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Chapter: Environmental Dimensions of Sustainable Development

CAN ENTERPRISE DIGITAL TRANSFORMATION REDUCE CARBON EMISSIONS? EVIDENCE FROM LISTED INDUSTRIAL ENTERPRISES IN CHINA

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Annotation. Digital transformation has emerged as a pivotal factor in corporate environmental governance, attracting increasing scholarly attention, yet existing literature lacks sufficient exploration of its impact on enterprise-level carbon emission reduction. Drawing on resource-based view and transaction cost theory, the relationship between digital transformation and carbon emission reduction was examined using panel data from Chinese A-share industrial listed companies spanning 2010-2021. By applying robust econometric methods, the direct effects of digital transformation on carbon emissions were analyzed, and the mediating mechanisms and heterogeneity across different enterprise types were further investigated. Results indicate that digital transformation significantly reduces corporate carbon emissions, with production efficiency improvement and information disclosure quality serving as key mediating pathways. The emission reduction effect is more pronounced in state-owned enterprises, firms under stringent environmental regulation, and high-tech companies. Further analysis reveals that those various digital technologies—artificial intelligence, blockchain, cloud computing, and big data—all demonstrate positive environmental governance effects. The conclusions not only contribute to the literature on digital transformation from an environmental perspective but also provide valuable insights for regulators and enterprises on leveraging digital capabilities to enhance environmental governance performance.

Keywords: digital transformation, carbon emission reduction, environmental governance, production efficiency.

JEL classification: M14, O12, Q55.

Introduction

Climate change has emerged as a critical global challenge in the 21st century, attracting significant attention from policymakers, businesses, and scholars worldwide. Since the 2009 Copenhagen World Climate Change Conference, "coping with climate change" has become a global issue. In pursuit of green economic development,

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countries around the world have paid attention to environmental governance, such as the development of the carbon emissions trading system in the European Union (EU) and the promulgation of Clean Air Act and Clean Water Act in the United States (US). As crucial micro-components of macroeconomies, enterprises' carbon emissions directly influence the efficacy of environmental governance. In China, industrial enterprises contributed approximately 5.046 billion tons to the country's 12.6 billion tons of carbon emissions in 2023, accounting for approximately 40% of the total (International Energy Agency, IEA). Therefore, effectively reducing industrial enterprises' carbon emission intensity has become a key environmental governance priority. Therefore, effectively reducing the carbon emission intensity of industrial enterprises has become a key factor of environmental governance.

The recent digital transformation of enterprises has emerged as a promising approach for reducing industrial carbon emission intensity. With the development of artificial intelligence (AI), cloud computing, blockchain, and big data, the new ecology is gradually being integrated into the production and management processes of enterprises, a development that has significantly changed the production and operation mode and information disclosure conditions of enterprises (Yan, 2019). On the one hand, digital transformation provides direct technical support for improving production efficiency by deeply integrating digital technology with enterprise production processes (Porter and Heppelmann, 2014). On the other hand, in accordance with transaction cost theory, enterprises' business processes can be digitalized and visualized using big data, AI, and blockchain. By optimizing information flow through digital technologies, enterprises can reduce the costs of information acquisition, disclosure, and processing (Leuz *et al.*, 2016; Jin *et al.*, 2023). Improvements in the levels of production efficiency and information disclosure indicate the reduction of resource consumption at the production end of enterprises and that their environmental pollution behaviors will be externally supervised to a greater extent (Li *et al.*, 2024; Li and Zhou, 2023). Given such information, can enterprises' carbon emission levels be effectively reduced by digital transformation?

Existing theoretical research has investigated factors influencing enterprises' carbon emission intensity from different perspectives, including institutional environment and internal reform. The core point of view expressed in the literature regarding institutional environment indicates that enterprises' carbon emission levels can be effectively reduced by powerful institutional constraints (Guo *et al.*, 2017; Garzón-Jiménez et *al.*, 2021; Testa *et al.*, 2018; Rogge *et al.*, 2011; Porter and Heppelmann, 2014; Lu *et al.*, 2023). Regarding enterprises' internal reform, enterprises' carbon emission intensity can be significantly curbed by improving productivity and/or strengthening external supervision due to the change in the ownership structure (Zhang and Feng, 2020; Ding *et al.*, 2023; Song *et al.*, 2023). However, insufficient attention has been paid to whether and how digital transformation affects carbon emission reduction.

In recent years, an increasing number of enterprises have begun to implement digital transformation. Can the application of digital technology become the new kinetic energy that will support enterprises in reducing their carbon emission intensity? The answer to this question not only provides new evidence for digital transformation that can boost the green development of the economy but also provide a "digital prescription" for improving the effectiveness of environmental governance from the enterprise side. Fortunately, the resource-based view (RBV) and transaction cost theory laid a theoretical foundation for the response to this question. In accordance with these ideas, we can assume that digital transformation will provide new technical resources for enterprises, change the conditions of enterprise information collection and transmission, and ultimately generate internal motivation and external pressure on the carbon reduction of enterprises. Thus, the current study attempts to explore the following research question based on the RBV and transaction cost theory: Can the implementation of digital transformation help enterprises reduce their carbon emissions?

The potential contributions of this study are threefold. First, at the theoretical level, it discusses how digital transformation promotes enterprises' carbon emission reduction based on RBV and transaction cost theory, expanding these theories' application scope. Second, at the literature level, from the perspective of enterprise internal transformation, the effect of digital transformation on the enterprises' carbon emission reduction was empirically tested, and new insights were provided for the economic consequences of enterprises' digital transformation. Most of the existing studies have discussed the influence of macro-policies on microenterprises' environmental governance behavior from the perspective of institutional environment (Tang *et al.*, 2022). However, policy requirements cannot provide sustainable endogenous motivation for enterprises to reduce carbon emissions, and they are also easily affected by policy changes (George *et al.*, 2014). Therefore, the present study expands the discussion on the influencing factors of corporate environmental governance. Furthermore, academic research on the economic consequences of digital transformation mostly focuses on economic benefits, such as input–output efficiency (Liu *et al.*, 2021; Wang *et al.*, 2023), and total factor productivity (TFP; Brynjolfsson *et al.*, 2020; Martin *et al.*, 2016). Under the guidance of the concept of economic green development, the current study extends the economic consequences of digital transformation to the field of low-carbon emission reduction, thereby providing new evidence demonstrating how digital transformation can boost economic green development (Ma *et al.*, 2022; Anderson *et al.*, 2003; Nambisan *et al.*, 2019). Third, at the practical level, the conclusion of this study is of enlightening significance for improving environmental policies. Compared to the innovation breakthroughs of certain technologies in the industry, digital transformation is more general and universal, and its low-carbon effect is not limited to the industry to a certain extent. Therefore, it provides reference for enterprises in other industries to tap into low-carbon potential with digital transformation as the starting point. This work also provides policy enlightenment for the digital economy to expedite green economic development.

The remainder of this study is organized into sections. Section 1 presents the theoretical analysis and research hypotheses, Section 2 discusses the sample selection and model design, Section 3 presents and analyzes the empirical results, Section 4 discusses the findings, and Section 5 presents the conclusions and managerial implications.

1. Theoretical Analysis and Hypothesis Development

1.1 Enterprises' Digital Transformation and Carbon Emission Intensity

Enterprises' carbon emission intensity can be reduced by improving production efficiency and information disclosure quality. Furthermore, a lower carbon emission level can be realized by ceasing economic activities with relatively high carbon emission intensity and/or reducing the unit carbon emissions produced during certain economic activities. However, for enterprises, economic organizations in pursuit of profits, reducing carbon emissions in exchange for economic benefits is not sustainable (Verhoef *et al.*, 2021). Therefore, enterprises must substantially improve their production efficiency to balance business objectives and low-carbon objectives, create the same or greater value with less carbon emissions, and reduce energy consumption attached to their unit products (Chi *et al.*, 2020). Additionally, to realize low-carbon transformation, enterprises must invest additional costs, such as increased investments in pursuing R&D and innovation as well as purchasing low-carbon environmental protection equipment (Lu *et al.*, 2025). Such extra costs can undoubtedly increase the burden on enterprises and reduce investments in their main businesses. Therefore, due to opportunistic motives or short-sighted psychology, management will be more inclined to invest resources in projects that can bring direct benefits (Chen *et al.*, 2020; Zhang and Feng, 2020).

The literature has also shown that strong external supervision will effectively improve the external constraints on enterprises' green production. For example, Flammer *et al.* (2015) and Zhang *et al.* (2021) pointed out that media supervision can effectively motivate enterprises to fulfill their environmental social responsibilities. The premise of supervision is high-quality information acquisition. Thus, the improvement of enterprise information disclosure quality will provide conditions for external stakeholders to implement supervision, which, in turn, will encourage enterprises to consider the environmental effects of economic activities more and reduce the carbon emission intensity (Chen *et al.*, 2022; Delmas and Toffel, 2008; Ghose *et al.*, 2024; Velte *et al.*, 2020).

