Enterprise Digital Transformation, ESG Performance and High-quality Development

Luling Yang
School of Economics, Nankai University, Tianjin, China
2213456@mail.nankai.edu.cn

Abstract. Enterprise ESG performance is the key point to achieving the goal of "dual carbon goals" in China, and the improvement of the digital level can effectively promote green transformation and high-quality development of enterprises. This paper focuses on the A-share listed companies in Shanghai and Shenzhen from 2010 to 2022. The empirical study shows that digital transformation has significantly improved the ESG performance of enterprises. After passing a series of tests such as the tool variable method and PSM-DID, the results are still stable. The digital transformation of enterprises can improve their ESG performance by improving their own green technology innovation level and enterprise responsibility awareness, reducing supply chain concentration and corporate risk. Tertiary industry, eastern enterprises, non-heavy polluting enterprises, and enterprises with high financing costs can achieve better ESG performance at a higher degree of digital transformation, and the promotion of big data and artificial intelligence technology is more significant. The research in this paper shows that it is of great significance to give full play to the role of enterprise digital transformation in promoting ESG performance, and to realize the coordinated and sustainable development of green transformation and the goal of "dual carbon goals".

Keywords: digital transformation; enterprise ESG performance; green technology innovation; supply chain concentration.

1. Introduction

2024 is the 20th anniversary of the ESG concept put forward by the United Nations Global Compact. With the deepening of the scientific and technological revolution and industrial transformation, digital technologies such as the Internet, big data, artificial intelligence, and blockchain have accelerated innovation, which has played an important supporting role in empowering green transformation, helping to achieve carbon neutrality in peak carbon dioxide emissions, and accelerating the development of new quality productivity. Digitalization and greening have increasingly become an important trend in global economic and social transformation and development.

This paper takes China Shanghai and Shenzhen A-share listed companies from 2010 to 2022 as research samples, empirically examines the influence of digital transformation on the ESG performance of enterprises, and ensures the reliability of core conclusions through a series of robustness tests and endogenous treatment. Its mechanism is that digital transformation can improve the level of green innovation technology and corporate social responsibility awareness, reduce supply chain concentration and corporate risk, and lead to the improvement of ESG performance and high-quality sustainable development of enterprises. From the heterogeneity perspective, it is analyzed that eastern enterprises, non-heavily polluting enterprises, and enterprises with high financing costs can achieve better ESG performance, and data and artificial intelligence can promote ESG more significantly.

Compared with the previous studies, the marginal contribution of this study is mainly reflected in the following points: ① from the micro perspective of listed companies, it provides evidence of the impact of digital transformation on ESG performance of enterprises; ② deepening the analysis of the influence mechanism from the perspectives of environment, social responsibility, and corporate governance; ③ using instrumental variables and PSMDID method to solve endogenous problems, and making a comprehensive heterogeneity analysis based on industry, geographical location, and digital technology; ④ using more objective digital intangible assets as variables to measure the degree of digital transformation.

2. Literature Review and Research Hypothesis

2.1 Literature review

2.1.1 Research on digital transformation

Literature research on digital transformation mainly focuses on influencing factors and economic consequences. Influencing factors include environmental change (Warner et al, 2019)[1]; macro-factors such as policy impact and market regulation (Fürstena et al, 2020) [2]; meso-factors, such as organizational inertia (Yi Jiabin et al. 2022) [5], internal resource allocation mechanism (Yi Jiabin et al., 2022) [6], digital strategic capabilities; endogenous micro-factors, including entrepreneurial management ability (Singh et al, 2020) [3] and technical factors. Enterprises can optimize their financial performance and improve the quality of information disclosure through digital transformation, and at the same time, they have shown a positive role in promoting corporate governance and capital market efficiency (Xiao Shuguang, 2009) [7]. Digital technology enhances the enterprise's insight into internal operations, effectively improves overall operational efficiency, and enhances production efficiency (Wang Jing and Han Qihao, 2021) [8]. Digitalization not only enhances the enterprises' information disclosure and management level, but also plays a positive role in voluntary information disclosure and market performance.

2.1.2 Research on ESG performance of enterprises

Most of the existing literature focuses on the analysis of the impact on the ESG performance of enterprises, such as making enterprises flexibly use external funds to support the development of enterprises through the improvement of stakeholders' confidence (Mohammad et al，2021) [4], or reducing the extra return required by investors for taking enterprise risks by reducing enterprise risks (Bai Xiong et al., 2022) [9]. Good ESG performance can reduce the information risk premium and enhance capital attraction by reducing the information asymmetry between the market and investors. Good ESG performance helps to improve the reputation of enterprises, enhance investor confidence (Mei Yali and Zhang Qian, 2023) [10], and then reduce financing costs. The influence of ESG performance on financial performance, improving the operational efficiency of enterprises, affecting the long-term competitiveness of enterprises, and enhancing the reputation value and management ability of enterprises. The ESG performance of enterprises is influenced by external factors, mainly from three aspects: economic policy (Zhang Changjiang et al., 2021) [11], government support (Chen Mingjing and Li Yuanchi, 2022) [12], and scientific and technological innovation. Influenced by internal factors, the system is huge and has not yet been formed completely based on the development characteristics and internal organizational structure of enterprises.

2.1.3 Research on the influence of digital transformation on ESG

With the introduction of digital technology, digitalization is affecting enterprises from many angles. Wang Haijun et al. [15] (2022) found that the adoption of digital strategy and technology can improve the ESG performance of enterprises, and enterprises can promote ESG performance by enhancing their innovation ability, information interaction, and financial performance. Hao Yuting and Zhang Yonghong [16] (2022) found that digital transformation had an obvious empowering effect on ESG's responsibility performance, and the promoting effect is more obvious in state-owned enterprises and enterprises with less management shareholding. Li Guolong and Zhu Peihua [17] (2022) examined the influence mechanism of urban information infrastructure on ESG. The results showed that information infrastructure can accelerate the digital transformation of enterprises, improve the contribution of digital elements in the production and operation activities of enterprises, and alleviate the information asymmetry in the market. Zhang Meng and Song Shunlin [18] (2023) found that enterprise digitalization can improve ESG performance by improving the level of green innovation and the quality of internal control; Innovation policy has a positive regulatory role in the relationship between enterprise digitalization and ESG. Liu Fangyuan and Wu Yunlong [19] (2024) studied the influence mechanism of digitalization to improve enterprises' environment, society, and governance.

