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Original Paper

Research on the Impact of Enterprise Digital Transformation on Pollution Reduction and Carbon Reduction in the Manufacturing Industry

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Abstract

In the context of sustainable development, the digital transformation of manufacturing enterprises is of great significance to reduce environmental pollution and carbon emissions. Taking listed companies in the manufacturing industry as a sample, this paper analyzes how digital transformation can achieve the goal of reducing pollution and carbon emissions by improving operational efficiency, promoting green supply chain management, and enhancing corporate environmental responsibility. The results show that digital transformation not only directly reduces the carbon emission level of enterprises, but also drives the environmental protection actions of other enterprises in the industry through the demonstration effect. In addition, the study also found that the effect of digital transformation on pollution reduction and carbon reduction showed certain differences among enterprises of different industries and sizes, while factors such as enterprise innovation ability, market orientation, and policy environment had a significant impact on the environmental protection effect of digital transformation. The conclusions of this paper provide useful inspiration for manufacturing enterprises to formulate digital transformation strategies and achieve green and sustainable development.

Keywords

digital transformation of enterprises, manufacturing, pollution and carbon reduction, impact mechanism

1. Introduction

In the context of global environmental protection and sustainable development, the manufacturing industry, as the pillar of China's national economy, has an urgent and arduous task of reducing pollution and carbon emissions, and its transformation is particularly critical. In recent years, with the in-depth implementation of China's digital transformation strategy, the digital transformation of enterprises has become a key force to promote the transformation and upgrading of the manufacturing industry. However, how digital transformation can specifically affect the reduction of pollution and carbon emissions in the manufacturing industry needs to be further explored.

Based on this practical demand, this paper takes pollution reduction and carbon reduction in the manufacturing industry as the core goal, and systematically analyzes the multi-dimensional impact of enterprise digital transformation on it. Through literature review and theoretical analysis, a theoretical framework for the relationship between digital transformation and pollution reduction and carbon reduction in the manufacturing industry is constructed. Then, empirical research methods are used to collect relevant data from various provinces in China, and quantitatively analyze the implementation effect of digital transformation and its promotion effect on pollution reduction and carbon reduction in the manufacturing industry.

This study not only helps to reveal the important role of digital transformation in the green transformation of the manufacturing industry, but also provides a scientific basis and decision-making reference for policymakers, which is of great significance for promoting the high-quality development of China's manufacturing industry.

2. Literature Review

With the increasing awareness of global environmental protection, pollution reduction and carbon reduction in the manufacturing industry has become an important topic for the sustainable development of enterprises. In recent years, the digital transformation of enterprises has become an important force to promote pollution reduction and carbon reduction in the manufacturing industry, and its impact mechanism and effect have gradually attracted extensive attention from the academic community.

2.1 The Potential of Enterprise Digital Transformation to Reduce Pollution and Carbon Emissions

Through the introduction of advanced information technology and digital tools, the digital transformation of enterprises can significantly improve production efficiency and resource utilization efficiency, thereby reducing pollutant emissions and carbon emissions. For example, the digital transformation of heavily polluting enterprises can improve green production efficiency by improving the level of enterprise innovation and curbing debt financing costs, and through the introduction of intelligent manufacturing systems, enterprises can accurately control material and energy consumption in the production process and reduce unnecessary waste. At the same time, digital transformation can increase the cohesion of enterprises to customers and suppliers by alleviating financing constraints and improving their innovation capabilities, thereby improving the voice of enterprises in the supply chain (Li & Zhou, 2024), In other words, digital transformation can help enterprises optimize supply chain management and reduce carbon emissions in the logistics process.

2.2 The Impact of Enterprise Digital Transformation on the Energy Structure of the Manufacturing Industry

The digital transformation of enterprises can help promote the optimization of the energy structure of the manufacturing industry. Digitalization is the driving force behind the ongoing energy industry revolution, catalyzing China's pursuit of carbon neutrality and sustainable development (Shi et al., 2024). By introducing clean and renewable energy, companies can reduce their dependence on traditional energy sources and reduce the use of fossil energy and carbon emissions. Optimizing the energy structure is an important mechanism to achieve decarbonization, and studies have shown that digitalization can significantly reduce the carbon intensity of power generation, and the impact of digitalization on reducing carbon intensity increases with the increase of the number of renewable energy sources (H et al., 2023).