Studies have also shown that digital transformation can also effectively improve enterprises' production efficiency. First, the integration of digital technology and production activities can directly exert the productivity effect (Brynjolfsson *et al.*, 2021). The RBV holds that (1) the competitive advantage of enterprises derives from scarce, unrepeatable, and irreplaceable resources and capabilities, and (2) the improvement of production efficiency depends on the support of technical resources. Digital transformation can provide enterprises with high-value technical resources, such as big data and blockchain, and the application of digital technology can produce significant scale effect, thereby improving enterprises' production efficiency (Hanelt *et al.*, 2021; Liu *et al.*, 2023; Dong *et al.*, 2023; Almaqtari *et al.*, 2023). In turn, this will create internal motivation for enterprises to reduce carbon emissions. Furthermore, digital transformation endows enterprises with the ability to accurately analyze consumer demands and improve their ability to cope with changes in the market environment using big data technology. Therefore, enterprises can use digital power to adjust production plans in time, improve their decision-making efficiency, and reduce losses induced by information asymmetry, such as by avoiding ineffective production and energy waste arising from the misjudgment of market demands (Leuz *et al.*, 2016; Gerged *et al.*, 2022; Kotsantonis *et al.*, 2016). In summary, digital transformation can improve enterprises' production efficiency and reduce the energy consumption attached to products.

Digital transformation is also conducive to improving the quality of enterprise information disclosure. Based on transaction cost theory, information asymmetry will increase the supervision cost of external regulators; thus, the reduction of transaction cost will help external regulators form constraints on enterprises' information disclosure behaviors. Information acquisition is the premise of supervision. In case of information asymmetry, supervisors will be forced to increase the cost of information collection; however, their willingness to supervise is low in this case (Ni *et al.*, 2022; Delmas and Toffel, 2008; Bedi and Singh, 2023). Through the application of big data, blockchain, and other technologies, digital transformation can improve enterprises' ability to obtain and process information, as well as facilitate more timely, accurate, and transparent information disclosure, thereby reducing the supervision cost and trust cost brought by information asymmetry to regulators and enhancing their willingness to supervise (Khatri *et al.*, 2022; Peterson *et al.*, 2023).

First, high-quality information disclosure depends on timely acquisition and efficient processing of information. Data mining, storage, and analysis technologies based on big data can transform no standardized and unstructured information into standardized information, enabling them to supplement traditional accounting information disclosure (Warren *et al.*, 2015). The application of blockchain technology in the financial system of enterprises can realize the automatic verification of financial statement data and effectively guarantee the authenticity and security of accounting information. Thus, the application of digital technology has improved corporate ability to process and analyze financial, operational, and management information, thereby laying the foundation for obtaining high-quality information.

Second, high-quality information disclosure depends on the willingness of management to disclose information objectively (Bharadwaj, 2013; Khandelwal *et al.*, 2023). Digital transformation can promote the transformation of an enterprise's organization to a flat-network organizational structure. Such a structure is supported by digital technology with nodes as operating units and has the characteristics of decentralization and disintermediation. Here, all departments of a company are independent nodes, and real-time connections are established between nodes through data and information transmission, resulting in more flexible communication between organizations (Davidson and Mueller, 2023; Harrison and Bartholomew, 2022). In short, the application of digital technology will significantly reduce the transaction costs of external regulators, enhance their willingness to supervise enterprises' information disclosure behaviors, and ultimately exert external pressure on enterprises to disclose information objectively (Fitzgerald and Saunders, 2022).

The above analysis reveals that digital transformation can effectively improve enterprises' production efficiency and information disclosure quality, thus providing technical support and external pressure and guidance for their low-carbon production. Accordingly, the core hypothesis H1 is proposed:

H1: With other conditions being certain, enterprises' carbon emission intensity can be markedly reduced through digital transformation.

1.2 Enterprise Property and Carbon Emission Effect

In the institutional context of China, state-owned enterprises (SOEs) have become an important carrier enabling the government to achieve its policy objectives because of their unique resource endowments and institutional embeddedness (Gatti *et al.*, 2019). Transaction cost theory points out that in case of incomplete market mechanism, SOEs can reduce transaction costs in policy implementation through administrative coordination. For example, the precise poverty alleviation policy involves multidimensional resource integration and cross-departmental coordination. SOEs rely on the advantages of government network resources and information, significantly reducing the negotiation cost and supervision cost in the process of policy implementation, thus undertaking social functions more efficiently. At the same time, private enterprises' resource acquisition is strongly constrained by the market, such that investments in emission reduction may lead to high conversion costs for the redistribution of production factors.

Transaction cost theory further reveals that when the emission reduction policy requirements contradict enterprises' economic objectives, private enterprises tend to adopt opportunistic strategies because they are more sensitive to changes in market transaction costs (Han *et al.*, 2024). Based on the above analysis, the present study assumes that due to the different social functions, SOEs will give full play to the benefits of digitalization in reducing carbon emissions and assume more environmental and social responsibilities. In comparison, private enterprises will make better use of the benefits of digitalization in enhancing enterprise value and would be more willing to reduce carbon emissions. Accordingly, the following hypothesis is proposed:

H2: Compared with private enterprises, the digital transformation of SOEs has a greater carbon emission reduction effect.

1.3 Environmental Regulation and Carbon Emission Effect

Supervision risk is one of the important sources of carbon risk for enterprises. By creating a new contractual relationship, environmental regulation internalizes the negative externality of pollution as a constraint condition for the investment decisions of enterprise-specific assets. For example, the implementation of the "Environmental Protection Tax Law" essentially establishes a bureaucratic governance structure that drives enterprises to reevaluate the cost-benefit structure of investments in emission reduction technology by increasing the asset-specific loss (punitive transaction costs, such as fines and subsidy reduction) (Kotsantonis *et al.*, 2016; Lian, 2021; Yu *et al.*, 2022). Based on the RBV, the difference in environmental regulation intensity shapes the foundation for the resource heterogeneity influencing the carbon management ability of enterprises. In areas that are subject to strong environmental regulations, policy pressure is transformed into the strategic resources of organizational absorptive capacity. To reduce the dynamic transaction costs caused by continuous compliance, enterprises tend to build green technology-specific assets through digital transformation (Fitzgerald and Saunders, 2022).

In comparison, due to the pressure of resource restructuring caused by the lack of policies, enterprises in weakly regulated regions tend to maintain the inertia of traditional production factors allocation. In this case, the carbon emission reduction function of digital transformation often gives way to the market competition demand for marginal productivity improvement (Shen and Zhou, 2020). Therefore, the present work argues that, on the one hand, enterprises in areas with strong environmental regulations have greater policy pressure and are more motivated to reduce carbon emissions through digital transformation to meet policy requirements. On the other hand, enterprises in areas with weak environmental regulations have less policy pressure and are not motivated enough to reduce carbon emissions through digital transformation. Accordingly, the following hypothesis is proposed:

H3: The carbon emission reduction effect of digital transformation on enterprises in areas with strong environmental regulation is more significant than on enterprises located in areas subject to weak environmental regulation.

1.4 High-tech Enterprises and Carbon Emission Effect

The differences in enterprises' carbon emission control efficiencies stem from the heterogeneity of their resource reconstruction ability. High-tech enterprises rely on special resources, such as digital infrastructure and technical talent pools, to deeply embed digital technology into carbon emission monitoring, process optimization through complementary investments, and form a green technology isolation mechanism to reduce the marginal cost of emission reduction (Blackburn, 2023; Porter and Heppelmann, 2014; Alareeni *et al.*, 2020). Nonhigh-tech enterprises are limited by the lack of specificity of human capital and the rigidity of organizational routines. When enterprises fail to adapt technological innovations into their organizational management and corporate strategies through dynamic resource management, digital investments often stop at general assets, such as equipment renewal, which cannot trigger substantive changes in production to reduce carbon emission intensity (Li *et al.*, 2021). For example, when enterprises lack the strategic awareness to generate the "value scarcity" of digital resources, their emission reduction behavior will be stuck in "efficiency illusion", that is, the superficial digital transformation fails to meet the efficiency requirements of carbon emission reduction. Based on the above analysis, the following hypothesis is proposed:

H4: The carbon emission reduction effect of digital transformation is more marked among high-tech enterprises than nonhigh-tech enterprises.

2. Methodology

2.1 Sample Selection and Data Source

Considering that industrial enterprises are an important source of social carbon emissions, discussing the emission reduction mechanism of this group is of great significance for realizing green economic development goals. Limited by the availability of sample data, the A-share listed industrial enterprises in the Shanghai and Shenzhen Stock Exchanges of China during 2010-2021 were selected as research samples. The data were acquired by matching the A-share listed enterprises in the Shanghai and Shenzhen Stock Exchanges and the enterprise list in China Industrial Enterprise Database. On this basis, the samples were screened as follows: First, the samples with missing values were excluded; second, the samples with such data abnormalities as ST, PT, and asset-liability ratio of >1 were excluded; and third, the enterprises delisted within the sample period were deleted, and 13,411 company-year observed values were finally obtained. To relieve the impact of extreme values on empirical results, all continuous variables were subject to ±1% winsorization. Unless specially explained, the relevant data were directly derived from Wind database or calculated based on the data found in this database.