Digitalization can promote enterprises' financial performance, reduce their risk level, and promote green technology innovation. Through mechanism analysis, He Dexu et al. [20] (2024) showed that digitalization affected the environmental responsibility effect by reducing environmental violations and sudden environmental incidents.

2.2 Theoretical analysis and research assumptions

2.2.1 The influence of digital transformation on ESG performance of enterprises

The digital transformation of enterprises can promote the construction of an accurate, efficient, and sustainable production ecosystem. Relying on the intelligent monitoring technology of big data, risks can be predicted and prevented in a forward-looking way, thus reducing the probability of accidents (Li Yanhua and Jiao Dekun, 2021) [21]. Digitalization helps to build a personalized and intelligent product and service system. From the perspective of brand image building, digital transformation promotes the transformation of enterprises to service, which helps to improve the quality management level of enterprises and establishes a good brand image in the market (Zhao Chenyu, 2022) [22]. Digital transformation makes enterprise information disclosure more transparent and helps investors make more reasonable investment choices. It can strengthen the production's ability to monitor real-time and make the internal management of enterprises more standardized and effective. Through big data analysis, enterprises can more accurately predict market demand and improve resource utilization efficiency (Luo Jinhui and Wu Yilong, 2021) [23]. This study proposes Hypothesis 1: A good enterprise's digital transformation can promote its ESG performance.

2.2.2 Environmental responsibility effect: Digital transformation, green innovation level, and enterprise ESG performance

Digital transformation promotes enterprises' green innovation ability (Wang Hui et al., 2021) [24], and the mechanisms to promote enterprises' green technology innovation include improving the quality of earnings information, easing financing constraints, and growth ability. Digitalization helps enterprises to achieve refined management of the whole production and improve the efficiency of production and management (Xu Xianchun et al., 2019) [25]; promotes the innovation of pollution control technology and forms the positive externality of the environment. Digital technology promotes the realization of social responsibility performance through green technology, that is, green innovation plays a partial intermediary role (Wang Haihua et al., 2023) [26]. This study puts forward Hypothesis 2: Digitalization of enterprises enhances the innovation level of green technology and improves the ESG performance of enterprises.

2.2.3 Social responsibility effect: Digital transformation, corporate social responsibility awareness and corporate ESG performance

The sustainable development report guide of GRI covers multi-dimensional disclosure requirements such as environment, society, and corporate governance. When enterprises refer to this guide, they will be prompted to sort out and examine their practices in ESG more systematically (Luo Xiying et al., 2018) [27]. Enterprises will strengthen the monitoring and management of their environmental impact indicators such as resource consumption and pollutant discharge to meet the disclosure requirements in the guidelines (Xu Yiqing and Zhang Changjiang, 2015) [28]. This study provides Hypothesis 3: Digitalization of enterprises enhances corporate social responsibility awareness and improves the ESG performance of enterprises.

2.2.4 Corporate governance effect: Digital transformation, supply chain concentration, enterprise risk and ESG performance

Digital transformation restrains enterprise risks. Digital technology improves the innovation level and financing ability of enterprises, and improves the risk-taking ability of enterprises through resource effect and information effect (Chen Xiaohui and Zhang Hongwei, 2021) [29]. Digitalization enhances enterprise management ability and total factor productivity (Zhao Na et al., 2022) [30]. Digitalization breaks the space restriction of industrial factor allocation, integrates internal and external resources, and strengthens information feedback to form a unique market position. Knowledge spillover of innovation effect can strengthen the cooperative relationship with suppliers (Xu Xingmei et al., 2022) [31]. This study puts forward Hypothesis 4: Enterprise digitalization can improve enterprise ESG performance by reducing supply chain concentration and enterprise risk.

3. Research Design

3.1 Samples and data

In this paper, the A-share listed companies in Shanghai and Shenzhen from 2010 to 2022 are selected as research samples, and the data are processed as follows: (1) the samples of listed companies in financial and insurance are excluded; (2) rejecting samples with abnormal operations such as ST and *ST; (3) eliminating the samples with missing key variable data. Finally, 22,285 observations of 3,252 listed companies were obtained; (4) to avoid the influence of extreme values, all continuous variables are truncated by 1% up and down. The sustainable development level data (ESG) comes from Sina Securities ESG and CNRDS databases. The data of other core variables are from the CSMAR database.

3.1.1 Explained variables

ESG rating refers to the rating method of evaluating enterprises from three aspects: environment, social responsibility, and corporate governance. Based on the ESG rating index and weight of CSI, this paper calculates the rating and distinguishes 9 grades of “AAA-C”, which are assigned 9-1 respectively. This paper takes its average value to get the annual rating.

3.1.2 Explanatory variables

The measurement of digitalization in previous studies includes: obtaining enterprise data through questionnaires (Liu Zheng et al., 2020) [32]; and constructing virtual variables according to whether the enterprise adopts digital transformation in that year (He Fan and Liu Hongxia, 2019) [33], which is limited to the inability to show the intensity of transformation. Previous studies also analyzed the structural index of statistical word frequency of annual reports of listed companies (Yi Luxia et al., 2021) [34], which is limited to strong subjectivity. This paper refers to Li Yingmei et al., [35] (2023) used the logarithm of enterprise digital intangible assets to measure the degree of enterprise digital transformation. The greater the DIA index value, the higher the degree of digital transformation of enterprises.

3.1.3 Mechanism variables

(1) Green technology innovation (Pat)

This study uses the total number of green patent applications (Ecoi1), the number of green invention patent applications (Ecoi2), and the sustainable green innovation level (OIP) of enterprises as the measures of green technological innovation. Among them, the first two measurements take logarithms. The calculation of sustainable innovation level refers to He Yubing, et al., [36] (2017), the innovation sustainability of an enterprise in the t year is equal to the chain growth rate of the sum of patent applications between t-1 and t years compared with the sum of patent applications between t-2 and t-1 years and then multiplied by the sum of patent applications between t-1 and t years.

$$OIP_t = \frac{OIN_t + OIN_{t-1}}{OIN_{t-1} + OIN_{t-2}} \times (OIN_t + OIN_{t-1})$$

(2) Social responsibility (Soc)

GRI’s sustainable development reporting guide reports the performance of enterprises from three angles: economy, environment, and society. This study selects whether the enterprise refers to the GRI sustainable development report guide as the mechanism variable of the social responsibility effect. GRI guide is a globally recognized social responsibility disclosure standard, and enterprises refer to it to prepare reports, which reflects the systematicness of social responsibility practice and is consistent with the logic of digital transformation to promote social responsibility performance.

