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Research on the Influence of Enterprise's Digital Transformation on Carbon Emission Intensity——A Moderated Mediation Model

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Abstract

Digitalization and low-carbon development are parallel in the digital economy. In what ways does the development of low-carbon economy can be contributed by the digital transformation of enterprises? This paper analyzes the impact of digital transformation on carbon emissions from a micro perspective. Based on unbalanced panel data from 278 listed companies between 2010 and 2018, a double fixed-effect model is used to test the overall effects of digitalization on carbon emission intensity, the intermediary role of green technology innovation capacity and the regulatory effect of absorptive capacity. Results show that digital transformation of enterprises contributes to the reduction of carbon emission intensity, green technology innovation capability partially mediates the impact of digital transformation on carbon emission intensity, and absorptive capacity moderates the impact of digital transformation on green technology innovation capacity. Based above, this paper puts forward corresponding countermeasures from the aspects of digitalization, greening and low carbon.

Keywords: digital transformation, carbon intensity, green technology innovation, absorptive capacity

1. Introduction

The world's temperature has been rising steadily as a result of excessive greenhouse gas emissions. There are now several environmental issues such as the greenhouse effect, which have a negative impact on social development and human life. So the international community is facing a collective challenge: reducing carbon emissions to combat climate change. As the world's largest manufacturing country, the total carbon emissions of China have always ranked first in the world, the task of reducing emissions is arduous. In recent years, a series of goals and policies have demonstrated China's determination and attitude to actively respond to and implement carbon emission reduction. At the general discussion of the 75th session of the United Nations General Assembly in September 2020, General Secretary Xi Jinping proposed that China should meet the "dual carbon" objective of reaching carbon neutrality before 2060 and reaching a peak in carbon emissions before 2030. The "dual carbon" objective was incorporated by the Chinese government in 2021 into the general framework of the 14th Five-Year Plan and the long-term objectives for 2035. At the same time, a new round of global revolution about science, technology and industry is accelerating, especially since COVID-19, digital technologies are being applied and popularized constantly, cloud computing, the Internet of Things, artificial intelligence and big data have accelerated the digital transformation process of the real economy and injected new momentum into economic and social development. China has entered a new era of the digital economy, where digital technology not only influences social production, daily living, and governance but also propels economic progress(Tao L,2021). Can enterprises reduce carbon emissions by enabling emission reduction and consumption reduction through digital technology change? What are the circumstances and its mode of operation? These issues require in-depth investigation.

In recent years, some scholars have theoretically studied the impact of digital transformation on carbon emissions, which provides a theoretical basis for analyzing the relationship between the two. Wang Tongliang et al. (2022) sorted out all aspects of oil and gas enterprises, showing that the digital effect of carbon emission reduction in oil and gas enterprises is obvious and that digital technology is a key element for them to achieve green and low-carbon development. Chen Xiaohong (2021) and Wu Zhangjian (2021) analyzed the problems of digital technology in the process of carbon neutralization in the energy industry and proposed corresponding solutions. Wang Shuo and Wang Hairong (2022) identified the problems faced by countries, enterprises and consumers in achieving digital carbon neutrality through a horizontal analysis of the internal mechanism between the digital economy and the dual carbon goal, and proposed coping strategies. Hu Yi and Jin Shuchang (2022) found that digital technology can achieve carbon emission reduction by solving problems such as insufficient technological innovation, information asymmetry, and external economic barriers, and built five major pathways for digital technology to help achieve the "dual carbon" goal.

There are also a few scholars who carry out quantitative research on the role of digital technology in carbon emissions. At the research level, these studies mainly focus on the meso-provincial and urban levels, and rarely pay attention to the national level. Wu Caixia and Gao Yuan (2020) found that the digital economy has a significant driving effect on low-carbon development in provinces through energy flow and resource flow based on China's provincial data. Ma et al.(2022) found that digitalization inhibits the carbon emissions of various provinces and R&D investment regulates this inhibitory effect; Xie Yunfei et al(2022) confirmed that the digital economy significantly reduces provincial carbon emission intensity by using China's interprovincial panel data, and there is obvious regional heterogeneity in this effect. Xu Weixiang et al. (2022) took above 286 prefecture-level cities in China as their research units and used the spatial Dubin model and the spatial DID model to find the spatial heterogeneity of the digital economy to reduce the influence of urban carbon emissions. In terms of research results, the empirical results of the above scholars supported the view that the development and application of digital technology can reduce carbon emissions. In addition, Liu Jingling and Chen Yanying's (2022) empirical studies of 284 Chinese cities in China and Chen's (2022) studies of BRICS countries also supported the idea that digitalization reduces carbon emissions. However, Miao Lujun et al. (2022) found the nonlinear inverted U-shaped impact of the digital economy on carbon emissions in 278 prefecture-level cities in China, and Li (2021) also found the inverted U-shaped nonlinear impact of the digital economy on CO_2 emissions based on panel data from 190 countries around the world.

In summary, existing empirical research on the impact of digital technologies and the digital economy on carbon emissions is in its infancy and has not yet reached a consensus conclusion, most of the research is still conducted from a theoretical perspective. For the dependent variable carbon emissions, scholars pay more attention to the impact of total carbon emissions and pay less attention to the impact on carbon emission intensity, carbon emission intensity can better reflect the effect of China's carbon emission reduction work as a relative quantity index. From the perspective of research objects, the role of digitalization on carbon emissions is mainly discussed at the national, provincial, or urban level, lacking the exploration of the micro-level of enterprises. While enterprises are the main micro-subjects of digital transformation and carbon emissions in China (Yao Xiaotao,et al.2022), exploration at the enterprise level is more conducive to guiding the behavior of micro-practice subjects. In addition, most scholars mainly examined the direct role of digitalization on carbon emissions, and the process mechanism or scenario mechanism of the impact of digitalization on carbon emissions needs to be further clarified.