2.2 Measurement of Variable

To test the impact of digital transformation on corporate carbon emissions, the following empirical model was constructed. Considering the hysteresis of the impact of digital transformation on enterprises' production and operation activities, the explained variable was subjected to lag 1 phase processing to alleviate the endogeneity problem arising from reciprocal causation.

$$Carbon_{i,t+1} = \alpha_0 + \alpha_1 Digit_{i,t} + \alpha_i Controls_{i,t} + \sum Id + \sum Year + \varepsilon_{i,t} \quad (1)$$

Here, the explained variable, *Carbon*, is the scale of enterprise carbon emissions, which we measured by dividing the enterprise carbon dioxide emissions by the main income in this study. Enterprise carbon dioxide emissions were estimated based on the energy consumption of the industry. The specific calculation method involves first obtaining the ratio of the total operating cost of the enterprise to the main business cost of the industry, and then multiplying it with the industry's total energy consumption and carbon dioxide conversion coefficient. The data of industries' main operating costs and total energy consumption came from the China Industrial Economic Statistical Yearbook and the China Energy Statistical Yearbook, respectively. In accordance with the carbon dioxide calculation standard of the Xiamen Energy Conservation Center, the carbon dioxide conversion coefficient for 1 ton of standard coal is 2.493. The obtained data on carbon dioxide emissions were divided by each enterprise's main business income, and the product was reduced by 1,000,000 times to obtain the enterprise's carbon emission intensity value. The greater the value, the higher the enterprise's carbon emission intensity. Chapple *et al.* (2013) and Shen and Huang (2019) measured enterprises' carbon emission intensity in a similar way to the current study.

The explanatory variable, *Digit*, is the degree of enterprise digital transformation, which is determined through the text analysis method. Specifically, the annual reports of A-share listed companies in the Shanghai and Shenzhen Stock Exchanges from 2010 to 2022 were acquired and consolidated with the help of Python crawler function, after which all the text contents were extracted as a data pool for subsequent feature word screening. Then, the frequencies of words related to digital transformation in the annual reports of listed companies were counted via Python software and added with 1 to take the natural logarithm, finally acquiring the enterprise digital transformation degree (*HardDigit*). As for the determination of feature words related to enterprise digital transformation, an index system for enterprise digital transformation was constructed with the following keywords: "artificial intelligence", "business intelligence", "cloud computing", "stream computing", "graph computing", "big data", "data mining", "text mining", "digital visualization", "blockchain", "digital currency", "mobile internet", and "industry internet" from four modules, namely, AI, blockchain, cloud computing, and big data.

In the literature, the abovementioned method has been commonly adopted to measure enterprises' digital transformation degree. To enhance the robustness of empirical results, the practices employed by Kretschmer *et al.* (2022) and Zhang *et al.* (2021) were referenced to remeasure the digital transformation degree (*SoftDigit*), using the ratio of input in digital transformation-related software to intangible assets. In the present study, the following variables that might affect enterprise carbon emission intensity were controlled from three levels (enterprise finance, governance, and regional environment): enterprise size (*size*, the natural logarithm of ending total assets), asset-liability ratio (*Lev*, total liabilities/total assets), profitability level (*Roe*, net profit/average balance of shareholders' equity), working capital (*Cashflow*, monetary fund/total assets), enterprise age (*Firmage*, the natural logarithm of the company's years of establishment), executive shareholding ratio (*Mshare*, the number of executives holding shares/the total number of shares), equity balance degree (*Top1*, the number of shares held by the largest shareholder/the total number of shares), proportion of independent directors (*Indep*, number of independent directors/total number of directors), regional economic development level (*Lngdp*, the natural logarithm of per capita GDP at the urban level), and regional environmental pollution control intensity (*Envir*, provincial industrial environmental pollution control investment/provincial industrial added value). Moreover, to control the year fixed effect (*Year*) and the enterprise individual fixed effect (*Id*) and thereby relieve the endogeneity problem caused by variable omission as far as possible, the above practice was actually referenced in previous studies (Bu and Zhao, 2022; Caballero *et al.*, 2008).

2.3 Descriptive Statistical Analysis

Table 1 reports the descriptive statistical results of all variables in Model (1). As shown in Table 1, the mean value of Carbon was 1.137, the variance was 1.564, the minimum value was 0.246, and the maximum value was 41.482, all indicating great differences in carbon emission levels among different enterprises. These figures also indicate that the green and low-carbon transformation of individual enterprises has not been carried out substantially, which also provides a realistic basis for the discussion on related topics in the present study. The mean value of *HardDigit* was 1.321, and the standard deviation was 1.431. The standard deviation was greater than the mean value, the maximum value was 5.169, and the minimum value was 0. This finding not only reveals significant differences in the digital transformation degree among different enterprises but also reflects that the digital transformation degree of listed enterprises in China has great room for promotion. Additionally, the distribution properties of control variables are basically consistent with the existing literature. Thus, they would not be detailed here.

Table 1. Descriptive statistical results

Variable	*N*	*Mean*	*SD*	*Min*	*Median*	*Max*
Carbon	13411	1.137	1.564	0.246	1.422	41.482
HardDigit	13411	1.321	1.431	0	1.524	5.169
SoftDigit	13411	0.121	0.254	0	0.026	1
Size	13411	22.155	1.272	19.525	22.007	26.395
Lev	13411	0.414	0.206	0.027	0.404	0.990
Roe	13411	0.059	0.151	-1.112	0.073	0.442
Cashflow	13411	0.044	0.068	-0.212	0.042	0.258
Firmage	13411	2.873	0.352	1.099	2.944	3.555
Msahre	13411	0.161	0.206	0	0.033	0.709
Top1	13411	0.322	0.140	0.084	0.300	0.758
Inde	13411	0.378	0.055	0.300	0.364	0.600
Lngdp	13411	6.713	4.526	2.523	8.800	14.860
Envir	13411	0.004	0.004	0	0.003	0.029

Source: authors' own results.

3. Results Analysis

3.1 Reliability and Validity Analysis

Although the positive effect of digital transformation on enterprises' carbon emission reduction was empirically tested, this might result from the bias of Model (1) establishment (e.g., the omission of important control variables, the reciprocal causation between explanatory and explained variables, the bias of sample selection, and the measurement bias of key variables). Therefore, to verify the robustness of the above conclusion, the necessary robustness test would be performed.

3.1.1 Instrumental Variables

Enterprises' digital transformation degree and intensity of carbon emissions are affected by the fundamentals of enterprises, which may adversely affect the main research conclusions of this study. Although the possible endogeneity problem was controlled through the lag 1 phase processing of the explained variable in the baseline regression section, the practice of Huang *et al.* (2019) and Yuan *et al.* (2021) was referenced to further enhance the preciseness of the above conclusion. This was done to relieve the endogeneity problem of Model (1) by taking the interaction term (Net) between the number of fixed-line telephones per one million period in each city in 1984 and the number of persons surfing the internet across China, which was lagged for 1 phase, as the instrumental variable. First, the communication mode used by enterprises in the past development process will affect the acceptance and application of new information technologies by enterprises in the sample period from the aspects of technical level and social preference, thus meeting the relevance conditions. Second, at the same time, posts and telecommunications, as social infrastructure, mainly provide communication services for the public while not directly acting upon enterprises' economic activities, thus meeting the exogeneity condition. Furthermore, the instrumental variable was statistically tested in this study. The results showed that the P value corresponding to the test result of Kleibergen-Paaprk LM statistics was 0.000, indicating the absence of any unidentifiable problem. Additionally, the first-stage regression showed that the F value was 144.19, which was much greater than the empirical value of 10, thereby reflecting the original assumption that the instrumental variable was weakly identifiable. In summary, the quality of the selected instrumental variable is high as proved by the above theoretical analysis and statistical test.

Table 2 reports the regression results of the instrumental variable. Based on the first-stage regression results of Columns (1) and (2), the coefficient of Net was significantly positive. This finding indicates that the higher the number of users gaining accesses to urban Internet broadband, the higher the digital transformation degree of local enterprises. Next, in accordance with the second-stage regression results of Columns (3) and (4), the coefficients of *HardDigit* and *SoftDigit* were significantly negative, indicating that the main conclusions of this study still held after alleviating the endogeneity problem through the instrumental variable.