(3) Supply chain concentration (Sup)

Supply chain concentration reflects the governance of enterprises in supply chain management. A higher concentration of the supply chain means that enterprises are highly dependent on a few suppliers, which will bring risks such as supply interruption and weak bargaining power. In this paper, measured by the average of customer concentration and supplier concentration, customer concentration is the proportion of the top five customers' sales to the total sales, and supplier concentration is the proportion of the top five suppliers' purchases to the total sales.

(4) Enterprise risk (DD_KMV)

A perfect corporate governance system should have effective risk identification, evaluation, and control mechanisms (Huang Linggen, 2024) [37]. The KMV model, also known as the expected default rate model, is based on the Merton model. When the future market value of enterprise assets is lower than the face value of liabilities that the enterprise needs to pay off, the enterprise will default. The distance between the expected value of the future market value of enterprise assets and the default point is the DD (Distance to Default). The farther the distance, the less likely the company will default. In this paper, the KMV model is used, and the default distance of KMV is used as the mechanism variable of enterprise risk. The bigger DD_KMV is, the smaller the risk is.

3.1.4 Control variables

This study refers to Yuan Chun et al. [38](2021) and Xiao Hongjun, et al., [39] (2024) and adds other enterprise characteristic control variables that may affect the digitalization of enterprises, including enterprise size (Size), listing age (taking logarithm of the value plus 1, L.age), asset-liability ratio (Lev), independent director ratio (IDR_ratio), board size (taking logarithm, L.Board), property right nature (Soe), business income growth rate (Growth), book-to-market ratio (BM) and Duality.

3.2 Model construction

3.2.1 Benchmark model

To test the influence of enterprise digital transformation on enterprise ESG performance, this paper constructs the following econometric model:

$$ESG_{\mathrm{i,t}} = \alpha + \beta DIA_{\mathrm{i,t}} + \gamma \mathrm{Controls} + Firm_i + Year_t + \varepsilon_{i,t} \qquad (1)$$

Where i stands for listed enterprises, t stands for year, ε stands for the residual term, Controls stands for the set of control variables, and Firm and Year stand for fixed effects at enterprise and year levels respectively. All regressions are clustered at the industry level with robust standard error.

3.2.2 Mechanism test model

$$Pat_{\mathrm{i,t}} = \alpha + \beta DIA_{\mathrm{i,t}} + \gamma \mathrm{Controls} + Firm_i + Year_t + \varepsilon_{i,t} \qquad (2)$$

$$Soc_{\mathrm{i,t}} = \alpha + \beta DIA_{\mathrm{i,t}} + \gamma \mathrm{Controls} + Firm_i + Year_t + \varepsilon_{i,t} \qquad (3)$$

$$Gn_{\mathrm{i,t}} = \alpha + \beta DIA_{\mathrm{i,t}} + \gamma \mathrm{Controls} + Firm_i + Year_t + \varepsilon_{i,t} \qquad (4)$$

Models (2-4) are used to test hypotheses H2, H3, and H4, and to investigate whether enterprise digitalization can improve enterprise ESG performance by improving enterprise green innovation level (Pat), enhancing enterprise responsibility consciousness (Soc), reducing enterprise supply chain concentration (Sup) and reducing enterprise risk (DD_KMV).

4. Empirical Results and Analysis

4.1 Descriptive statistics

Descriptive statistical results of the main variables are shown in Table 1. The average score of ESG is 3.992, which is low, and is consistent with the current development of ESG in China and close to the previous literature. The average DIA is 14.899, which shows that the degree of digital transformation in China needs to be improved. The standard deviation of the degree of digital transformation of enterprises is 2.079, which shows that there are great differences among enterprises. The distribution of other variables is within a reasonable range.

Table 1 Descriptive Statistics

Variable	Variable name	Obs	Mean	SD	Min	P25	Median	P75	Max
Hz_ESG	Sina Securities ESG	22285	3.992	1.183	0.000	3.250	4.000	5.000	6.250
DIA	Digital intangible assets of enterprises	22285	14.899	2.079	8.804	13.630	14.940	16.254	19.908
Size	Size	22285	22.204	1.299	19.650	21.260	22.030	22.950	26.190
L.Age	Age to market plus 1 to take logarithm	22285	2.027	0.945	0.000	1.386	2.197	2.833	3.497
Lev	Asset-liability ratio	22285	0.424	0.211	0.051	0.253	0.413	0.579	0.960
ROA	Net profit rate of total assets	22285	0.038	0.066	-0.332	0.015	0.040	0.070	0.204
IDR_ratio	Proportion of independent directors	22285	37.563	5.259	33.330	33.330	36.360	42.860	57.140
L.Board	The logarithm of the size of the board of directors	22285	2.124	0.200	1.609	1.946	2.197	2.197	2.639
Soe	Nature of the property right	22285	0.370	0.483	0.000	0.000	0.000	1.000	1.000
Growth	Operating income growth rate	22285	0.390	1.019	-0.750	-0.023	0.142	0.436	7.470
BM	Book-to-market ratio	22285	0.626	0.246	0.106	0.441	0.627	0.809	1.177
Duality	Duality	22285	0.288	0.453	0.000	0.000	0.000	1.000	1.000

4.2 Benchmark regression analysis

Table 2 reports the benchmark regression results of the influence of enterprise digital intangible assets on enterprise ESG rating level. Column (2) controls the characteristic factors at the enterprise level. Column (3) considers time-fixed effect. Column (4) considers both firm and time-fixed effects and uses industry-level clustering standard error. The results show that the DIA coefficients are all positive, which are all significant at the level of 1%. The digital transformation of enterprises can empower enterprises to achieve sustainable development.