Based on this, this paper empirically examines the impact of the digital transformation of enterprises on carbon emission intensity from a micro perspective, taking enterprises as the research object and carbon emission intensity as the outcome variable, which supplements the evidence at the micro enterprise level of this research theme. Enterprises should take a green and low-carbon road by applying digital technology to promote the coordinated development of economy and environment in response to the state's call. So this study introduces the green technology innovation capability as the intermediary variable to explore whether carbon emissions can be reduced through the process mechanism of green technology innovation by the digital transformation of enterprises, making up for the lack of current direct effect research. At the same time, the regulating variable of absorption capacity is introduced to analyze the moderating role of enterprises' own dynamic capabilities in the digital transformation of enterprises and green technology innovation capabilities to expand the research on the boundary conditions of digital transformation on green technology innovation capabilities and carbon emissions. As we all know, enterprises, as the basic units of social economy, are the micro-subjects of digital transformation. (Yao Xiaotao,et al.2022). This paper has important theoretical and practical significance for accelerating the widespread application of digital technology in enterprises, developing the digital economy, responding to the national call for low-carbon development by exploring the impact of enterprise digital transformation on carbon emission intensity. It is also committed to providing new inspiration for the realization of the "dual carbon" goal from a micro perspective.

2. Theoretical Basis and Research Hypotheses

2.1 The Direct Impact of Digital Transformation on Carbon Emission Intensity

For enterprises, the digital transformation by introducing digital technology and combining it with all aspects of enterprise production and operation is a strategic behavior. (Yang Wei,et al.2022), so as to realize the digitalization of enterprise procurement, production, management, sales, and other levels (Qi Yudong & CAI Chengwei,2020) by gradually replacing or empowering traditional technical means. Digital technology is an important support for China to achieve the goal of "double carbon" in the era of the digital economy (Liu Jingling & Chen Yanying,2020). In theory, we believe that enterprises can reduce their carbon emission intensity by using digital technology to conduct digital transformations of their enterprise operations. First of all, enterprises apply digital technology to traditional business processes and drive the transformation of all links from traditional mode to digital mode through digital transformation, which can improve the production efficiency and resource utilization of enterprises (Yao Xiaotao,et al.2022), optimize the input-output ratio of enterprises, reduce production costs, reduce the use and loss of original production resources, and thus reduce the carbon emission intensity of enterprises. Secondly, using big data, cloud computing, blockchain, and other digital technologies to conduct real-time intelligent monitoring, supervision, and analysis of enterprise carbon behavior will promote the enterprise's ability to obtain more perfect carbon information, improve the accuracy and transparency of data, achieve the rational allocation of enterprise energy elements (Wu C X & Gao Y,2020), reduce energy mismatch caused by information asymmetry, avoid energy consumption and waste, and reduce carbon emissions, so as to reduce the carbon emission intensity. In addition, the application of enterprise digital technology can break the space-time barrier, change the traditional trading and resource search methods of enterprises, realize the integration of carbon trading processes, reduce energy consumption and process costs (Miao Jun Jun,et al.2022), and thus have a positive impact on the reduction of carbon emission intensity. In summary, the following assumptions are proposed:

H1: Digital transformation helps reduce the carbon intensity of the enterprise.

2.2 The Impact of Enterprise Digital Transformation on Green Technology Innovation

The realization of the "dual carbon" goal is driven by low-carbon technology and green technology innovation strategies. Digital technology as an important mean of low-carbon technology can promote the green technology innovation of enterprises effectively. For one thing, digital technology has the characteristics of spillover and sharing (Lun XiaoBo&Liu Yan,2022), spillover makes it easier to copy and imitate innovation, and the green technology innovation of any leading enterprise can spill over to other enterprises more quickly; Sharing ability enables enterprises to complement resources and supplement the stock of relevant green resources of enterprises (Han Zhao-An,et al.2022) to improve the green technology innovation ability of enterprises. For another, enterprise digitalization is conducive to breaking the traditional extensive economic development mode and developing towards environment-friendly development, data as an important and new production factor, with clean and pollution-free (Hu Y & Jin Shushang,2022) and non-consumable (Wang Shuo & Wang Hairong,2022) characteristics, it not only has low dependence on natural resources but also can integrate innovative resources quickly and effectively, conducive to squeezing traditional high-pollution, high-energy-consuming technologies and products, promoting enterprises to carry out green technology innovation, and realizing the optimization and upgrading of technology and product structure (Li Shaolin&Feng Yafei,2021). At the same time, the positive externalities brought about by the digital transformation of enterprises will stimulate entrepreneurship (Lun XiaoBo&Liu Yan,2022), and the top-down environmental awareness of enterprises will promote enterprises' willingness to green transformation (Li Shaolin,&Feng Yafei,2021). In addition, the application of enterprise digital technology is also conducive to enterprises to timely capture the demand status of consumers for green technology and green products, and force enterprises to carry out green technology innovation. In summary, the following assumptions are made:

H2: Digital transformation can improve the green technology innovation capability of enterprises.

