control variable	Age	Age of business	The number of years from the time of establishment of the enterprise to the current year plus 1 to take the natural logarithm
	ROA	Total asset margin	Net profit to total assets
	Lev	financial leverage	Ratio of net profit to average balance of shareholders' equity
	Cashflow	Operating cash flow	Net operating cash flow to total assets ratio
	Director	Proportion of independent directors	Ratio of the number of independent directors to the total number of board members
	Exeholdings	Executive Shareholding Ratio	Number of shares held by executives to total shares
	Tobin Q	Tobin Q.	Market capitalization to (total assets - net intangible assets - net goodwill) ratio

3.3.4. Mechanism Variables

Dynamic Capabilities (DC). This study posits that digital transformation amplifies organizational dynamic capabilities, thereby curbing greenwashing tendencies. Adapting the framework proposed by Yang Lin [19], dynamic capabilities are categorized across three dimensions: innovation capacity, absorptive capacity, and adaptive capacity, operationalized as follows:

a) Absorptive Capacity (IC): A composite measure reflecting innovation capacity, calculated as the normalized aggregate of annual R&D investment intensity (R&D expenditure divided by total revenue) and the proportion of technical personnel. The formula is:

$$IC = \frac{X_{RD} - min_{BD}}{max_{RD} - min_{BD}} + \frac{X_{IT} - min_{IT}}{max_{IT} - min_{IT}} \tag{5}$$

b) Absorptive capacity: Measured as annual R&D spending relative to total operating revenue, capturing resource allocation for knowledge assimilation.

c) Adaptive capacity: Assessed via the inverse of the coefficient of variation (CV) across annual expenditures in R&D, capital, and marketing. A higher CV indicates stronger adaptive capacity, reflecting flexibility in resource reconfiguration.

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4. Analysis of Empirical Results

4.1. Descriptive Statistics

Table 3 presents summary statistics for the variables under study, with all measures falling within acceptable ranges and no significant biases detected. The dependent variable, greenwashing behavior (GWL), has a mean of 0.16 and standard deviation (SD) of 0.37, suggesting that greenwashing practices are relatively uncommon overall, though instances are present among certain firms. The primary independent variable, digital transformation (EDT), ranges from 0 to 5.04 (mean = 1.51, SD = 1.39), highlighting that while some firms have yet to initiate digital adoption, others exhibit advanced digital integration, reflecting substantial cross-firm variability. For the mediating variable, dynamic capabilities (DC), the mean is 0.26 (SD = 0.78) with a median of 0.21, indicating dynamic capabilities are moderate for most firms, yet substantial variability exists between high (max = 4.09) and low (min = -1.03) performers. Among control variables, return on assets (ROA) averages 3% (SD = 8%), and financial leverage (Lev) averages 42% (SD = 21%), confirming that the overall profitability and debt level of the sample firms are moderate. No extreme outliers are found for each variable, and the variable measures are reliable.

Table 3: Results of descriptive statistics

Variables	Observations	Mean	SD	Min	Median	Max
EDT	23174	1.510	1.390	0	1.390	5.040
GWL	23174	0.160	0.370	0	0	1
DC	23174	0.260	0.780	-1.030	0.210	4.090
Age	23164	7.600	0	7.580	7.600	7.610
ROA	23174	0.0300	0.0800	-2.570	0.0300	0.810
Lev	23174	0.420	0.210	0.0100	0.410	1.960
Cashflow	23174	0.0500	0.0700	-0.740	0.0500	0.880
Director	23172	0.380	0.0600	0.170	0.360	0.800
Exeholdings	23174	0.110	0.170	0	0	0.810
TobinQ	23174	2.400	2.480	0.690	1.830	133.1

4.2. Benchmark Regression Model

Table 4 demonstrates the core regression analysis outcomes using GWL as the dependent variable. The coefficient for the primary independent variable, EDT, is -0.00582 and statistically significant at the 1% level. This implies that a one-unit increase in digital transformation reduces greenwashing practices by approximately 0.58 percentage points, directly supporting Hypothesis H1. These findings validate the pathway through which digital adoption mitigates environmental data manipulation by improving transparency and oversight mechanisms. The model's explanatory power (R2=0.158) aligns with panel data characteristics, and robustness checks confirm the reliability of the results.

Table 4: Benchmark regression and robustness regression results

	Benchmark regression	EDT2	18-22 years
	GWL	GWL	GWL
EDT	-0.00582 ***	-0.628***	-0.00576*
	(0.00214)	(0.110)	(0.00317)
Age	1.224	1.246	1.246
	(0.921)	(0.921)	(1.320)

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Table 4: (continued).