Table 2. Test results of instrumental variables

Variable	(1)	(2)	(3)	(4)
	HardDigit	*SoftDigit*	*Carbon*	*Carbon*
Net	0.764*** (8.290)	0.663*** (7.534)		
HardDigit			-0.005*** (-2.929)	
SoftDigit				-0.015*** (-3.085)
Size	8.054*** (7.806)	7.785*** (7.749)	0.943*** (56.791)	0.964*** (28.359)
Lev	-2.051 (-0.622)	-4.310 (-1.324)	0.987*** (11.064)	1.876*** (4.164)
Roe	-0.954 (-0.531)	-1.313 (-0.845)	0.897*** (10.051)	2.101*** (3.251)
Cashflow	-4.145 (-1.053)	-6.031 (-1.463)	1.845*** (11.961)	3.023*** (4.801)
Firmage	20.826** (2.465)	17.601 (1.531)	0.092** (2.019)	0.193** (2.507)
Mshare	-5.782 (-1.047)	-5.053 (-1.235)	-0.129** (-1.982)	-0.318** (-2.388)
Top1	-9.990* (-1.754)	-8.560 (-1.437)	0.492*** (5.145)	0.924*** (3.805)
Indep	-21.743*** (-2.727)	-14.221* (-1.912)	-0.642*** (-3.203)	-1.184*** (-2.741)
Lngdp	0.048 (0.673)	0.055 (0.645)	-0.009*** (-2.872)	-0.050** (-2.397)
Envir	159.889 (1.326)	-7.193 (-0.072)	1.106 (0.167)	-18.431 (-1.401)
_cons	-213.155*** (-6.909)	-207.832*** (-5.435)	-8.071*** (-17.009)	-9.202*** (-8.991)
Year & Id FE	YES	YES	YES	YES
N	11959	11959	11959	11959
R^2	0.242	0.244	0.507	0.519

Note: *** p<0.001, ** p<0.01, * p<0.05.

Source: authors' own results.

3.1.2 Heckman Two-Stage Regression

As mentioned above, the first measure of enterprises' digital transformation in this study was based on the annual report information disclosed by them. Due to certain reasons, some enterprises might have manipulated the information disclosure in digital transformation, which would lead to the loss of randomness in the sample selection of this study. To alleviate the possible sample selection bias, the Heckman two-stage regression was implemented by referring to Nie *et al.* (2022). In the first stage, the dummy variable (*Isdigit*) of enterprise digitalization degree was defined by the median of the digitization degree of the sample in the current year. On the basis of controlling the control variables of the principal regression model, the variable of the mean digitalization transformation degree (*Mean_digit*) of listed enterprises in the same year was added. Finally, the probability (*IMR*) of enterprise digital transformation was estimated by Probit. In the second stage, *IMR* was added as a control variable to Model (1) for the regression. Columns (1) and (2) of *Table* 3 present results of the abovementioned related regression. As shown in Column (1) of *Table* 3, the coefficient of *Mean_digit* was significantly positive, indicating that enterprises' digital transformation strategy referred to the decisions of other enterprises in the same industry. As shown in Column (2), the coefficient of *HardDigit* was still significantly negative after adding *IMR*, indicating that the main conclusion of this study remained valid after controlling the possible sample selection bias.

Table 3. Heckman two-stage and PSM regression results

Variable	**(1)**	**(2)**	**(3)**	**(4)**
	Isdigit	***Carbon***	***Carbon***	***Carbon***
Mean_digit	0.561*** (6.042)			
HardDigit		-0.006*** (-3.819)	-0.008*** (-4.681)	
SoftDigit				-0.035*** (-8.721)
IMR		-0.102*** (-3.306)		
Size	6.263*** (5.333)	0.808*** (16.953)	0.769*** (12.738)	0.677*** (12.944)
Lev	-4.678 (-1.507)	0.249** (2.100)	0.632*** (4.880)	0.431*** (3.511)
Roe	0.686 (0.473)	0.272*** (3.411)	0.555*** (5.543)	0.246*** (2.694)
Cashflow	-3.275 (-0.722)	0.661*** (5.101)	0.770*** (5.190)	0.532*** (3.841)
Firmage	0.933 (0.085)	0.790*** (2.597)	0.707*** (2.859)	0.294 (1.442)
Mshare	-3.522 (-1.120)	0.082 (0.749)	0.118 (0.900)	0.255** (2.312)
Top1	-14.628** (-2.461)	0.044 (0.179)	-0.301 (-1.024)	-0.314 (-1.123)
Indep	-4.596 (-0.631)	0.328 (1.374)	-0.064 (-0.277)	0.094 (0.408)
Lngdp	0.280*** (3.010)	0.009*** (3.204)	0.009** (2.329)	0.009*** (3.310)
Envir	34.596 (0.351)	4.388 (0.850)	2.197 (0.306)	4.877 (0.836)
_cons	-129.255*** (-3.523)	-7.763*** (-5.927)	-6.175*** (-4.468)	-2.890** (-2.409)
Year & Id FE	YES	YES	YES	YES
N	11959	11959	10644	10644
R^2	0.153	0.455	0.497	0.525

Note: *** p<0.001, ** p<0.01, * p<0.05.

Source: authors' own results.

3.1.3 PSM Regression

The PSM regression test was conducted to alleviate the negative impact of the possible sample self-selection on the main conclusions of this study. Specifically, the median of the digitalization degrees of samples in the present year was still taken as the dummy variable of enterprise digitalization degree, after which the samples were grouped to facilitate the analysis. Then, all control variables in Model (1) were taken as covariables for nonplacement 1:1 and nearest-neighbor matching. Finally, the matched samples were subjected to regression, with relevant results listed in Columns (3) and (4) of Table 4. The results revealed that after the self-selection problem of samples was relieved through PSM matching, the coefficients of the main explanatory variables remained significantly negative, manifesting, once again, the good robustness of the baseline regression conclusion.

3.1.4 Replacement of Key Variable Measurement Methods

To alleviate the adverse effects of the measurement errors of key variables on the above main conclusions, the explained variable and explanatory variables were remeasured. First, enterprises' pollutant emissions mainly included the chemical oxygen demand and ammonia nitrogen emissions in industrial wastewater, along with the sulfur dioxide and nitrogen oxide emissions in industrial waste gas. In this study, referring to the practice of Mao *et al.* (2022) and in accordance with the pollution equivalent values (i.e., the hazard extent of pollutants or pollutant discharge activities to the environment and the technical economy of pollutant treatment, and the comprehensive indicators or measuring units measuring the environmental pollution of different pollutants) determined in the Measures for the Administration of Fee Collection Standards, the emission amount of the above four pollutants was summed and added with 1 to take the logarithm. Then, the product was employed to reflect enterprises' pollutant discharge levels (*Carbon2*).

Second, the digital transformation index (*IndexDigit*) of Chinese listed enterprises established by Guangdong University of Finance was taken as the explanatory variable. After changing the measurement method for key variables, the relevant regression results are listed in *Table* 4. As revealed by the coefficient symbols of relevant variables and their significance, the main conclusions of this study still held true after relieving the bias of key variable measurement methods.

Table 4. Regression results after the replacement of key variable measurement methods

Variable	**(1)**	**(2)**	**(3)**
	Carbon2	***Carbon2***	***Carbon***
HardDigit	-0.007*** (-5.449)		
SoftDigit		-0.018*** (-5.298)	
IndexDigit			-0.095*** (-2.952)
Size	0.757*** (19.058)	0.772*** (14.667)	1.711*** (3.895)
Lev	0.586*** (5.983)	0.599*** (5.251)	-4.335*** (-2.924)
Roe	0.526*** (6.566)	0.566*** (6.258)	9.178*** (8.156)
Cashflow	0.685*** (5.600)	0.758*** (5.612)	6.986*** (3.331)

Table 4 *(continuation*). Regression results after the replacement of key variable measurement methods

Firmage	0.462*** (2.752)	0.597*** (2.747)	5.377** (2.258)
Mshare	0.042 (0.420)	-0.001 (-0.005)	4.117** (2.238)
Top1	-0.158 (-0.790)	-0.120 (-0.492)	0.857 (0.360)
Indep	0.097 (0.486)	0.050 (0.237)	-0.747 (-0.261)
Lngdp	0.009*** (2.947)	0.010*** (2.790)	0.040 (0.822)
Envir	1.877 (0.361)	2.317 (0.376)	0.979*** (2.786)
_cons	-5.328*** (-5.958)	-5.998*** (-4.886)	60.378*** (5.264)
Year & Id FE	YES	YES	YES
N	11959	11959	11959
R^2	0.503	0.513	0.552

Note: *** p<0.001, ** p<0.01, * p<0.05.

Source: authors' own results.

3.2 Correlation Analysis

Table 5 reports the regression results of Model (1) in this study. As seen in Columns (1) and (2), without control variables, the coefficients of the explanatory variables *HardDigit* and *SoftDigit* were significantly negative. This finding preliminarily indicates that digital transformation is conducive to realizing low-carbon transformation and reducing carbon emissions. Furthermore, as shown in Columns (3) and (4), after adding the control variables, the coefficients of *HardDigit* and *SoftDigit* remained markedly negative, further demonstrating the above conclusion. In summary, the baseline regression results of Model (1) indicate that digital transformation is helpful for enterprises to realize green and low-carbon development, thereby verifying the main hypothesis of this study.