2.3 The Intermediary Role of Green Technology Innovation

Green technology innovation can significantly improve environmental and economic performance (Wang Mingyue,et al,2022), is the main means to cope with CO_2 emissions and climate change (Xu Jianzhong,et al,2022), and can effectively reduce carbon emissions, help enterprises achieve the reduction of carbon emission intensity, and promote sustainable development. For enterprises, the "technology dividend effect" shown by green technology innovation (Shao Shuai,et al,2022) is beneficial for the upgrading and optimization of energy structure; through green technology innovation, the original inefficient technology is upgraded, energy efficiency is improved, and energy consumption is reduced (Xu Jianzhong,et al,2022), so as to promote carbon emission reduction and reduce carbon emission intensity of enterprises. Like other innovations, green technology innovation has a spillover effect, contributing to the diffusion of green knowledge and technologies (Zhou J & Liu Y,2021), promoting enterprises to develop and apply more low-carbon and environmentally friendly equipment and tools, breaking the inertia of enterprises following traditional high-energy-consuming technologies, thereby breaking carbon locking (Yang W W,2021), driving equipment upgrades and process optimization, improving production efficiency and energy utilization, and achieving a reduction in carbon emission intensity. Therefore, when enterprises carry out digital transformation, the ability to innovate with green technology can be improved, thereby promoting the reduction of corporate carbon emissions. Based on this, hypotheses are made:

H3: Green technology innovation plays a mediating role between digital transformation and carbon emission intensity.

2.4 Moderating Effect of Absorption Capacity

Absorption capacity was first proposed by Cohen & Levinthal (1990) in 1990, which is the core variable restricting the spillover effect of technology introduction (Xu B, 2019) and will affect the role of digital transformation in enterprises in promoting innovation ability. Absorptive capacity is used to measure the ability of enterprises to acquire, digest, and utilize new external knowledge in practice, reflecting the efficiency of digestion, absorption, transformation, and utilization of new technologies and knowledge after the innovation subject identifies and introduces new technologies and knowledge, which is the key endogenous driving force of the main body's technological innovation (Jiang Jie,et al,2021). The absorption capacity of enterprises affects the degree of knowledge acquisition and transformation of innovation subjects (Zhao jianyu,et al,2019), promotes organizational learning and R&D activities effectively (Daghfous,2004), improves the integration of external resources obtained by enterprises, accelerates the effective integration of internal and external resources(Mohamed Aboelmaged & G Hashem, 2019), and adjusts the relationship between enterprise digitalization and innovation performance significantly(Summer Tim & Fu Yueqiang,2020). When enterprises introduce digital technology for digital transformation, enterprises with high absorption capacity have high efficiency in digesting and applying new technology knowledge, thereby accelerating the digital transformation process of enterprises, enhancing the role of digital transformation in enterprise green technology innovation, and improving green technology innovation capabilities. Based on this, hypotheses are made:

H4: Absorptive capacity positively regulates the role of the digital transformation of enterprises in promoting green technology innovation.

Based on the above analysis, the theoretical model of this paper is constructed, as shown in Figure 1.

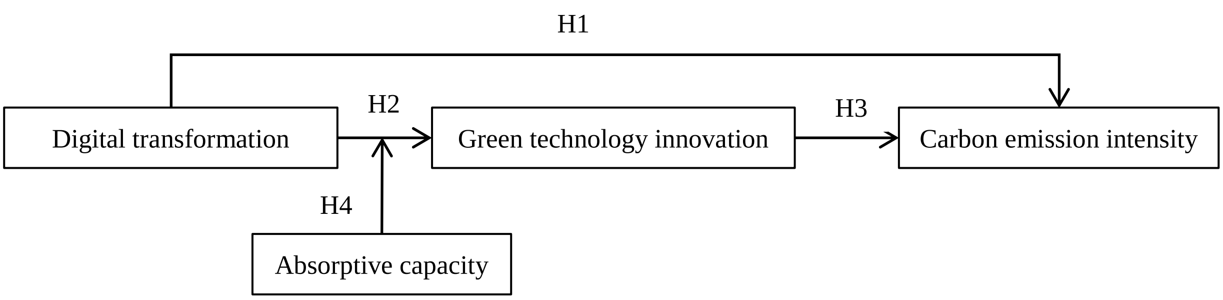

Figure 1. Theoretical model

3. Study Design

3.1 Sample Selection and Data Acquisition

According to the World Resources Institute (WRI), the carbon emissions in the power and heat production and supply industries account for about 41.6% of China's total carbon emissions. As energy suppliers, the electricity, heat production and supply industry are major users who needs to save energy and carry out "carbon neutrality" to achieve energy conservation and emission reduction, only when they achieve "clean" can the downstream industry truly move towards "low carbon". In addition, 23.2% of China's total carbon emissions come from energy use in manufacturing and buildings, while the main equipment manufacturers for energy use and export come from electrical and mechanical manufacturing in the manufacturing industry, and the energy-saving and emission-reducing devices produced by it contribute to low-carbon development. Only when these two industries achieve energy reduction and consumption reduction, the realization of the "dual carbon" goal will be just around the corner. Therefore, the electric power, heat production and supply industries, as well as the electrical and mechanical manufacturing industries, are selected as the source of the sample enterprises in this article. The data includes all A-share Main Board listed companies in these two industries from 2010 to 2018. In this paper, the data are processed as follows: (1) Exclude enterprises that were ST and *ST during the sample period; (2) Eliminate enterprises with serious missing key data after matching all variables. After the above processing, a total of 1726 observational samples from 274 enterprises were obtained. The data source is as follows: The frequency data for the digital transformation comes from the annual reports of listed companies crawled from Juchao Information Network, and some of the missing annual reports are manually downloaded from the official websites of the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The raw data required for other variables are obtained from the Cathayan database (CSMAR), and some of the missing financial indicators are supplemented from the company's annual reports.