Table 2 Benchmark Regression: Enterprise Digitalization Level and ESG Performance

VARIABLES	(1)	(2)	(3)	(4)
DIA	0.111***	0.042***	0.041***	0.042***
	(0.004)	(0.004)	(0.004)	(0.010)
Size		0.205***	0.243***	0.225***
		(0.010)	(0.010)	(0.028)
L.Age		0.220***	0.204***	1.10***
		(0.010)	(0.010)	(0.044)
Lev		-0.749***	-0.764***	-1.342***
		(0.048)	(0.046)	(0.097)
ROA		2.083***	1.958***	0.589***
		(0.128)	(0.128)	(0.127)
IDR_ratio		0.0166***	0.016***	0.0120***
		(0.002)	(0.002)	(0.003)

L.Board		0.0647	0.023	0.118
		(0.047)	(0.047)	(0.107)
SOE		0.003	0.009	-0.130**
		(0.019)	(0.019)	(0.054)
Growth		0.007	0.0136*	-0.021**
		(0.007)	(0.007)	(0.0104)
BM		0.004	-0.257***	0.096
		(0.038)	(0.041)	(0.070)
Duality		-0.033*	-0.036**	-0.039
		(0.018)	(0.018)	(0.026)
Constant	2.337***	-2.143***	-2.648***	-4.022***
	(0.0562)	(0.200)	(0.201)	(0.605)
Firm FE	N	N	N	Y
Year FE	N	N	Y	Y
N	22,285	22,285	22,285	22,011
AdjR2	0.038	0.130	0.151	0.580

Note: * * *, * *, and * mean significant at the level of 1%, 5%, and 10% respectively. Unless otherwise specified, the same in the following tables.

4.3 Endogenous problems

In this paper, when studying the relationship between enterprise digital transformation and enterprise sustainable development, other related control variables may be omitted, and there may be mutual causal problems.

4.3.1 Tool variable 2SLS

Referring to Yuan Chun et al. [38] (2021), this study selects the post and telecommunications data of cities in 1984 as the tool variable. This data is cross-sectional data, and we introduce a time series variable to construct panel tool variables (Zhao Tao et al., 2020) [40]. This paper uses the number of fixed telephones per 10,000 people in prefecture-level cities in 1984 and the number of Internet surfers in China that lags by one period as instrumental variables for the degree of digitalization of enterprises. The number of fixed telephones in the development process before the enterprise is located will affect the application and update of digital equipment technology in the sample period, which is in line with the correlation. The fixed telephones in cities basically disappeared in 1984, and the influence of traditional communication sites on the current flow of entrepreneurs between cities hardly exists, which does not directly affect the process of digital transformation of enterprises, which is in line with exogenous factors.

Taking the time variable of Internet penetration rate in prefecture-level cities from 2001 to 2013 as a tool variable. In areas with a high level of Internet infrastructure, individuals and enterprises are also more likely to use the Internet, which is relevant. The Internet penetration rate is mainly influenced by external factors such as policies, which align with exogenous factors.

Table 3 Tool Variable Method and PSM Test Results

	(1)	(2)	(3)	(4)
VARIABLES	DIA	Hz_ESG	DIA	Hz_ESG
Iv1	3.06e-06***			
	(1.30e-07)			
Iv2			0.719***	
			(0.0368)	
DIA		0.085***		0.135***
		(0.028)		(0.034)
Constant	-8.478***	-1.752***	-9.149***	-1.287***
	(0.304)	(0.319)	(0.306)	(0.361)

Controls	Y	Y	Y	Y
Anderson canon. corr.LM statistic(p)	536.63*** (0.000)		374.51*** (0.000)	
Cragg-Donald Wald Fstatistic	549.57*** (16.380)		380.76*** (16.380)	
Observations	22,285	22,285	22,091	22,091
R-squared		0.126		0.110

The first two columns and the last two columns in Table 3 are the regression results of instrumental variables. The results of the weak IV test show that the Cragg-Donald Wald F values are all greater than the critical value of 10% level, which passes the weak instrumental variable test. Anderson canon. corr.LM statistic of identifiable test rejects the original hypothesis at the level of 1% and satisfies the identifiability of tool variables.

After considering endogenous problems, the regression coefficient of digitalization level to enterprise ESG is significant at 1% level, which shows that the benchmark model results are robust to some extent. The results in columns (2) and (4) of Table 3 show that the coefficients of iv1 and iv2 are significantly positive, and the conclusions are the same as those of the benchmark regression, indicating that the benchmark regression in this paper is robust.

4.3.2 PSM-DID

In this paper, the combination of propensity score matching and difference-in-differences (DID) method is used to alleviate the endogenous problems caused by selection bias. The logit model is used to estimate the tendency score, allowing the existence of juxtaposition, and 1: 1, 1: 2 nearest neighbor matching, and kernel matching are carried out based on the common support domain. This study matches the samples of the control group with the closest tendency score and extracts all the samples of the treatment group enterprises and the control group enterprises during the sample period. This study takes 1: 1 nearest neighbor matching with put back as an example. As shown in Table 4, there is no significant difference in covariates after matching, and they pass the balance test. Figure 1-3 shows that the coincidence degree of the two curves of the experimental group and the control group is higher, which meets the common support hypothesis. Figures 1-1 and 1-2 show that most of the observed values are within the common range, and some samples will be lost after matching. The standardized deviation of all variables is reduced after matching, which proves that the matching is effective.

Table 4 PSM Balance Hypothesis Test

Variable	Unmatched Matched	Mean Treated	Control	%bias	%reduct |bias|	t-test t	p>|t|	V(T)/ V(C)
Size	U	22.50	22.23	20.40		15.99	0	1.25*
	M	22.50	22.48	1.500	92.60	0.950	0.343	1.07*
L.age	U	2.005	1.985	2.100		1.590	0.112	1.08*
	M	2.005	1.994	1.200	forty-four	0.760	0.446	1.13*
Lev	U	0.422	0.429	-3.400		-2.590	0.010	0.95*
	M	0.422	0.418	2.100	36.90	1.410	0.160	0.980
ROA	U	0.0331	0.0397	-10		-7.810	0	1.24*
	M	0.0332	0.0333	-0.100	98.50	-0.0900	0.931	0.86*
IDR_ratio	U	38.14	37.24	16.80		13.09	0	1.17*
	M	38.14	38.10	0.700	95.60	0.470	0.641	1.020
L.Board	U	2.102	2.139	-18.50		-14.31	0	1.09*
	M	2.102	2.103	-0.300	98.60	-0.170	0.866	0.980
SOE	U	0.354	0.406	-10.90		-8.320	0	
	M	0.354	0.346	1.500	85.80	1.030	0.305	.
Growth	U	0.391	0.360	3.100		2.380	0.0170	1.010
	M	0.391	0.368	2.300	24.90	1.510	0.132	0.980

BM	U	0.631	0.614	6.800		5.250	0	1.05*
	M	0.631	0.625	2.400	64.90	1.540	0.123	one
Duality	U	0.320	0.256	14.30		11.13	0	
	M	0.320	0.323	-0.700	95.10	-0.440	0.659	

The DID method is used to investigate the impact of big data experimental areas on the sustainable development of enterprises, and the model is set as follows:

$$ESG_{it} = \alpha + \beta bigdata_j \times post_t + \gamma \text{Controls} + Firm_i + Year_t + \varepsilon_{i,t}$$

In the above model, i and t represent the enterprise and the year, respectively. $bigdata_j$ is the virtual variable of whether the city j belongs to the big data experimental area, with a value of 1 indicating yes and a value of 0 indicating no; $post_t$ is a dummy variable before and after the implementation of the big data pilot zone policy, which is set to 0 before 2016 and 1 after 2016. The other variables are the same as the benchmark regression.