Table 5. Regression results of digital transformation and enterprise carbon emissions

Variable	**(1)**	**(2)**	**(3)**	**(4)**
	Carbon	***Carbon***	***Carbon***	***Carbon***
HardDigit	-0.004*** (-3.664)		-0.006*** (-5.873)	
SoftDigit		-0.050*** (-12.965)		-0.035*** (-11.305)
Size			0.784*** (21.248)	0.703*** (22.503)
Lev			0.545*** (6.105)	0.376*** (4.311)
Roe			0.495*** (6.561)	0.235*** (3.350)
Cashflow			0.736*** (6.587)	0.576*** (5.433)

Table 5 *(continuation)*. Regression results of digital transformation and enterprise carbon emissions

Firmage			0.518*** (3.231)	0.318** (2.072)
Mshare			0.050 (0.515)	0.100 (1.088)
Top1			-0.066 (-0.361)	-0.079 (-0.426)
Indep			0.214 (1.167)	0.288 (1.640)
Lngdp			0.010*** (3.566)	0.011*** (4.758)
Envir			5.075 (1.130)	8.872** (2.268)
_cons	12.293*** (211.289)	12.729*** (202.995)	-6.101*** (-7.150)	-3.529*** (-4.634)
Year & Id FE	YES	YES	YES	YES
N	11959	11959	11959	11959
R^2	0.038	0.042	0.499	0.517

Note: *** p<0.001, ** p<0.01, * p<0.05.

Source: authors' own results.

3.3 Mechanism Test

Thus far, the positive effect of digital transformation on the reduction of enterprise carbon emissions has been verified through the strict empirical test. However, a further question must be answered: What factors allow digital transformation to help enterprises realize carbon emission reduction? The current study proposes that the improvement of production efficiency and information disclosure quality serves as the potential mechanism enabling digital transformation to promote enterprises' green development. First, the improvement of production efficiency can effectively reduce resource consumption in the production process of products, thus reducing enterprises' carbon emission level overall. Furthermore, digital transformation has a positive effect on improving enterprises' production efficiency. On the one hand, the application of digital technology can greatly improve the intelligence and automation level of enterprises, optimize production processes, and improve their production efficiency (Hanelt *et al.*, 2021). On the other hand, big data technology enables enterprises to monitor market demands in real time, enables them to improve their sensitivity and ability to predict changes in demand, and reduces enterprises' efficiency losses through the accurate and dynamic adjustment of production plans (Liu *et al.*, 2023; Tang *et al.*, 2022).

Furthermore, apart from affecting production efficiency, digital transformation also reconstructs enterprises' organizational mode and promotes the efficient flow of information within enterprises (Lin and Kunnathur, 2019). Meanwhile, digital technology also plays an important role in mining nonstandardized information and ensuring the authenticity of enterprise information (Leuz *et al.*, 2016; Barman and Mahakud, 2024; Zhang and Yang, 2022), thus laying the foundation for high information disclosure and efficient external supervision of enterprises. Such a development also guides enterprises to low-carbon production and operating activities, allowing them to meet the green expectations of external stakeholders.

To test the correctness of the above two mechanisms, the mediator effect was tested based on Baron and Kenny (1986). Specifically, the following mediating model was constructed:

$$Inter_{i,t} = \alpha_0 + \alpha_1 Digit_{i,t} + \alpha_i Controls_{i,t} + \sum Id + \sum Year + \varepsilon_{i,t} \quad (2)$$

$$Carbon_{i,t} = \gamma_0 + \gamma_1 Digit_{i,t} + \gamma_2 Inter_{i,t} + \gamma_i Controls_{i,t} + \sum Id + \sum Year + \varepsilon_{i,t} \quad (3)$$

Where Inter represents mediator variables, namely, enterprise production efficiency (*Eff*) and information disclosure quality (*KV*). With reference to Hu *et al.* (2020), enterprise production efficiency was measured through the TFP obtained by the OLS method; the data was directly derived following Kim and Verrecchia (2001) and Lin *et al.* (2016); and enterprises' information disclosure quality was measured using the *KV* index.

Table 6. Mechanism test results of production efficiency

Variable	**(1)**	**(2)**	**(3)**	**(4)**
	Eff	***Carbon***	***Eff***	***Carbon***
HardDigit	0.001*** (2.656)	-0.005*** (-5.398)		
SoftDigit			0.001*** (2.693)	-0.028*** (-4.725)
Eff		-0.187*** (-3.116)		-0.184*** (-3.188)
Size	0.190*** (8.897)	0.755*** (20.490)	0.203*** (6.599)	0.749*** (12.680)
Lev	0.343*** (4.935)	0.445*** (4.893)	0.424*** (4.680)	0.465*** (3.582)
Roe	0.837*** (16.875)	0.261*** (3.549)	0.821*** (13.507)	0.297*** (3.113)
Cashflow	0.277** (2.482)	0.724*** (6.512)	0.081 (0.589)	0.836*** (5.662)
Firmage	-0.191** (-2.537)	0.604*** (3.724)	-0.446*** (-3.759)	0.801*** (3.166)
Mshare	0.065 (0.880)	0.036 (0.363)	0.001 (0.018)	0.026 (0.199)
Top1	0.105 (0.905)	-0.110 (-0.600)	-0.077 (-0.517)	-0.216 (-0.792)
Indep	0.102 (0.557)	0.219 (1.173)	0.063 (0.275)	-0.007 (-0.029)
Lngdp	-0.001 (-0.507)	0.011*** (3.958)	-0.001 (-0.206)	0.011*** (2.802)
Envir	-6.308 (-1.567)	6.282 (1.479)	-7.572 (-1.237)	4.662 (0.711)
_cons	-3.539*** (-7.430)	-5.670*** (-6.701)	-3.070*** (-4.328)	-5.966*** (-4.343)
Year & Id FE	YES	YES	YES	YES
N	11959	11959	11959	11959
R^2	0.139	0.510	0.143	0.521

Note: *** p<0.001, ** p<0.01, * p<0.05.

Source: authors' own results.

Table 6 reports the mediating effect regression results of enterprise production efficiency. Taking *HardDigit* as an explanatory variable, for example, as shown in Column (1), when *Eff* served as an explanatory variable, the coefficient of the key variable *HardDigit* was significantly positive, indicating that enterprises digital transformation can effectively improve their production efficiency and that the energy consumption in the production process will be reduced simultaneously. As shown in Column (2), the coefficient of *HardDigit* was still significantly negative after adding the mediator variable *Eff* to Model (1), and the absolute value of the coefficient was lower than that of Model (1). Furthermore, the coefficient of *Eff* was also significant. When *SoftDigit* was used as the explanatory variable, the correlation regression results were basically the same. Based on the above regression results and the mediating effect test method, the mediating effect of *Eff* was established. Digital transformation can reduce enterprises' carbon emissions by improving their production efficiency. To further verify the correctness of the above conclusions, the Sobel test was further carried out in this study, with the results indicating that, when *HardDigit* and *Digi2* were used to measure enterprises' digital transformation levels, the corresponding *P* values were all less than the empirical value of 0.05, thus verifying the above mediating effect test results again.

Table 7. Mechanism test results of information disclosure quality

Variable	**(1)**	**(2)**	**(3)**	**(4)**
	KV	***Carbon***	***KV***	***Carbon***
HardDigit	0.001** (2.259)	-0.006*** (-5.869)		
SoftDigit			0.002** (2.283)	-0.024*** (-4.841)
KV		-0.008** (-2.208)		-0.021** (-2.365)
Size	0.068*** (4.899)	0.784*** (21.664)	0.049*** (2.834)	0.779*** (13.742)
Lev	-0.248*** (-5.696)	0.547*** (6.147)	-0.189*** (-3.508)	0.592*** (4.782)
Roe	-0.022 (-0.930)	0.495*** (6.568)	-0.031 (-0.979)	0.543*** (5.626)
Cashflow	-0.078 (-1.642)	0.737*** (6.582)	-0.084 (-1.484)	0.784*** (5.487)
Firmage	-0.585*** (-7.716)	0.523*** (3.231)	-0.860*** (-7.505)	0.692*** (2.844)
Mshare	0.326*** (5.504)	0.048 (0.497)	0.350*** (5.325)	0.055 (0.438)
Top1	-3.307*** (-27.538)	-0.039 (-0.170)	-3.563*** (-23.468)	-0.264 (-0.735)
Indep	-0.433*** (-4.359)	0.218 (1.174)	-0.456*** (-3.997)	-0.066 (-0.284)
Lngdp	-0.002** (-2.144)	0.010*** (3.569)	-0.003** (-2.374)	0.010** (2.554)
Envir	1.050 (0.639)	5.061 (1.132)	-0.690 (-0.306)	2.929 (0.421)
_cons	2.177*** (6.205)	-6.115*** (-7.009)	3.371*** (7.660)	-6.322*** (-4.482)
Year & Id FE	YES	YES	YES	YES
N	11959	11959	11959	11959
R^2	0.394	0.510	0.430	0.522

Note: *** *p*<0.001, ** *p*<0.01, * *p*<0.05.