3.2 Variable Measurement

Explanatory variable: digital transformation. This paper draws on the practices of Wu Fei et al. (2021) to measure the degree of digital transformation of enterprises, and the degree of digital transformation of enterprises is measured according to the sum of the frequency of keywords related to digitalization in the annual report of the enterprises. The specific steps are as follows: (1) use Python to crawl the annual reports of sample enterprises during the observation period in Juchao Information Network and then convert them into text format; (2) drawing on the digital technology-related keywords selected in the existing literature (Wu Fei,et al.2021&Ho,et al.2007), combined with the specific annual report content of the enterprise, the keywords related to the digital transformation characteristics of the enterprise related to this paper are manually screened from the two aspects of the underlying digital technology and digital technology application, and the keyword thesaurus used is shown in Table1; (3) use Python to capture relevant texts in corporate annual reports; (4) use Excel to sum the frequency of the captured enterprise digital keywords. Considering the "right-biased" characteristics of these data, this article logarithmicly treats the sum of word frequencies of these keywords as the final indicator to measure the degree of digital transformation of enterprises.

Table 1. Keywords of digital transformation of enterprises

Digital technology	keywords
Underlying digital technologies	digital technology, intelligent technology, business intelligence, image processing, automatic driving, distributed computing, augmented reality, virtual reality, information system, system integration, automatic control, information technology, artificial intelligence, robotics, machine learning, deep learning, intelligent software, intelligent recognition, face recognition, speech recognition, intelligent system, blockchain, cloud computing, private cloud, Internet of Things, big data, data mining, data visualization, data analysis, data integration
Digital technology applications	e-commerce, digital marketing, online marketing, online retail, network design, digital transformation, digital city, digital R&D, R&D software, intelligent, smart energy, intelligent upgrade, smart wear, intelligent transportation, intelligent medical, intelligent manufacturing, smart home, smart product, smart office, intelligent equipment, intelligent research and development, smart factory, intelligent system, intelligent production, intelligent terminal, intelligent equipment, intelligent operation and maintenance, smart grid, platform economy, cloud platform, cloud service, industrial cloud, industrial software, Industry 4.0, digital factory, industrial Internet, mobile Internet, smart agriculture

Variable to be explained: carbon intensity. Drawing on Chapple et al. (2014), the carbon emission intensity of enterprises is measured by the ratio of carbon emissions to main business income in the current year. Since it is difficult to directly obtain the carbon emissions of enterprises, the carbon emissions of enterprises are indirectly estimated according to the carbon emissions of their industries by drawing on the practices of Chen Xiaobei and Chen Xueting (2021), and using the ratio of the main operating costs of the enterprise in the current year to the main operating costs of the enterprise's industry in the current year as the weight,. The specific formula is as follows:

$$\text{The carbon intensity of the enterprise} = Ln\,\frac{\text{The carbon emssions of the enterprise}}{\text{The main revenue of the enterprise}}$$

$$\text{The carbon emissions of the enterprise} = \frac{\text{The main cost of the business}}{\text{The main cost of the industry}} * \text{The carbon emissions of the industry}$$

Mediating variable: green technology innovation capacity. In the existing literature, scholars mostly use the number of green patent applications or green patent authorizations (Wang Zhenyu, et al ,2021) to measure the green technology innovation ability of enterprises. Because the number of green patent applications cannot reflect the actual application value of green patents for enterprises, and cannot accurately represent the actual technological innovation capabilities of enterprises (Qi Shaozhou,et al,2018), this paper draws on the research of Wang Banban and Zhao Cheng (2019) to measure the green technology innovation ability of enterprises with the number of green patent authorizations.

Moderating variable: absorptive capacity. Most scholars use R&D investment (Rachel Griffith,2006), R&D personnel ratio (Wang Shixiang,et al,2014)or R&D intensity (Cohen & Levinthal,1900) as proxy indicators to measure the absorption capacity of enterprises. Since the absorption capacity of enterprises is closely related to the R&D intensity of enterprises, This paper adopts the practice of Cohen and Leventhal (1900) to express the absorption capacity of enterprises in terms of the proportion of R&D investment to main business income.

Control variables: The main basis for selecting control variables in this paper is the characteristic variables that may have an impact on the carbon emission intensity of enterprises. The industry type (Industry: dummy variable, 0 for electric power, heat production, and supply, and 1 for electrical and machinery manufacturing), enterprise nature (Nature:dummy variable, 1 for state-owned enterprises and 0 for others), enterprise size (Size:the natural logarithm of the enterprise's year-end operating income), listing age (Age: the natural logarithm of the listing age (observation year - listing year +1)), financial leverage (Lev:total liabilities as a percentage of total assets), and cash flow level (Cash:net cash flow from operating activities as a proportion of total assets) were selected as the control variables.

3.3 Model Setting and Empirical Strategy

In order to examine the impact of digital transformation on carbon emission intensity and its action path and regulation, the following model is designed:

$$Carbon_{i,t+1} = \beta_0 + \beta_1 EDT_{i,t} + \sum \beta_k Control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \quad (1);$$

$$TIA_{i,t} = \beta_0 + \beta_1 EDT_{i,t} + \sum \beta_k Control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \quad (2);$$

$$\mathrm{Carbon}_{\mathrm{i,t+1}} = \beta_0 + \beta_1 EDT_{i,t} + \beta_2 \mathrm{TIA}_{\mathrm{i,t}} + \sum \beta_k Control_{i,t} + \sum \mathrm{Year} + \sum Industry + \varepsilon_{\mathrm{i,t}} \quad (3);$$

$$TIA_{i,t} = \beta_0 + \beta_1 EDT_{i,t} + \beta_2 AC_{i,t} + \beta_3 (EDT_{i,t} * AC_{i,t}) + \sum \beta_k Control_{i,t} + \sum Year + \sum Industry + \varepsilon_{i,t} \quad (4);$$

In the above model, carbon represents the carbon emission intensity of the enterprise, EDT represents the degree of digital transformation of the enterprise, TIA represents the ability of green technology innovation, AC represents the absorption capacity, Year is the time dummy variable, Industry is the industry dummy variable, Control is the control variable, i is the enterprise, t is the time, β represents the parameter value to be estimated by the preceding variable and all control variables, and ε is the random error term. (1) examines the impact of digital transformation on carbon emission intensity; equations (1)(2)(3) test the mediating role of green technology innovation capabilities; Equation (4) is used to test the regulating effect of absorption capacity.