This paper sorts out the areas of the national big data comprehensive experimental zone approved in 2016 by the Chinese government network. The Pearl River Delta is affected by other cities in Guangdong Province, and all cities in Guangdong are treated as treatment groups in this paper. In the sample after propensity score matching, the enterprises in the treatment group have similar characteristics to those in the control group in the year before digital technology innovation, which makes the digital technology innovation behavior of the sample enterprises closer to the setting of quasi-natural experiments.

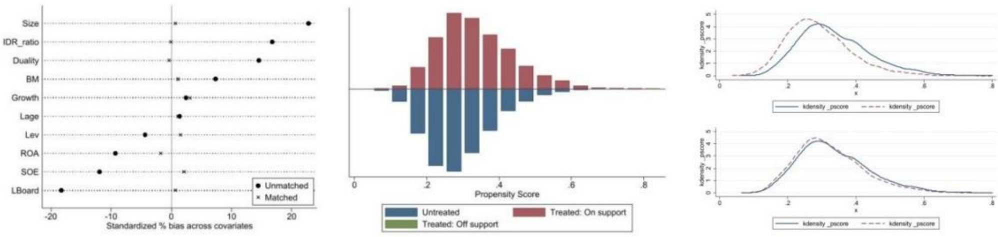

Figure 1-1 Diagram of Standardized Deviation of Variables Figure 1-2 Common Value Range of Tendency Score Figure 1-3 Kernel Probability Density

The result of DID regression is shown in Figure 5, in which columns (1-3) are 1:1 nearest neighbor matching with replacement, and 1:2 nearest neighbor matching with replacement and kernel matching respectively. The coefficient is significant at the level of 5%, which demonstrates that the establishment of a big data experimental area can promote ESG score. This is consistent with the conclusion of benchmark regression.

Table 5 PSM-DID Regression Results, Clustering at the Industry Level

VARIABLES	(1) 1:1 with nearest neighbor matching	(2) 1:2 with nearest neighbor matching	(3) Kernel matching
DIA	0.018**	0.019**	0.020**
	(0.009)	(0.009)	(0.008)
Constant	-3.289***	-3.262***	-2.910***
	(0.937)	(0.733)	(0.660)
Controls/Firm&Year FE	Y	Y	Y
	Y	Y	Y
Observations	10,774	13,929	21,172
R-squared	0.717	0.690	0.656

4.4 Other robustness tests

4.4.1 Changing variables

Referring to Xie Hongjun and Lv Xue [41] (2022), this study uses the shareholding of enterprise ESG investment funds as its substitute variable. Explanatory variables use digital technology words in the Chinese Stock Market & Accounting Research, such as artificial intelligence, big data, cloud computing, blockchain, digital technology, etc. The frequency addition of these words is another measure of the degree of digital transformation, totaldigital. Column (1) of Table 6 uses the ESG score of CNRDS as the explained variable; Column (2) uses the ESG score of CNRDS and digital word frequency of CSMAR; Column (3) uses the shareholding of enterprise ESG investment fund as the explained variable. The conclusion is still valid when the variables are measured differently.

4.4.2 Screening samples

The digitalization level of Beijing, Shanghai, and Guangdong Province is ahead of other regions, and the company has strong innovation ability. To avoid the influence of selection bias and extreme value, the samples from these three regions were excluded for regression. Table 6 (4) is the regression result, and digitalization still has a positive effect on the sustainable development of enterprises, and it is significant at the level of 5%.

Table 6 Robustness Test Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	CNRDS_ESG	CNRDS_ESG	ESG_IF	Hz_ESG	Hz_ESG	Industry level clustering	Enterprise level clustering	Regional level clustering
DIA	0.227***		1.365***	0.034***	0.0353***	0.042***	0.042***	0.042***
	(0.046)		(0.395)	(0.007)	(0.00617)	(0.010)	(0.008)	(0.009)
totaldigital		0.008*** (0.002)						
Constant	-20.99***	-5.064***	-1,141***	-4.272***	-3.142***	-4.022***	-4.022***	-4.022***
	(2.825)	(1.545)	(18.40)	(0.494)	(0.350)	(0.605)	(0.579)	(0.419)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	N	N	Y	Y	Y	Y	Y
Year FE	N	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	Y	N	N	N
Observations	22,006	22,279	21,017	14,121	22,285	22,011	22,011	22,011
R-squared	0.683	0.433	0.237	0.572	0.569	0.580	0.580	0.580

4.4.3 Dealing with the influence of extreme values

In order to avoid the influence of extreme values on the regression results, we truncate DIA at 5% and ESG at 1% and re-estimate the model (1). The estimation coefficient of DIA in column (5) of Table 6 is significantly positive at the level of 1%, which shows that the estimation results in this paper are still robust.

4.4.4 Change the clustering method

Column (6) of Table 6 clusters standard errors at the industry level. In order to control the autocorrelation problem of random disturbance terms in different periods of enterprises, this study refers to Hong Jun and Lv Xue [41] (2022), to cluster standard errors at the enterprise level. Enterprises in the same region may be affected by the same policy and environment, and there is autocorrelation. The Column (8) mistakenly clusters the standards at the regional level. The estimation coefficient of DIA is still significantly positive at the level of 1%, indicating that digital transformation has significantly promoted the sustainable development of enterprises, and the core conclusion of this paper will not change with the change of clustering dimensions.