Source: authors' own results.

Table 7 reports the mediating effects of the regression results of information disclosure quality. Taking *HardDigit* as an example to measure enterprises' digital transformation levels, when Ann was subjected to regression using *HardDigit*, the coefficient of *HardDigit* was significantly positive, indicating that information disclosure quality was significantly improved after the digital transformation of enterprises. This finding is consistent with the research conclusions of Lin *et al.* (2022). After adding the mediator variable Ann to Model (1), the coefficients of the related main variables were all significant, and the absolute value of the coefficient of *HardDigit* was lower than that of Model (1). In addition, when *SoftDigit* was used to measure enterprises' digital transformation levels, the relevant regression results remained basically the same. The above results indicate that Ann plays a mediating role in enterprises' digital transformation by facilitating their low-carbon transformation. Similarly, the Bootstrap test was carried out in this study, with the results indicating that the 95% confidence intervals (*CI*) were (0.023, 0.033) and (0.019, 0.046), respectively. Neither set of values included 0, regardless of whether *HardDigit* or *Digit2* was used as the explanatory variable, further verifying the abovementioned conclusions. In summary, improving information disclosure quality is one of the effective mechanisms for enterprises to implement digital transformation and reduce carbon emissions.

3.4 Heterogeneity Analysis

Specific internal and external conditions are required by digital transformation for the effect of reducing enterprise carbon emissions to take place. For instance, enterprises with greater willingness to reduce their carbon emission intensity are more motivated to realize carbon emission reduction through digital technology, while digital transformation is supposed to generate a more obvious carbon emission reduction effect on such enterprises. At the same time, digital transformation is a systematic project that requires the cooperation of corporate organizational structure and management culture. Thus, significant differences are found between different enterprises in their potential release of digital transformation. To further identify the heterogenous scenarios in which digital transformation can exert a positive carbon emission reduction effect, the above main conclusions were subjected to the corresponding heterogeneity analysis.

3.4.1 Heterogeneity Analysis Based on Differences in Property Rights

To test *H2*, the samples were divided into the group of SOEs and the group of non-SOEs based on the nature of property rights, followed by grouped regression, with relevant results listed in *Table* 8. As shown in the results, in the SOE group, the coefficients of the explanatory variables *HardDigit* and *SoftDigit* were significantly negative, while their corresponding coefficients were no longer significant in the group of non-SOEs. The regression results indicated that digital transformation exerted a more evident positive effect on carbon emission reduction among SOEs, thus verifying the above guess. To obtain more robust research conclusions, the Suest intergroup difference test was also performed. The results showed that when *HardDigit* and *SoftDigit* served as the explanatory variables, the *P* values were 0.021 and 0.026, respectively, thus passing the relevant test.

Table 8. Heterogeneity test results based on differences in nature of property rights

Variable	***Group of state-owned enterprises***		***Group of non-state-owned enterprises***	
	(1)	**(2)**	**(3)**	**(4)**
	Carbon	***Carbon***	***Carbon2***	***Carbon2***
HardDigit	-0.011*** (-2.884)		-0.004 (-1.013)	
SoftDigit		-0.042*** (-5.075)		-0.022 (-1.089)
Size	0.749*** (12.889)	0.717*** (18.833)	0.694*** (12.237)	0.696*** (9.281)
Lev	0.676*** (3.385)	0.542*** (5.314)	0.641** (2.582)	0.606*** (4.243)
Roe	0.477*** (3.484)	0.498*** (6.097)	0.486*** (2.626)	0.543*** (4.477)
Cashflow	0.405* (1.947)	0.762*** (5.595)	0.365* (1.789)	0.762*** (3.824)
Firmage	1.464*** (3.907)	0.370** (2.002)	1.733*** (3.214)	0.468* (1.670)
Mshare	0.558* (1.659)	0.028 (0.290)	0.432 (0.478)	-0.007 (-0.049)
Top1	-0.229 (-0.910)	-0.090 (-0.380)	-0.209 (-0.839)	-0.118 (-0.226)
Indep	0.068 (0.223)	0.090 (0.396)	-0.199 (-0.552)	-0.242 (-0.804)
Lngdp	0.002 (0.328)	0.012*** (3.267)	0.002 (0.357)	0.008 (1.594)
Envir	-0.744 (-0.116)	1.554 (0.309)	-7.467 (-1.050)	1.092 (0.113)
_cons	-7.432*** (-5.272)	-4.402*** (-4.790)	-6.893*** (-4.004)	-4.230** (-2.366)
Year & Id FE	YES	YES	YES	YES
N	4192	4192	7767	7767
R^2	0.489	0.510	0.495	0.502

Note: *** p<0.001, ** p<0.01, * p<0.05.

Source: authors' own results.

3.4.2 Heterogeneity Analysis Based on Differences in Environmental Regulation Intensity

To test *H3*, the samples were divided into the group of strong environmental regulation and the group of weak environmental regulation based on the median of environmental regulation intensity. This categorization was followed by the grouped regression, with relevant results listed in *Table* 9. Specifically, referring to the method proposed by Acemoglu *et al.* (2012), the proportion of the word frequency related to "environmental protection" in local government work reports in the total number of words in the entire text of reports was regarded as a proxy variable of environmental regulation (Baalouch *et al.*, 2019).

Specifically, the concrete construction steps of government environmental governance indicators in this study were as follows. First, the government work reports of each city from 2008 to 2022 were collected manually; second, the texts of government work reports were segmented; finally, the frequencies of environment-related words were determines, and their corresponding proportions in the total number of words in the whole text of government reports were multiplied by 100 to obtain the regional environmental regulation index. The environment-related words specifically included the following: environmental protection, pollution, energy consumption, emission reduction, sewage discharge, ecology, green, low carbon, air, chemical oxygen demand, sulfur dioxide, carbon dioxide, PM10, and PM2.5.

As shown in *Table* 9, in the group with strong environmental regulation, the coefficients of principal explanatory variables were all significantly negative, while in the group with weak environmental regulation, the coefficients of the same variables were all negative but not significant. The regression results indicated that under the high pressure of environmental regulation, enterprises were more inclined to comply with policy requirements and actively give full play to the carbon emission reduction effect of digital transformation. Similarly, the Suest intergroup difference test was performed on the above results. The relevant results showed that when *HardDigit* and *SoftDigit* served as the explanatory variables, the P values were 0.008 and 0.013, respectively, further supporting the above conclusion.

Table 9. Heterogeneity test results based on differences in environmental regulation intensity

Variable	***Group of strong environmental regulation***		***Group of weak environmental regulation***	
	(1)	**(2)**	**(3)**	**(4)**
	Carbon	***Carbon***	***Carbon2***	***Carbon2***
HardDigit	-0.009*** (-2.932)		-0.005 (-1.539)	
SoftDigit		-0.038*** (-4.496)		-0.010 (-1.284)
Size	0.775*** (16.065)	0.702*** (15.020)	0.744*** (10.885)	0.674*** (8.878)
Lev	0.585*** (3.819)	0.574*** (4.639)	0.679*** (2.981)	0.663*** (4.066)
Roe	0.509*** (4.569)	0.428*** (4.854)	0.569*** (3.515)	0.453*** (3.562)
Cashflow	0.462** (2.340)	0.752*** (5.372)	0.586* (1.964)	0.683*** (3.986)
Firmage	0.579** (1.981)	0.515** (2.350)	0.728 (1.572)	0.913** (2.411)
Mshare	0.063 (0.436)	0.115 (0.878)	0.057 (0.293)	0.140 (0.691)
Top1	-0.180 (-0.583)	-0.119 (-0.529)	-0.428 (-0.859)	-0.044 (-0.114)
Indep	0.330 (0.966)	-0.177 (-0.755)	0.007 (0.015)	-0.310 (-1.085)
Lngdp	0.016*** (4.001)	0.007 (1.603)	0.012*** (2.640)	0.005 (0.896)
Envir	12.825 (1.634)	-3.755 (-0.736)	7.760 (0.679)	-4.654 (-0.582)
_cons	-6.211*** (-5.207)	-4.104*** (-3.669)	-5.963*** (-2.953)	-4.560** (-2.390)
Year & Id FE	YES	YES	YES	YES
N	5741	5741	6218	6218
R^2	0.477	0.511	0.467	0.495

Note: *** p<0.001, ** p<0.01, * p<0.05.

Source: authors' own results.