4. Empirical Analysis

This paper use Stata 16 to perform correlation tests and regression analysis on the data. We selected the double fixed-effect model for the regression test of the empirical results after the F-test, LM test, and Hausman test. To avoid the influence of discrete values of variables on the regression results, all continuous variables are indented by 1%. Some of the data were processed logarithmically, in order to eliminate the effect of heteroscedasticity.

4.1 Descriptive Statistics, Correlation Analysis and VIF Test

Table 2 presents the results of descriptive statistics, correlation analysis, and VIF tests for selected variables in this paper. According to the descriptive statistical results, the minimum value of carbon emission intensity is 3.809 and the maximum value is 11.177, indicating that there are large differences in the carbon emission intensity of the sample enterprises. The minimum value of digital transformation is 0 and the maximum value is 4.867, indicating that the selected companies also have differences in digital transformation, which may be the reason for the large difference in carbon emission intensity between enterprises. In terms of correlation analysis, the correlation coefficient between digital transformation and carbon emission intensity was -0.528, which passed the significance test of 10%, indicating that there was a negative correlation between digital transformation and carbon emission intensity. The correlation coefficient between digital transformation and green technology innovation capability was 0.167, which passed the significance test of 10%, indicating that there is a positive correlation between digital transformation and green technology innovation. At the same time, the correlation coefficient between green technology innovation and carbon emission intensity is -0.074, which also passes the 10% significance test, indicating that green technology innovation is negatively correlated with carbon emission intensity, which provides preliminary support for the verification of the hypothesis in the next step. Through the VIF test, it can be seen that the average VIF of all explanatory variables is 1.49, the maximum value is 1.98, which is much lower than the threshold of 10, and it can be seen from the correlation analysis that only the correlation coefficient between individual variables is greater than 0.5, indicating that there is no serious multicollinear problem between variables.

Table 2. Descriptive statistics, correlation analysis and VIF test results

variables	TIA	Nature	Cash	Lev	EDT	Age	Size	AC	Carbon
TIA	1.000								
Nature	-0.012	1.000							
Cash	0.112*	-0.186*	1.000						
Lev	0.108*	-0.480*	0.150*	1.000					
EDT	0.167*	0.349*	-0.051*	-0.173*	1.000				
Age	0.038	-0.538*	0.193*	0.490*	-0.149*	1.000			
Size	0.304*	-0.277*	0.288*	0.556*	0.016	0.382*	1.000		
AC	0.007	0.382*	-0.073*	-0.378*	0.373*	-0.335*	-0.337*	1.000	
Carbon	-0.074*	-0.640*	0.241*	0.416*	-0.528*	0.427*	0.244*	-0.627*	1.000
Mean	6.959	0.620	0.042	0.453	1.890	1.935	21.420	1.396	6.738
variance	25.245	0.485	0.067	0.208	1.284	0.933	1.394	0.554	2.715
Min	0	0	-0.148	0.066	0	0	18.599	0.058	3.809
Max	463	1	0.226	0.894	4.867	3.178	25.408	2.413	11.177
VIF	1.18	1.43	1.09	1.78	1.28	1.59	1.98	1.58	

*note：*p<0.05*

4.2 Regression Results

The regression results for all hypothesis validations are listed in Table 3, and Model 1 shows the regression results for the impact of all control variables on carbon emission intensity. Model 2 is the result of adding enterprise digital transformation to Model 1 and regression of carbon emission intensity, and the regression result was negatively significant(β=-0.057, P<0.01), indicating that enterprise digital transformation plays a positive role in reducing carbon emission intensity, and H1 is verified. Model 2—4 uses the three-step step-by-step regression method of Wen Zhonglin et al. (2014) to test the mediating effect, and the coefficient of digital transformation in Model 3 is positive and significant (β=0.075, P<0.05), indicating that digital transformation improves the green technology innovation ability of enterprises; Compared with Model 2, after adding the green technology innovation capability, the absolute value of the regression coefficient of digital transformation became smaller but still significantly negative (the β value decreased from 0.057 to 0.055), indicating that the green technology innovation capability plays a partial mediating role between digital transformation and carbon emission intensity, and H2 and H3 have been verified. Model 5 adds absorptive capacity and multiplier terms of digital transformation and absorptive capacity on the basis of Model 3, and the results show that the regression coefficient of the multiplier term of digital transformation and absorptive capacity is significantly positive (β=0.060, P<0.05), indicating that absorptive capacity positively regulates the role of digital transformation in promoting green technology innovation, and H4 is verified.