ROA	0.122 ***	0.120 ***	0.144 ***
	(0.0330)	(0.0330)	(0.0436)
Lev	0.267 ***	0.268 ***	0.353 ***
	(0.0131)	(0.0131)	(0.0197)
Cashflow	0.180 ***	0.180 ***	0.254 ***
	(0.0331)	(0.0331)	(0.0497)
Director	0.0125	0.0144	0.0303
	(0.0408)	(0.0408)	(0.0595)
Exeholdings	-0.109 ***	-0.109 ***	-0.187 ***
	(0.0150)	(0.0150)	(0.0227)
TobinQ	-0.00806 ***	-0.00813 ***	-0.0203 ***
	(0.000969)	(0.000969)	(0.00214)
Nnindcd	Yes	Yes	Yes
Year	Yes	Yes	Yes
_cons	-9.406	-9.576	-9.462
	(7.003)	(6.997)	(10.03)
N	23162	23162	13112
R^2	0.158	0.159	0.169
adj. R^2	0.154	0.155	0.164

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

4.3. Robustness Check

To validate the reliability of this study on the impact of digital transformation on enterprises' greenwashing behavior, two methods are employed for testing in this paper. The specific test data are presented in Table 4 above.

4.3.1. Replacement of Core Variable Measures

In the benchmark regression, the "annual report text keyword word frequency method" of Wu Fei et al. (2021) [1] is used for measurement, and in order to test its robustness, reference is made to the digital transformation measurement method of Zhao Chenyu et al. [20], which measures the degree of digital transformation of enterprises by the combination of "text analysis method" and "expert scoring method". In order to test its robustness, we refer to the measurement method of Zhao Chenyu et al [20], and use the combination of "text analysis method" and "expert scoring method" to measure the degree of digital transformation of enterprises. Using the alternative indicator EDT2, its coefficient is -0.628*** (p<0.01), and the direction of significance is consistent with the baseline regression, indicating that the inhibitory effect of EDT on GWL is robust regardless of the digitalization measurement method.

4.3.2. Shorter Sample Periods

Since ESG-related concepts emerged late in China, in order to verify the core variable connectivity, we chose to keep only the 2018-2022 data to test its robustness. According to the results, the EDT coefficient is -0.00576* (p<0.1), which is a slight decrease in significance but the direction remains unchanged, and the coefficients of the control variables remain stable (e.g., the significance of ROA and Lev remains unchanged).

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Together, the two tests suggest that the conclusion that digital transformation inhibits greenwash behavior is robust.

4.4. Mechanism Testing

In order to explore the mediating role of dynamic capabilities in the impact of digital transformation on corporate drift green behavior, this paper conducts further tests, and the regression results are shown in Table 5.

As can be seen in Table (1) below, the coefficient of EDT on Dynamic Capability (DC) is 0.0860*** (p<0.01), which indicates that digital transformation significantly improves firms' dynamic capability; after the introduction of DC, the coefficient of EDT on GWL decreases from -0.00582 in the baseline regression to -0.00481** (p<0.05), and the coefficient of DC itself is -0.0117*** (p<0.01).

The above results suggest that dynamic capabilities partially mediate the effect of EDT on GWL, i.e., digital transformation indirectly reduces greenwash by enhancing the agility of firms to adapt to environmental changes (e.g., technology iteration and resource reorganization).The Sobel test further verifies that the mediating effect is significant (Z=-3.12, p<0.01), and the hypothesis H2 is valid. As a result, the negative path of "digital transformation → (promote) homogeneous dynamic capabilities → (inhibit) greenwashing behavior" is formed.

Table 5: Intermediation regression results

	(1)	(2)
	DC	GWL
EDT	0.0860 ***	-0.00481**
	(0.00344)	(0.00217)
controls	Yes	Yes
DC		-0.0117***
		(0.00410)
_cons	-130.5 ***	-10.94
	(11.25)	(7.023)
N	23162	23162
R^2	0.518	0.158
adj. R^2	0.516	0.155

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

4.5. Heterogeneity Analysis

To evaluate the effects of corporate digital adoption on greenwashing tendencies across distinct organizational structures and geographic contexts, this research classifies firms into state-owned entities, private enterprises, and regional categories (eastern, central, and western zones). The corresponding regression analyses are detailed in Table 6.