4.5 Heterogeneity analysis

4.5.1 Industrial heterogeneity

There are differences in the level of digitalization in different industries, and there are significant differences in resource allocation, production mode, and market demand response among industries. As shown in columns (1-3) of Table 7, the DIA coefficient of the primary industry is not significant, but the coefficients of the secondary and tertiary industries are significant, and through the Fisher test of 1000 samples, the P value is 0.017, and the tertiary industry is greater than the secondary industry with significant differences. The production and operation mode of the primary industry is relatively traditional, and the infrastructure construction is relatively weak, so the DIA coefficient is not significant. The coefficient of the secondary industry is smaller than that of the tertiary industry because the traditional production mode is deeply rooted and the integration of digitalization and ESG is slow. The digital transformation of the tertiary industry has a more obvious role in promoting ESG performance, which benefits from its characteristics of light assets and high innovation, and can quickly integrate digital technology into business.

Table 7 Heterogeneity Analysis Results 1

VARIABLES	(1) Primary industry	(2) Secondary industry	(3) Service sector	(4) Eastern Region	(5) Central Region	(6) Western Region
DIA	0.061	0.032***	0.060***	0.052***	0.001	0.044***
	(0.060)	(0.007)	(0.010)	(0.007)	(0.015)	(0.016)
Constant	-2.486	-3.524***	-5.218***	-3.182***	-5.998***	-4.029***
	(3.324)	(0.481)	(0.675)	(0.493)	(0.993)	(1.074)
Controls/Firm/Year FE	Y	Y	Y	Y	Y	Y
Observations	199	15,569	6,243	14,933	3,268	2,598
R-squared	0.610	0.566	0.612	0.584	0.595	0.610

4.5.2 Regional heterogeneity

In order to explore whether the spatial and geographical differences between regions will affect the empirical results, empirical regression is carried out according to regions. As shown in the column (4-6) of Table 7, the digital transformation of enterprises has a significant positive impact on the sustainable development level of the eastern and western regions, and the promotion to the eastern region is greater than that to the western region, but the role to the central region is not significant. The eastern region has strong economic strength, can quickly use digital technology, accurately match market demand through big data analysis, and has a significant promotion effect compared to other regions. Supported by the national Western development policy, the Western region has made some progress in digital construction, but there is still a gap in technical talents and capital investment. The industrial structure in central China is traditional, and some enterprises don’t know enough about the importance of digitalization, so the effect on the level of sustainable development is not significant.

4.5.3 Digital heterogeneity

Digital technology includes artificial intelligence, blockchain, cloud computing, big data, and digital technology. As shown in Table 8(1-5), the coefficients of the four technologies have different significance levels. The coefficient significance level of AI and BD is high, and the coefficient of cloud computing is the smallest and insignificant because it is not easy to form a perfect application system. Blockchain and digital technology are also used in practice, and the coefficient of blockchain technology is greater.

Table 8 Heterogeneity Analysis Results 2

	(1)	(2)	(3)	(4)	(5)	（6）	（7）	（8）	（9）
VARIABLES	AI	BC	CC	BD	DT	Heavy pollution	Non-heavy pollution	High financing cost	Low financing cost
	0.003***	0.031**	0.001	0.002***	0.0006**	0.025**	0.048***	0.060***	0.022***
	(0.001)	(0.013)	(0.001)	(0.001)	(0.0005)	(0.011)	(0.007)	(0.010)	(0.008)
Constant	-3.846***	-2.522***	-4.263***	-3.854***	-2.508***	-4.646***	-4.177***	-2.054**	-4.997***
	(0.201)	(0.197)	(0.387)	(0.201)	(0.197)	(0.771)	(0.464)	(0.838)	(0.505)
Controls/Firm/ Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	22,285	22,285	22,011	22,285	22,285	6,261	15,713	10,391	11,035
R-squared	0.208	0.126	0.579	0.208	0.126	0.594	0.585	0.590	0.657

4.5.4 Heterogeneity of heavily polluting enterprises

According to the 14 polluting industries specified in the *Catalogue of Classified Management of Environmental Verification of Listed Enterprises* in 2008 by the Ministry of Environmental Protection, they were screened out as heavily polluting industries according to the industry classification in the *Guidelines for Industry Classification of Listed Enterprises* in 2012 by the CSRC. The coefficient passed the Fisher test with the sampling number of 1000, and the P value was 0.039, so the coefficient was heterogeneous. The digital transformation listed in Table 8(6-7) has a positive effect on heavily polluting enterprises, and the coefficient of 0.025 is significant at the level of 5%, which means that the ESG level of heavily polluting enterprises has been improved to some extent by adopting digital means despite the fact that improvement range is smaller than that of non-heavily polluting enterprises. The coefficient of non-heavily polluting enterprises reaches 0.048 and is significant at the level of 1%, which shows that digital means can effectively help them fulfill their environmental responsibilities and improve the corporate governance system.

4.5.5 Heterogeneity of financing cost

In this paper, enterprises with financing costs greater than the annual industry median are defined as high financing costs. The regression results are shown in the column of Table 8(8-9), and the coefficient passed the Fisher test of 1000 samples, with a p-value of 0.006, which shows that the coefficient is heterogeneous. The enterprise coefficient of high financing cost is 0.060, which is significant at 1%, indicating that it can improve ESG performance through digital transformation and continuously improve its ESG performance and market competitiveness. Enterprises with low financing costs also have a significant promotion effect, although the coefficient is lower than those with high financing costs.

4.6 Test of influence mechanism

4.6.1 Environmental responsibility effect test

Model (2) is used to test the digital environmental responsibility effect, and the estimated results are shown in Table 11(1-3). The coefficients of the total number of green patent applications, the number of green invention patent applications, and the sustainable green innovation level of enterprises are all greater than zero, and the coefficients of the first two are significant at the 1% level, and OIP is also significant at the 5% level. It is beneficial to show that digitalization has promoted the strategic vision and sustainable development ability of enterprises in green development.

4.6.2 Social responsibility effect test

In this paper, model (3) is used to test the social responsibility effect of digitalization, and the estimated results are shown in Table 11(4). The positive coefficient is significantly different from 0 at the level of 1% significance, which strongly shows that digitalization can effectively urge enterprises to refer to the GRI sustainable development report guide, and the sense of social responsibility has been significantly improved.

4.6.3 Corporate governance effect test

In this paper, model (4) is used to test the digital corporate governance effect, and the estimated results are shown in Table 11(5-6). Digital transformation has a significant inhibitory effect on the concentration of the supply chain, which encourages enterprises to plan and control the supply chain structure reasonably to reduce potential risks. Column (6) shows that digital transformation can significantly promote the default distance by more than 1%, which shows that digital transformation enables enterprises to better cope with market changes and risks.