Table 3. Regression results

variable	Model 1 Carbon	Model 2 Carbon	Model 3 TIA	Model 4 Carbon	Model 5 TIA
EDT		-0.057*** (0.014)	0.075** (0.032)	-0.055*** (0.014)	0.042 (0.038)
TIA				-0.031*** (0.011)	
EDT*AC					0.060** (0.029)
AC					0.063 (0.042)
Lev	-0.127* (0.075)	-0.133* (0.075)	0.049 (0.175)	-0.131* (0.074)	-0.028 (0.213)
Cash	-0.196 (0.139)	-0.192 (0.138)	0.091 (0.325)	-0.189 (0.138)	0.024 (0.379)
Size	-0.049** (0.019)	-0.039** (0.019)	0.089** (0.045)	-0.036* (0.019)	0.188*** (0.057)
Age	-0.327*** (0.027)	-0.331*** (0.027)	0.039 (0.064)	-0.330*** (0.027)	0.136* (0.078)
Nature	0.251 (0.161)	0.270* (0.160)	-0.095 (0.377)	0.267* (0.160)	0.174 (0.437)
Industry	control	control	control	control	control
Year	control	control	control	control	control
Constant	6.889*** (0.103)	6.855*** (0.103)	-0.013 (0.242)	6.855*** (0.103)	0.014 (0.357)
R-squared	0.733	0.736	0.036	0.737	0.051

*Note: Standard error in parentheses; p<0.01,**p<0.05,*p<0.1*

4.3 Robustness Test

In order to ensure the robustness of the regression results, the following methods are used to test the robustness.

4.3.1 Substitution Variable Method

Because carbon dioxide accounts for 77% of total greenhouse gases, CO_2 emissions are the main reason for the increase in carbon emissions. Referring to the calculation of industrial carbon emissions by Shen Hongtao et al. (2019), the carbon emission intensity was recalculated, the industrial carbon emissions were replaced with industrial carbon dioxide emissions, calculated by the product of total industrial energy consumption and carbon dioxide conversion coefficient, in which the data of total industrial energy consumption came from CSMAR, and the carbon dioxide conversion coefficient 2.493 was adopted the standard of Xiamen Energy Conservation Center. The regression results are shown in Table 4 and are still supported all assumptions.

Table 4. Regression results of substitution variables

variable	Model 1 Carbon	Model 2 Carbon	Model 3 TIA	Model 4 Carbon	Model 5 TIA
EDT		-0.011** (0.005)	0.075** (0.032)	-0.010* (0.005)	0.042 (0.038)
TIA				-0.014*** (0.004)	
EDT*AC					0.060** (0.029)
AC					0.062 (0.042)
Lev	0.032 (0.029)	0.031 (0.029)	0.049 (0.175)	0.031 (0.029)	-0.028 (0.213)
Cash	-0.296*** (0.053)	-0.296*** (0.053)	0.091 (0.325)	-0.294*** (0.053)	0.023 (0.379)
Size	0.019** (0.007)	0.021*** (0.007)	0.089** (0.045)	0.022*** (0.007)	0.188*** (0.057)
Age	-0.065*** (0.011)	-0.066*** (0.011)	0.039 (0.064)	-0.066*** (0.010)	0.136* (0.078)
Nature	0.128** (0.062)	0.132** (0.062)	-0.095 (0.377)	0.131** (0.062)	0.174 (0.438)
Industry	control	control	control	control	control
Year	control	control	control	control	control
Constant	7.535*** (0.040)	7.528*** (0.040)	-0.013 (0.242)	7.528*** (0.040)	0.014 (0.357)
R-squared	0.424	0.426	0.036	0.430	0.051

*Note: Standard error in parentheses; p<0.01,**p<0.05,*p<0.1*

4.3.2 Mediation Effect Test

In order to verify the robustness of the mediating role of green technology innovation, this paper uses the Sobel method and the Bootstrap method to conduct the mediation test. In the Sobel test, the Z value is -2.015 and the P value is less than 0.05. During the Bootstrap test, 1000 samples and a 95% confidence interval are set, and the results show that the confidence interval does not include 0, both reject the null hypothesis that there is no mediating effect, indicating that the mediation effect is significant. Therefore, the intermediary role of green technology innovation is robust, and the test results are shown in Table 5 and 6.

Table 5. Results of Sobel test

	Coef	Sed .Err	Z	P>|Z|
Sobel	-0.003 714 17	0.001 843 36	-2.015	0.043 916 43
Goodman-1	-0.003 714 17	0.001 875 83	-1.98	0.047 702 28
Goodman-2	-0.003 714 17	0.001 810 31	-2.052	0.040 201 32
Proportion of total effect that is mediated: 0.019 032 95				
Ratio of indirect to direct effect: 0.019 402 23				

Table 6. Bootstrap test results

	Observed Coef.	Bias	Bootstrap Sed.Err	[95% conf. Interval]		
_bs_1	-0.003 714 17	-0.000 215 6	0.001 810 82	-0.007 694 3	-0.000 806 2	(P)
				-0.007 612 7	-0.000 563 6	(BC)
_bs_2	-0.191 430 13	0.000 884 4	0.014 668 8	-0.219 926 6	-0.163 973 9	(P)
				-0.221 798 9	-0.166 381	(BC)

It can be seen from the above that after the robustness test of the substitution variable method, the Sobel method, and the Bootstrap method, the test results are consistent with the benchmark results, indicating that the regression results in this paper are robust and the conclusions have strong credibility.

5. Research Conclusions and Discussion

This paper conducts an empirical study on the impact and mechanism of digital transformation on carbon emission intensity based on the unbalanced panel data of 274 listed companies in China from 2010 to 2018. The results show that the technological changes brought about by the digital transformation of enterprise can help to reduce carbon emission intensity by improving the resource utilization rate of enterprises and reducing energy consumption. Green technology innovation plays an intermediary role on this path, that is, the digital transformation of enterprises promotes low-carbon development and reduces carbon emission intensity by improving green technology innovation capabilities; The stronger the absorption capacity of the enterprise itself, the greater the role of promoting green technology innovation in the digital transformation, and the more conducive it is to reducing the carbon emission intensity of the enterprise.