3.4.3 Heterogeneity Analysis Based on Differences in Enterprises' Technological Attributes

To test *H4*, it referred to the general practice of the existing literature and classified enterprises in mechanical industry, electronic manufacturing industry, pharmaceutical manufacturing industry, and chemicals manufacturing industry as high-tech enterprises, while others were classified as non-high-tech enterprises. This step was followed by the grouped regression, with regression results listed in *Table* 10. As shown in the table, in the group of high-tech enterprises, the coefficients of all main explanatory variables were markedly negative, while in the group of non-high-tech enterprises, the influence of digital transformation on enterprise carbon emission intensity failed to pass the statistical significance test. Furthermore, the corresponding Suest intergroup difference test was conducted. The related results indicated that when *HardDigit* and *SoftDigit* served as the explanatory variables, the *P* values were 0.021 and 0.020, respectively. Thus, the assumption above was verified by the regression results.

Table 10. Heterogeneity test results based on differences in enterprises' technological attributes

Variable	***Group of high-tech enterprises***		***Group of non-high-tech enterprises***	
	(1)	**(2)**	**(3)**	**(4)**
	Carbon	***Carbon***	***Carbon2***	***Carbon2***
HardDigit	-0.017*** (-4.448)		-0.007 (-1.606)	
SoftDigit		-0.048*** (-11.352)		-0.024 (-1.031)
Size	0.889*** (6.779)	0.752*** (21.737)	0.868*** (3.804)	0.729*** (12.747)
Lev	0.669 (1.480)	0.530*** (5.780)	0.269 (0.423)	0.541*** (4.224)
Roe	1.449*** (4.451)	0.482*** (6.636)	2.221*** (3.145)	0.512*** (4.998)
Cashflow	0.323 (0.993)	0.710*** (5.880)	-0.240 (-0.375)	0.679*** (4.272)
Firmage	1.157 (1.361)	0.446*** (2.607)	-1.990 (-1.486)	0.713*** (2.731)
Mshare	-0.584** (-2.096)	0.054 (0.536)	-37.197** (-2.042)	-0.015 (-0.100)
Top1	-1.347*** (-3.379)	-0.067 (-0.347)	-1.716*** (-4.876)	-0.019 (-0.053)
Indep	-1.116 (-1.508)	0.087 (0.451)	-2.005*** (-2.704)	-0.033 (-0.139)
Lngdp	0.001 (0.124)	0.009*** (3.086)	-0.000 (-0.006)	0.007* (1.666)
Envir	-0.930 (-0.087)	0.545 (0.126)	11.868 (1.032)	-1.927 (-0.284)
_cons	-8.835** (-2.439)	-5.226*** (-6.187)	1.309 (0.160)	-5.425*** (-3.878)
Year & Id FE	YES	YES	YES	YES
N	3157	3157	8802	8802
R^2	0.498	0.503	0.448	0.487

Note: *** *p*<0.001, ** *p*<0.01, * *p*<0.05.

Source: authors' own results.

3.5 Further Analysis

To further investigate the relationship between digital transformation and enterprise carbon emission, digital transformation (*HardDigit*) was subdivided into four subindicators: AI, blockchain, cloud computing, and big data, which were substituted into Model (1) for regression. The regression results are listed in *Table* 11. As revealed by the results, the coefficients of the key explanatory variables under the four subindicators were all significantly negative, indicating that carbon emission reduction was influenced by all levels of enterprise digital transformation. Additionally, the digital transformation under the subindicator AI performed best in reducing enterprises' carbon emissions. This result is possibly due to the deep application of AI as a new generation of general information technologies, which not only realizes dynamic and refined management in economic activities but also provides information reference for optimizing the decision mechanism of pollution prevention and control. In turn, this further improves the efficiency of energy conservation and emission reduction.

Table 11. Regression results after the subdivision of digital transformation

Variable	*Artificial intelligence*	*Blockchain*	*Cloud computing*	*Big data*
	(1)	**(2)**	**(3)**	**(4)**
	Carbon	*Carbon*	*Carbon*	*Carbon*
HardDigit	-0.036*** (-7.390)	-0.004*** (-2.972)	-0.001* (-1.698)	-0.007** (-2.389)
Size	0.893*** (4.737)	0.765*** (16.955)	0.761*** (11.579)	0.756*** (7.944)
Lev	0.061 (0.151)	0.589*** (5.570)	0.582*** (4.379)	0.480** (2.464)
Roe	0.557 (1.452)	0.574*** (6.622)	0.564*** (5.314)	0.673*** (4.675)
Cashflow	1.011*** (3.078)	0.747*** (5.821)	0.714*** (4.619)	0.795*** (4.168)
Firmage	0.105 (0.143)	0.482*** (2.707)	0.687*** (2.619)	0.759 (1.571)
Mshare	-0.432 (-0.119)	0.038 (0.362)	-0.022 (-0.144)	0.334 (1.552)
Top1	-0.462 (-1.044)	-0.206 (-0.936)	-0.201 (-0.591)	-0.597 (-1.577)
Indep	-0.288 (-0.448)	0.116 (0.557)	-0.067 (-0.290)	-0.244 (-0.817)
Lngdp	0.015 (1.599)	0.010*** (3.129)	0.007* (1.820)	0.004 (0.743)
Envir	11.386 (0.704)	1.951 (0.351)	3.497 (0.452)	5.442 (0.650)
_cons	-5.563*** (-5.532)	-5.951*** (-3.935)	-5.668*** (-2.680)	-6.591 (-1.591)
Year & Id FE	YES	YES	YES	YES
N	11959	11959	11959	11959
R^2	0.518	0.486	0.497	0.489

Note: *** *p*<0.001, ** *p*<0.01, * *p*<0.05.

Source: authors' own results.

4. Discussion

Enterprises are the main producers of social carbon emissions. Thus, finding ways to effectively reduce enterprises' carbon emission levels is the key to achieving low-carbon development. Furthermore, digital technologies have been continuously integrated into the production and management processes of enterprises in recent years, thus providing new opportunities for enterprises to accelerate low-carbon development. On this basis, the influence of digital transformation on enterprises' carbon emission levels was empirically tested using the data on industrial listed enterprises in China. This research is associated with the existing literature in the following aspects.

First, this study finds that digital transformation can significantly reduce enterprises' carbon emission levels in which the improvement of production efficiency and the improvement of information disclosure level are two potential paths. Although sufficient attention has been paid to the microeconomic effect of digital transformation, and its positive role in improving enterprise management efficiency (Verhoef *et al.*, 2021) and production efficiency (Liu *et al.*, 2023) has been discussed in the existing literature, whether digitalization has a positive role in reducing enterprises' carbon emission levels has not been explored sufficiently.

Based on the data of listed companies in China, this question was theoretically analyzed and empirically answered in this study. While affirming the notion that digital technology contributes to enterprises' low-carbon development, the specific influence mechanism was further analyzed, thereby beneficially expanding the existing related literature. In addition, based on the RBV and transaction cost theory, the factors enabling digital transformation to promote enterprises' carbon emission reduction was theoretically analyzed, and the application scenarios of both theories were expanded. For example, the traditional RBV focuses on the tangible and intangible resources owned by enterprises, emphasizing their scarcity and no imitation. In the scenario of digital transformation and carbon emission reduction, this study expanded the dynamic connotation of resources and regarded green governance as a new strategic resource. This study argues that green governance not only has the traditional attributes of resources but can also optimize carbon emission efficiency through resource reconfiguration and dynamically gain external support (e.g., stakeholders' trust). For another example, transaction cost theory was incorporated into the analytical framework, helping explain the idea that digital transformation could promote the scenario extension of transaction cost theory from market contract governance to environmental regulation governance by reducing the information search cost and supervision cost of regulators.

Second, the low-carbon effect of digital transformation is more significant in SOEs, enterprises in areas with strong environmental regulations, and high-tech enterprises. When applied, digital technologies objectively enhance enterprises' ability to reduce carbon emissions. However, individual differences exist in terms of the effect exerted by such ability. If considering political goals while pursing economic benefits, enterprises will be more motivated to give full play to the role of digital technology in carbon emission reduction. Those enterprises that are highly constrained by environmental systems will more actively utilize digital technology to reduce carbon emissions and meet legal requirements. Furthermore, high-tech enterprises are more proficient in using digital technology, thus having greater advantages in exerting the carbon emission reduction effect of digitalization. Like the conclusions drawn by Nambisan *et al.* (2019) and Kim and Zhang (2016), the current study verifies the existence of individual differences in the microeconomic effects of digital technology. Such a finding is helpful in providing pertinent reference suggestions for regulators and enterprises to make better use of "digital power".