Table 11 Mechanism Test

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	OIP	Ecoi1	Ecoi2	Soc	Sup	DD_KMV
DIA	2.447**	0.020***	0.018***	0.004***	-0.559***	0.044***
	(1.107)	(0.005)	(0.004)	(0.001)	(0.069)	(0.017)
Constant	-573.6***	-7.578***	-6.315***	-1.360***	82.80***	29.41***
	(72.47)	(0.303)	(0.264)	(0.0851)	(4.518)	(1.120)
Controls/Firm&Year FE	Y	Y	Y	Y	Y	Y
Observations	18,658	22,011	22,011	22,009	20,961	19,809
R-squared	0.325	0.758	0.735	0.612	0.764	0.571

5. Conclusions and Policy Suggestions

Based on the sample of A-share listed companies in Shanghai and Shenzhen from 2010 to 2022, this paper explores the influence and mechanism of digital transformation on the ESG performance of enterprises, and draws the following conclusions: ① The degree of digital transformation of enterprises is positively correlated with ESG performance. ② Enterprises in the tertiary industry, eastern enterprises, non-heavily polluting enterprises, and enterprises with high financing costs can achieve better ESG performance at a higher degree of digital transformation, and big data and artificial intelligence technologies have a more significant role in promoting ESG. ③ Digital transformation has promoted the ESG performance of enterprises by improving the level of green innovation technology, enhancing corporate social responsibility awareness, and reducing supply chain concentration and corporate risks.

The enlightenment of this paper is as follows: ① Enterprises should effectively use digital transformation to improve ESG responsibility performance. Firstly, enterprises should make full use of the digital environmental responsibility effect, promote the improvement of the green innovation level of enterprises, improve the awareness of corporate environmental responsibility, and then improve the ESG level. Secondly, enterprises should pay attention to the social responsibility effect of digitalization, pay attention to the protection of the rights and interests of shareholders, creditors, and employees, promote the green production process, and provide environmentally friendly and high-quality products that are more in line with customers' expectations; Thirdly, enterprises need to face up to the effect of governance responsibility, make the internal governance system standardized and intelligent by using digital technology, optimize the concentration of supply chain, reduce enterprise risks, and improve governance capacity and level. ② The government should promote the digital transformation and development of the real economy. Firstly, it is important to create a favorable environment for enterprises' green digital technology innovation and urge state-owned enterprises to play a leading role in the process of digital green transformation. Secondly, the government needs to conduct a full investigation to understand the expected effect and real dilemma of the transformation of different types of enterprises, solve common problems, and solve special problems to provide assistance for the digital and green transformation of enterprises. Thirdly, the government needs to encourage green transformation of enterprises, build an ESG mandatory information disclosure system, give play to the supervisory role of the government and people, cultivate corporate social responsibility awareness, and give play to the macro-risk control role of the government.

There are still some shortcomings in this study: first, the sample selected in this study is A-share listed companies in Shanghai and Shenzhen, and the sample coverage is limited. Second, the research of this paper is based on the data of listed companies in China under the background of the Chinese system, and it is impossible to observe the differences in different countries and regions. Third, there is no recognized authoritative measurement method for digital transformation at present. Although the variables selected in this paper refer to relevant research, their scientificity needs further demonstration and testing.

References

[1] Warner, Karl SR, and Maximilian Wäger. "Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal." Long-range planning 52.3 (2019): 326-349.

[2] Fürstenau, Daniel, Catherine Cleophas, and Natalia Kliewer. "How do market standards inhibit the enactment of digital capabilities? A case study of airline pricing." Business & Information Systems Engineering 62 (2020): 279-287.

[3] Singh, Anna, and Thomas Hess. "How chief digital officers promote the digital transformation of their companies." Strategic information management. Routledge, 2020. 202-220.

[4] Mohammad, Wan Masliza Wan, and Shaista Wasiuzzaman. "Environmental, Social and Governance (ESG) disclosure, competitive advantage and performance of firms in Malaysia." Cleaner Environmental Systems 2 (2021): 100015.

[5] Yi Jiabin, Zhang Ziyi, Yang Xiaoping, et al. Organizational inertia, digital capability and business model innovation of Internet enterprises [J]. nankai business review, 2022,25(05):29-42.

[6] Su Jingqin, Sun Yue, Gao Xin. The evolution mechanism of digital capability under the background of continuous digital transformation based on the perspective of resource arrangement [J]. Science Research, 2022,40 (10): 1853-1863. DOI: 10.16192/J.CNKI.1003-2053 ..

[7] Xiao Shuguang. Integration and separation of the two rights under the leading paradigm of human capital [J]. China Industrial Economy, 2009, (03): 111-119. DOI: 10.19581/j.cnki.ciejournal.2009.03.011.

[8] Wang Jing, Han Qihao. An empirical study on the impact of the digital economy on the profits of the commercial circulation industry [J]. Commercial Economic Research, 2021(17):29-31.

[9] Bai Xiong, Zhu Yifan, Han Jinmian. ESG Performance, Institutional Investor Preference and Enterprise Value [J]. Statistics and Information Forum, 2022,37(10):117-128.

[10] Mei Yali, Zhang Qian. The influence of ESG performance on corporate debt financing costs [J]. Finance and Economy, 2023, (02): 51-63. DOI: 10.19622/j.cnki.cn36-1005/f.2023.02.005.

[11] Zhang Changjiang, Zhang Yue, Chen Yuqing. ESG performance, investor confidence and performance of listed companies [J]. Environmental Economic Research, 2021,6 (04): 22-39.doi: 10.19511/j.cnki.jee.2021.04.003.

[12] Chen Mingjing, Yuan Lee Chi. Analysis of the impact of economic policy uncertainty on ESG rating [J]. Business News, 2022, (11):167-170.

[13] Zhou Lili, Tian Fei, Xu Weibin. Does the chain shareholders' meeting affect the ESG performance of enterprises? [J]. Financial Theory and Practice, 2024, (01):90-100.

[14] Chen Xiaoshan, Liu Hongduo. Institutional investors' shareholding and ESG performance of companies [J]. Financial Forum, 2023,28 (09): 58-68. DOI: 10.16529/J.CNKI.11-4613/F.2023.09.004.