According to our findings, this paper has the following enlightenments: the state should introduce relevant digital favorable policies and promote the digital transformation behavior of enterprises vigorously; Formulate reasonable low-carbon development goals, increase environmental policy intervention, and use policy tools to stimulate enterprises' emission reduction potential and green innovation behavior continuously; Local governments should respond to relevant policies actively, encourage the low-carbon behavior of enterprises, and guide enterprises to actively introduce low-carbon technologies such as digital technologies. Enterprises should keep up with the pace of the times, raise awareness of the development of digital technology and energy conservation and carbon reduction, use digital technology to accelerate the pace of transformation, optimize low-productivity links in a timely manner, and update high-energy-consuming equipment, so as to improve the production efficiency and energy utilization rate of all links and reduce carbon emission intensity; At the same time, enterprises should make good use of the path of green technology innovation, encourage green innovation behavior, promote the coordinated development of digitalization, greening, and low-carbon enterprises, and help achieve the "dual carbon" goal.

This paper supplements the existing research on how digital transformation affects carbon intensity from three aspects: the research level, process mechanism, and scenario conditions, but it still needs to be further improved. Firstly, due to insufficient disclosure it is difficult to obtain carbon emission from the enterprise, this paper estimates the carbon emission of its industry when making calculations and can further improve the measurement of relevant carbon emission data at the micro level. Secondly, the mechanism of digitalization affecting carbon emission intensity is not unique, and the path of research between the two needs to be further enriched.

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References

Chapple, L., Clarkson, P., & Gold, D. (2014). The Cost of Carbon: Capital Market Effects of the Proposed Emission Trading Scheme (ETS) [J]. *Social Science Electronic Publishing, 34*(1), 54-61. https://doi.org/10.1080/0969160X.2014.885191

Chen, L. J. (2022). How CO2 emissions respond to changes in government size and level of digitalization? Evidence from the BRICS countries [J]. *Environmental Science and Pollution Research, 29*(1), 457-467. https://doi.org/10.1007/s11356-021-15693-6

Chen, X. B., & Chen, X. T. (2021). Media pressure, Financing Constraint and Carbon Emission of Industrial Enterprises: the moderating effect of green invention patents [J]. *Science and Technology Progress and Countermeasures, 38*(12), 69-78.

Chen, X. H., Hu, D. B., & Cao, W. Z. et al. (2021) Research on the path of digital technology boosting the carbon neutrality goal of China's energy industry [J]. *Bulletin of Chinese Academy of Sciences, 36*(9), 1019-1029.

Cohen, W. M., &Levinthal, D. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation[J]. *Administrative Science Quarterly, 35(*1), 128-152. https://doi.org/10.2307/2393553

Daghfous, A. (2004) Absorptive capacity and the implementation of knowledge-intensive best practices[J]. *Sam Advanced Management Journal, 69*(2), 21-27.

Han, Z. A., WU, H. Z., & Zhao, J. F. (2022) Digital economy drives innovation development: The mediating role of knowledge flow [J]. *Studies in Science of Science.* (pp. 1-17).

Ho, J. L. Y., Wu, A., & Xu, S. X. (2007) Corporate Governance and Returns on Information Technology Investment: Evidence from an Emerging Market[J]. *Strategic Management Journal, 32*(6), 595-623. https://doi.org/10.2139/ssrn.1000851

Hu, Y., & Jin, S. S. (2022). Digital Technology to help realize "double Carbon" Target: Theoretical mechanism and practical path [J]. *Journal of Finance and Accounting, 6*, 111-118.

Jiang, J., Tang, C. Y., & Zhang, Q. H. et al. (2021). Interactive influence of industrial characteristics on the effect of technological innovation incentive policies [J]. *Research management, 42*(11), 71-81.

Li, S. L., & Feng, Y. F. (2021). How does blockchain promote the green development of manufacturing? Quasi-natural experiments based on key cities of environmental protection [J]. *China Environmental Science, 41*(3), 1455-1466.

Liu, J. l., & Chen, Y. Y. (2022). Digital technology development, spatio-temporal dynamic effects and regional carbon emissions [J]. *Studies in Science of Science.* (pp. 1-17).

Lun, X. B., & Liu, Y. (2022). Digital government, digital economy and green technology innovation [J]. *Journal of Shanxi University of Finance and Economics, 44*(4), 1-13.

Ma, Q., Tariq, M., & Mahmood, H, et al. (2022). The nexus between digital economy and carbon dioxide emissions in China: The moderating role of investments in research and development[J]. *Technology in Society, 68*(4), 101910. https://doi.org/10.1016/j.techsoc.2022.101910

Miao, L. J., Chen, J., & Fan, T. Z. et al. (2022). Impact of digital economy development on carbon emission: Based on panel data analysis of 278 prefecture-level cities [J]. *Southern Finance, 2022*(2), 45-57.

Mohamed, A., & Hashem, G. (2019). Absorptive capacity and green innovation adoption in SMEs: The mediating effects of sustainable organisational capabilities[J]. *Journal of Cleaner Production, 220*(5), 853-863. https://doi.org/10.1016/j.jclepro.2019.02.150

Qi, S. Z., Lin, S. X., & Cui, J. B. (2018). Can Environmental Rights Trading Market Induce Green Innovation? -- Evidence based on green patent data of Chinese listed companies [J]. *Economic Research Journal, 53*(12), 129-143.

Qi, Y. D., & CAI, C. W. (2020). Research on multiple effects of digitalization on manufacturing enterprise performance and its mechanism [J]. *Learning and Exploration, 6*, 108-119.