4.5.1. Differences in the Nature of Enterprises

Grouped by the nature of equity, the EDT coefficient is -0.00908*** (p<0.01) in non-SOEs, while it is not significant in SOEs. This suggests that digital transformation has a stronger inhibitory effect on greenwash behavior in non-SOEs, probably due to the fact that non-SOEs are highly marketized and digital technology acts more directly on business decisions, whereas SOEs are subject to more administrative interventions and the marginal effect of digital governance is limited.

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4.5.2. Regional Disparity

Grouped by region, the EDT coefficient is -0.00885*** (p<0.01) in the eastern region, and the effect is not significant in the central and western regions. This result is related to the regional institutional environment, the eastern region is more mature in terms of marketization and environmental protection regulation, and the digital technology can be more effectively embedded in the corporate environmental governance system; the central and western regions may have a weaker effect of digitalization in suppressing greenwash due to institutional lag or resource constraints. Therefore, the effect of digitization on greenwash is more significant in the eastern region, where marketization is high and regulation is strict.

The heterogeneity results indicate that the nature of the firm and the regional institutional environment are important boundary conditions affecting the environmental effects of digital transformation, providing a basis for policymakers to categorize their policies.

Table 6: Heterogeneity test regression results

	nationalized business	non-state enterprise	eastern part	western region	Central Region
	GWL	GWL	GWL	GWL	GWL
EDT	-0.00159	-0.00908 ***	-0.00885 ***	0.0138**	-0.00380
	(0.00434)	(0.00243)	(0.00240)	(0.00653)	(0.00684)
controls	Yes	Yes	Yes	Yes	Yes
Nnindcd	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
_cons	1.069	-16.16 **	-14.96*	-7.917	42.27 *
	(15.34)	(8.010)	(7.764)	(22.37)	(23.80)
N	8058	15104	16793	3055	3314
R^2	0.176	0.160	0.155	0.215	0.228
adj. R^2	0.167	0.155	0.151	0.194	0.211

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

5. Conclusion

Utilizing the data of China's A-share listed companies from 2013 to 2022, this paper conducts a systematic exploration of the impact of digital transformation (EDT) on corporate greenwashing behavior (GWL) and its underlying action mechanisms. The following key conclusions are drawn: 1. Digital transformation significantly curbs corporate greenwashing behavior. This conclusion remains valid even after undergoing robustness tests. 2. Through mechanism analysis, it is found that digital transformation indirectly restrains greenwashing behavior by enhancing the dynamic capabilities (DC) of corporations. 3. Compared to state-owned enterprises and those in the central and western regions, the inhibitory effect of digital transformation on greenwashing behavior is more pronounced in non-state-owned enterprises and those in the eastern region.

This paper further expands the field of non-economic environmental governance of digital transformation, reveals the mechanism of digital technology to inhibit greenwash behavior, and fills the research gap of "how technology-driven factors affect corporate environmental behavior" in the existing literature; combining with the theory of dynamic capability, it proposes the mediating path of "digital transformation → dynamic capability → greenwash inhibition", which provides a new perspective for understanding the relationship between technology and corporate environmental responsibility. By integrating the dynamic capabilities framework, this study identifies a cascading mechanism of "digital transformation → enhanced dynamic capacities → reduced greenwashing incentives," offering an innovative lens to examine how technological adoption reshapes corporate environmental accountability. It provides empirical evidence for enterprises to optimize their environmental governance through digital transformation, and guides them to apply digital technology to environmental information disclosure and compliance management; it also provides reference for policy makers to identify the heterogeneous effects of digital transformation (such as differences in the nature of regions and enterprises), and helps them to accurately implement policies.

Drawing on the insights from this study, the following strategic recommendations are proposed to inform policy development:

a) Strengthening inclusive support for digital transformation. For central and western regions, increase investment in digital infrastructure construction (e.g., 5G networks, cloud computing centers), reduce the cost of digital transformation for enterprises, and narrow the technology application gap between regions. Provide special subsidies or tax incentives to non-state-owned enterprises to encourage them to enhance the transparency of environmental governance through digital technology.

b) Improving the digital environmental regulatory system. Promote the application of blockchain and Internet of Things (IoT) technologies in environmental data collection and verification, establish a nationally unified environmental information disclosure platform, and enhance data tamperability and traceability.

Encourage third-party organizations to develop digital monitoring tools (e.g., real-time carbon emissions tracking systems) to strengthen the effectiveness of social supervision.

c) Classification and optimization of policy effects. For State-owned enterprises, it is necessary to strengthen the administrative assessment of digital governance and incorporate the quality of environmental information disclosure into the management performance assessment system. Pilot "digital environmental protection demonstration zones" in the eastern region, explore market-based incentives (e.g., green credit priority support for digitally advanced enterprises), and develop replicable models.

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