[15] Wang Haijun, Wang Songzheng, Zhang Chen, et al. Does digital transformation improve the ESG responsibility performance of enterprises? -empirical research based on the MSCI index [J]. Foreign Economy and Management, 2023,45 (06): 19-35. doi: 10.16538/j.cnki.fem.21128.200100001026

[16] Hao Yuting, Zhang Yonghong. Research on the influence of digital transformation on ESG performance of enterprises under the goal of “double carbon” [J]. Science and Technology and Management, 2022,24 (04): 80-91. DOI: 10.16315/j.stm.2022.04.007.

[17] Li Guolong, Zhu Peihua. Has information infrastructure improved the ESG performance of enterprises? [J]. Finance and Economy, 2022, (09): 52-61. DOI: 10.19622/j.cnki.cn36-1005/f.2022.09.005.

[18] Alina Zhang, Song Shunlin. Enterprise digitalization, innovation-driven policies and ESG performance [J]. Journal of Beijing Technology and Business University (Social Science Edition), 2023,38(06):34-46+101.

[19] Liu Fangyuan, Wu Yunlong. Digital transformation and ESG responsibility performance of enterprises under the goal of “double carbon”: impact effect and mechanism [J]. Science and technology C progress and countermeasures, 2024,41(05):40-49.

[20] He Dexu, Shen Chengcheng, Xu Ziyao. Enterprise Digitalization, ESG Performance and High-quality Development [J]. Economics Trends, 2024, (07):21-37.

[21] Li Yanhua, Jiao Dekun. An empirical study on the impact of digital level on regional energy efficiency differences [J]. Systems Engineering, 2021,39(06):1-13.

[22] Zhao Chenyu. Study on the impact of digital transformation on corporate social responsibility [J]. Contemporary Economic Science, 2022,44(02):109-116.

[23] Luo Jinhui, Wu Yilong. Digital Operation Level and Real Earnings Management [J]. Management Science, 2021,34(04):3-18.

[24] Shine Wong, Xia Tian, Ma Yong, et al. How can the digital transformation of SMEs improve innovation efficiency? Investigation based on empirical sampling method [J]. Research on Science and Technology Management, 2021,41(18):168-174.

[25] Xu Xianchun, Ren Xue, Chang Zihao. Big Data and Green Development [J]. China Industrial Economy, 2019, (04): 5-22. DOI: 10.19581/j.cnki.ciejournal.2019.04.001.

[26] Wang Haihua, Tan Qinying, Li Ye. Application of digital technology, green innovation, and sustainable development performance of enterprises-the moderating effect of institutional pressure [J]. Scientific and Technological Progress and Countermeasures, 2023,40(07):124-135.

[27] Luo Xiying, Zhang Yuan, Wang Yuqiu. Construction of enterprise carbon performance evaluation index system based on the “3E” triangle model [J]. Accounting Communication, 2018, (29): 61-64+129. doi: 10.16144/j.cnki.ISSN 1002-8072.

[28] Xu Yiqing, Zhang Changjiang. Case Analysis of Environmental Performance Information Disclosure of Heavy Pollution Industry Based on Sustainable Development Report [J]. Accounting Monthly, 2015, (02): 40-43. doi: 10.19641/j.cnki.42-1290/f.2015.02.

[29] Chen Xiaohui, Zhang Hongwei. How does the digital economy affect the risk-taking level of enterprises [J]. Economic Management, 2021,43 (05): 93-108. DOI: 10.19616/j.cnki.bmj.2021.05.006.

[30] Zhao Na, Song Zixiang, Li Pei, et al. The impact of digital transformation on corporate financial risks [J]. Scientific decision-making, 2022, (12):21-36.

[31] Xu Xingmei, Quan Xiaofeng, Zhu Shanshan. Supply chain concentration and enterprise innovation-an empirical study based on China manufacturing listed companies [J]. Journal of Business Economics, 2022, (04): 5-16. DOI: 10.14134/J.CNKI.CN33-1336/F.2022.

[32] Liu Zheng, Yao Yuxiu, Zhang Guosheng, et al. Enterprise Digitalization, Specialized Knowledge and Organizational Authorization [J]. China Industrial Economy, 2020, (09): 156-174. DOI: 10.19581/J.CNKI.CIEJournal.2020.09.008.

[33] He Fan, Liu Hongxia. Evaluation of performance improvement effect of digital transformation of entity enterprises from the perspective of digital economy [J]. Reform, 2019, (04):137-148.

[34] Yi Luxia, Wu Fei, Chang Xi. The digital transformation process of enterprises and the main business performance-empirical evidence from the text recognition of annual reports of listed enterprises in China [J]. Modern Finance and Economics (Journal of Tianjin University of Finance and Economics), 2021,41 (10): 24-38. DOI: 10.19559/j.cnki.12-.

[35] Li Yingmei, Jiao Wanru, Yang Zhonghai. Enterprise Digital Transformation and Auditor's Risk Decision [J]. Accounting Monthly, 2023,44 (19): 111-119. DOI: 10.19641/J.CNKI.42-1290/F.2023.10.

[36] He Yubing, Zhou Hui, Ding Jiamin. How does technological diversification affect the continuous innovation of enterprises? [J]. Research on Science of Science, 2017,35 (12): 1896-1909. DOI: 10.16192/j.cnki.1003-2053.2017.12.017.

[37] Huang Linggen. Research on the credit risk of listed companies in China based on EGARCH-GA-KMV model [D]. Lanzhou university of finance and economics, 2024. doi: 10.27732/d.cnki.gnzsx.20007.000000000606

[38] Yuan Chun, Xiao Tusheng, Geng Chunxiao, et al. Digital transformation and enterprise division of labor: specialization or vertical integration [J]. China Industrial Economy, 2021, (09): 137-155. DOI: 10.19581/j.cnki.CIE Journal.2021.09.00

[39] Xiao Hongjun, Shen Hongtao, Zhou Yankun. Digitalization of customer enterprises, ESG performance of supplier enterprises, and sustainable development of supply chain [J]. Economic Research, 2024,59(03):54-73.

[40] Zhao Tao, Zhang Zhi, Liang Shangkun. Digital economy, entrepreneurial activity, and high-quality development-empirical evidence from China [J]. Management World, 2020,36 (10): 65-76. DOI: 10.19744/J.CNKI.11-1235/F.

[41] Xie Hongjun, Lv Xue. Responsible international investment: ESG and China OFDI[J]. Economic Research, 2022,57(03):83-99.