Rachel, G., Rupert, H., & John, V. R. (2006). How Special Is the Special Relationship? Using the Impact of U.S. R&D Spillovers on U.K. Firms as a Test of Technology Sourcing[J]. *American Economic Review, 96*(5), 1859-1875. https://doi.org/10.1257/aer.96.5.1859

Shao, S., Fan, M. T., & Yang, L. L. (2022). Economic restructuring, Green technology Progress and China's low-carbon Transition: An empirical study from the perspective of overall technology frontier and spatial spillover effect [J]. *Management World, 38*(2), 46-63.

Shen, H. T., & HUANG, N. (2019). Can carbon emission trading system improve enterprise value [J]. *Finance and Trade Economics, 40*(1), 144-161.

Summer, T., & Fu, Y. Q. (2020). Interorganizational linkages, collaborative innovation and enterprise innovation performance [J]. *Journal of Technology Economics and Management, 10,* 24-30.

Tang, X. H., & Chi, Z. M. (2022) An empirical study on industrial intelligence improving the efficiency of industrial green development [J]. *Economist, 2,* 43-52.

Tao, L. (2021). Digitalization is a golden key to low-carbon life [J]. *Environmental Education, 9*(35).

Wang, B. B., & Zhao, C. (2019). Green technology innovation in China: Patent statistics and influencing factors [J]. *Industrial Technical Economics, 38*(7), 53-66.

Wang, M. Y., Li, Y. M., & Wang, Z. T. (2022). Research on the Transmission of green technology innovation Performance of Industrial Enterprises and the moderating Effect of government market regulation [J]. *Chinese Journal of Management, 19*(7), 1026-1037+1091.

Wang, S. X., Wei, J., & Lu, Y. (2014). Research on the Relationship between absorptive capacity and technological Performance in cross-border technology M&A: Based on Evolutionary Game Theory [J]. *Studies in Science of Science, 32*(12), 1828-1835.

Wang, S., & Wang, H. R. (2022). Strategic Research on the healthy development of China's digital Economy under the background of dual carbon target [J]. *Contemporary Economic Management, 44*(8), 11-16.

Wang, T. L., Xu, P., & Hao, H. N. (2022). Practice and thinking of digital technology to help oil and gas enterprises with low-carbon development [J]. *Petroleum Science and Technology Forum, 41*(1), 87-91. https://doi.org/10.1080/10916466.2022.2092497

Wang, Z. Y., Cao, Y., & Lin, S. L. (2021). Impact characteristics and heterogeneity of environmental regulation on green technology innovation: Based on green patent data of Chinese listed companies [J]. *Studies in Science of Science, 39*(5), 909-919.

Wen, Z. L., & Ye, B. J. (2014). Moderated Mediation Model Testing: Competition or Substitution? [J]. *Journal of Psychology, 46*(5), 714-726. https://doi.org/10.3724/SP.J.1041.2014.00714

Wu, C. X., & Gao, Y. (2020). Research on the mechanism and effect of digital economy driving low-carbon industry development [J]. *Guizhou Social Sciences, 11,* 155-161.

Wu, F., Hu, H. Z., & Lin, H. Y. et al. (2021). Enterprise Digital Transformation and Capital Market Performance: Empirical Evidence from Stock Liquidity [J]. *Management World, 37*(7), 130-144.

Wu, Z. J. (2021). Thinking on digital transformation of carbon neutral future energy development. [J]. *Energy, 2,* 54-57.

X, L., J, L., & P, N. (2021). The Impact of the Digital Economy on CO 2 Emissions: A Theoretical and Empirical Analysis[J]. *Sustainability, 13*(13), 7267. https://doi.org/10.3390/su13137267

Xie, Y. F. (2022). Effect and mechanism of digital economy on regional carbon emission intensity [J]. *Contemporary Economic Management, 44*(2), 68-78.

Xu, B. (2019). Technology absorption, technology transformation and domestic and foreign technology acquisition: Based on static and dynamic panel data of high-tech industry [J]. *Science and Technology Progress and Countermeasures, 36*(22), 60-66.

Xu, J. Z., Tong, B. J., & Wang, M. (2022). Research on the impact of green technology innovation on CO2 emission from a spatial perspective [J]. *Studies in Science of Science.* (pp.1-20)

Xu, W. X., ZHOU, J. P., & LIU, C. J. (2022). Spatial effects of digital economy development on urban carbon emissions. [J]. *Geographical Research, 41*(1), 111-129.

Yang, W. W. (2021). Research on the impact of green technology innovation on carbon emissions of manufacturing industry [D]. *Henan University of Economics and Law.*

Yang, W., Ji, L. X., & Zhou, Q. (2022). The Impact of enterprise Digital Transformation on innovation Ecosystem: A Multi-Agent model based on Market size dynamics [J]. *China Management Science, 30*(6), 223-232.

Yao, X. T., Qi, H., & Liu, L. L. et al. (2022). Enterprise digital transformation: Re-understanding and re-starting [J]. *Journal of Xi 'an Jiaotong University: Social Sciences Edition*, *42*(3), 1-9.

Zhao, J. Y., Ren, Z. Y., & Xi, X. (2019). The Effect of knowledge embeddedness on knowledge synergy in cooperative Networks: the moderating role of absorptive capacity [J]. *Journal of Management Engineering. 33*(4), 49-60.

Zhou, J., & Liu, Y. (2021). Institutional embeddedness, green technology innovation and carbon emission reduction of entrepreneurial enterprises [J]. *China Population, Resources and Environment*, *31*(6), 90-101.

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