Third, the digital transformation supported by AI, blockchain, cloud computing, and big data plays a positive role in carbon emission reduction. Enterprises' digital transformation is a systematic project-one that must be supported by various technologies. For instance, Del Giudice *et al.* (2021) and Brynjolfsson *et al.* (2020) found that only some levels of digital transformation have positive micro-effects. In comparison, in the current study, the digital transformations at the bottom-layer technical level (e.g., cloud computing and big data) and the practice level (e.g., blockchain) manifest significant carbon emission reduction effects. Such a finding not only further verifies the main conclusion of this study but also provides evidence for the deep fusion of digital technology with the sustainable development of the real economy.

In other words, the great tide of enterprise digital transformation was combined with the realistic appeal for green and sustainable economic development (i.e., the actual economic development status) to test whether and how digitalization could boost enterprises' low-carbon development. Moreover, what kind of environment digital transformation could positively affect enterprises' carbon emission reduction was discussed. From the research perspective, this study provides a new direction for testing the microeconomic consequences of digital transformation. In conclusion, this study renders evidence for the green governance effect of digital transformation. Therefore, this research continues and extends the existing literature while also providing specific directions for follow-up research.

Conclusions and Implications

Main Findings

Energy conservation and emission reduction at the enterprise level constitute the key to green and sustainable economic development. Given this information, A-share listed industrial enterprises in China were selected as research samples to empirically discuss the effect of digital transformation on enterprises' carbon emission reduction. The conclusions were obtained from this study: (1) the higher the digital transformation level of enterprises, the lower their carbon emission level in which digital transformation exhibits an evident green effect. (2) The improvement of production efficiency and information disclosure quality both serve as important mechanisms therein. (3) Digital transformation exerts a more evident effect on enterprises' carbon emission reduction, especially in areas with strong environmental regulation and high-tech enterprises. (4) Digital transformation in four levels such as AI, blockchain, cloud computing and big data-can all effectively help enterprises to realize carbon emission reduction, and the transformation effect is the best in aspect of artificial intelligence.

Managerial Implications

At the enterprise level, first, enterprises should correctly understand the positive effects of carbon emission reduction and take the initiative to assume environmental and social responsibilities. As an important subject of carbon emissions, enterprises must continuously increase carbon emission reduction to realize their economic green development goals. The descriptive statistical results in this study show that the carbon emissions of listed enterprises in China are generally at a high level and that huge differences exist among different enterprises. These findings indicate that there is room for further carbon emission reductions for enterprises in China. Combined with the conclusion of this study, enterprises should reduce carbon emissions by pursuing the organic integration of digital technology, initiating enterprise production business and information collection and disclosure, smoothing the mechanism of digital transformation to help enterprises achieve carbon emission reduction, and giving full play to the role of digital technology in energy conservation and emission reduction. Second, enterprises should formulate differentiated transformation strategies. The conclusion of this study indicates that SOEs, high-tech enterprises, and enterprises in areas with strict environmental regulations can give full play to digital transformation's carbon emission reduction potential. Such a finding implies that SOEs and high-tech enterprises must play a benchmarking role and reduce the negative externalities of production and business activities. For example, SOEs can take advantage of the government's policy support and resource advantages to take the lead in building digital emission reduction benchmarking projects in heavy industries, such as steel and electric power. In addition, high-tech enterprises must turn the advantages of digital technology into emission reduction solutions and export intelligent emission reduction systems, including providing an efficient carbon management platform for manufacturing. Additionally, enterprises in areas with strong environmental regulations must take the initiative to link with local emission reduction policies and turn digital investment into compliance competitiveness. Meanwhile, enterprises in areas with weak regulations should predict policy trends and decide in advance to avoid a sharp increase in future transformation costs.

At the level of regulators, first, regulators should attach greater importance to the effect of digital technology in promoting the transformation of economic development mode and the high-quality economic development. Digital transformation is a realistic choice for modern enterprises to integrate into the new ecology of digital economy and seize the commanding heights of future development. At the same time, it is also the core engine for the current economy to achieve high-quality development. However, most enterprises generally face the problem of "will not, cannot, and dare not conduct transformation". Furthermore, digital transformation among Chinese enterprises is still in its infancy. This study finds that digital transformation can help enterprises achieve carbon emission reduction by improving their production efficiency and information disclosure quality. This finding inspires government departments to help enterprises solve problems in digital transformation by further strengthening digital infrastructure and setting up digital transformation support funds for them. In turn, such digital support can help enterprises realize green economic development. Second, regulators should strengthen environmental regulation and classified incentives. This study holds that in areas with strong environmental regulations, the carbon emission reduction effect of digital transformation is more remarkable. This finding underscores the idea that regulators should maximize environmental regulatory tools and promote carbon emission reduction in high-emission industries through the combination of "mandatory regulation + precise incentives". For example, the implementation of stricter carbon quotas and monitoring standards in carbon-intensive industries, such as chemicals and construction materials, will force enterprises to adopt digital means to achieve compliance. The authorities can also provide high-tech enterprises special tax subsidies for digital transformation, such as offsetting or exempting taxes to purchase AI emission reduction equipment and set up a mechanism for linking emission reduction performance with management assessment for SOEs. The synergistic effect of regulation and incentive will help accelerate high-emission industry breakthroughs in terms of technology application and compliance.

Limitations and Future Directions

There are still some research limitations. First, the research perspective remains to be further deepened. The independent emission reduction effects of four digital technologies, AI, blockchain, cloud computing, and big data, were verified in this study, but no answer was given as to whether a multiplication effect could be achieved by their collaboration. Furthermore, this research was unfolded based on short-term panel data, making it difficult to observe the long-term dynamic impact of digital transformation on carbon emission reduction. However, the changes in the carbon emission reduction effect of digital transformation after technology iteration were not discussed. These aspects can be further explored in the future research.

Second, limitations were observed in the research samples, which were A-share industrial listed enterprises in China. That this study did not cover non-listed enterprises and nonindustrial sectors, which might restrict the universality of research conclusions. In the follow-up research, the conclusion can be tested through a larger sample size and stricter research design, thus obtaining more universal research conclusions.

Finally, there might be some unidentified endogeneity problems. Although the disturbance caused by endogeneity to the principal regression conclusions was relieved as far as possible through the instrumental variable method, a two-way causal relationship may exist between digital transformation and carbon emission reduction. For example, low-carbon policies may reversely force enterprises' digital transformation. In the future, a stricter causality identification design is required to more comprehensively eliminate the potential endogeneity problem. Such problems as reverse causation can be evaded by selecting appropriate quasinatural experiments.

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AR SKAITMENINĖ ĮMONIŲ TRANSFORMACIJA GALI SUMAŽINTI ANGLIES DIOKSIDO EMISIJĄ? ĮRODYMAI IŠ LISTINGUOJAMŲ KINIJOS PRAMONĖS ĮMONIŲ

Yu Hu, Xiaofang Chen, Xin Chen, Zhitao Wang

Santrauka. Skaitmeninė transformacija tapo esminiu veiksniu įmonių aplinkosaugos valdyme ir sulaukia vis didesnio mokslininkų dėmesio. Tačiau esamoje literatūroje vis dar nepakankamai išnagrinėtas jos poveikis įmonių lygmens anglies dioksido emisijų mažinimui. Remiantis išteklių pagrindu grindžiama teorija (angl. *Resource-based view*) ir sandorių kaštų teorija, buvo analizuojamas skaitmeninės transformacijos ir anglies dioksido emisijų mažinimo ryšys. Naudoti Kinijos A tipo akcijų pramonės įmonių 2010–2021 m. paneliniai duomenys. Pasitelkus patikimus ekonometrinius metodus, buvo įvertintas tiesioginis skaitmeninės transformacijos poveikis anglies dioksido emisijoms, taip pat išnagrinėti tarpiniai veikimo mechanizmai ir skirtingų įmonių tipų heterogeniškumas.

Rezultatai atskleidė, kad skaitmeninė transformacija reikšmingai mažina įmonių anglies dioksido emisijas, o gamybos efektyvumo didėjimas ir informacijos atskleidimo kokybės gerėjimas veikia kaip pagrindiniai tarpiniai kanalai. Emisijų mažinimo poveikis yra ryškesnis valstybinėse įmonėse, įmonėse, veikiančiose griežto aplinkosaugos reguliavimo sąlygomis, taip pat aukštųjų technologijų bendrovėse. Tolesnė analizė atskleidė, kad įvairios skaitmeninės technologijos – dirbtinis intelektas, blokų grandinės (angl. *blockchain*), debesų kompiuterija ir didieji duomenys taip pat teigiamai veikia aplinkosaugos valdymą.

Šios išvados ne tik papildo skaitmeninės transformacijos tyrimus aplinkosaugos perspektyvoje, bet ir suteikia vertingų įžvalgų reguliuotojams ir įmonėms dėl to, kaip pasitelkiant skaitmeninius gebėjimus gerinti aplinkosaugos valdymo rezultatus.

Reikšminiai žodžiai: skaitmeninė transformacija; anglies dioksido išmetimo mažinimas; aplinkosauginis valdymas; gamybos efektyvumas.