2.3 The Digital Transformation of Enterprises Promotes Green Technology Innovation

Digital transformation provides strong technical and talent support for green technology innovation. The study shows that accelerating the improvement of regional digitalization level is of great significance to promote the green technology innovation of resource-based enterprises (Wang et al., 2022). Industry-university-research collaboration can promote the output of digital outcomes by promoting the degree of digital transformation (Su & Wang, 2023). In this process, the digital transformation of enterprises can promote cooperation between enterprises, scientific research institutions, universities, etc., and jointly promote the research and development and application of green technologies. Improving the level of digital transformation of enterprises can not only improve the information transparency of enterprises and strengthen the positive expectations of the market, but also promote enterprises to increase R&D investment, which in turn will improve the level of green technology innovation of enterprises (Liu et al., 2024).

In summary, the digital transformation of enterprises has a positive impact on pollution reduction and carbon reduction in the manufacturing industry. Different enterprises face different challenges and opportunities in the process of digital transformation, so the academic community needs to further explore the specific paths and strategies of enterprise digital transformation to better promote the realization of the goal of pollution reduction and carbon reduction in the manufacturing industry.

3. Theoretical Analysis and Research Hypothesis

3.1 The Direct Effect of Digital Transformation on Enterprise Pollution Reduction and Carbon Reduction

Digital transformation has become an important way for enterprises to improve the level of pollution reduction and carbon reduction, and through the deep integration of digital technology and data elements, enterprises can be empowered in production, operation, decision-making and other links (Yang, Jia, Guo, et al., 2024), and achieve significant economic and environmental benefits. Digital transformation promotes the optimal allocation and efficient use of internal resources. Through the introduction of intelligent control systems and Internet of Things (IoT) technologies, and the technological changes carried out within enterprises based on regional and enterprise digital infrastructure, they are widely seen in the manufacturing process of manufacturing enterprises (Sun, Liu, & Chen, 2017). Enterprises can achieve refined management of production equipment and processes, reduce resource waste and energy consumption, promote their own green transformation (Lin & Wu, 2024), and effectively improve pollution and carbon reduction. At the same time, digital transformation has also strengthened the substitution of clean energy for traditional fossil energy, improved the energy use structure of enterprises, increased the proportion of clean energy, and reduced dependence on non-clean energy sources such as coal and oil [10]. This shift not only reduces pollutant emissions, but also further reduces carbon emissions in the production process. The optimization of resource allocation and the improvement of energy efficiency directly promote the realization of the goal of reducing pollution and carbon emissions.

Therefore, this paper proposes research hypothesis 1: the digital transformation of enterprises can improve the level of pollution and carbon reduction of enterprises.

3.2 The Mechanism of Digital Transformation on Enterprise Pollution Reduction and Carbon Reduction

In today's vigorous development of the digital economy, digital transformation has become an indispensable transformation path for enterprises, which not only directly improves the production efficiency of enterprises, but also its indirect mechanism is worth discussing.

The digital transformation of enterprises can curb their carbon emissions by improving energy efficiency, thereby promoting the reduction of pollution and emissions. The digital transformation of enterprises deeply integrates digital technology into all aspects of their organizational system, including raw material manufacturing, product research and development, and production processes, and promotes the comprehensive digital transformation of enterprise innovation processes and organizational systems (Zhou, Zhang, & Zhang, 2022). This process not only accelerates technological innovation and product iteration, but also promotes the intelligence and refinement of the production process. Digital transformation enables companies to implement more granular energy management. Through the application of technologies such as the Internet of Things, big data, and artificial intelligence, enterprises can monitor and record energy usage in the production process in real time, including energy consumption, energy efficiency, and pollution emissions. This kind of refined management not only helps companies identify the source of energy waste, but also optimizes energy use plans through data analysis to reduce unnecessary energy consumption and pollution emissions. The continuous improvement of the energy structure, the decline of traditional energy consumption, and the gradual increase in the proportion of renewable energy and clean energy will effectively improve the energy efficiency of enterprises (Zhang & Bu, 2024).

Therefore, this paper proposes a research hypothesis 2: the digital transformation of enterprises can reduce pollution and carbon emissions by improving energy efficiency.

The digital transformation of enterprises will promote the innovation of green technology through the use of digital technology and the use of green energy, so as to promote the reduction of pollution and carbon emissions. Circular economy believes that green technology innovation is not only a simple optimization of product design, but also a deep integration of circular thinking into every aspect of enterprise operations, so as to significantly improve production efficiency, effectively reduce energy consumption, and curb carbon emissions. Through the use of advanced virtual technology, enterprises can carry out highly simulated simulation processes in the initial stage of product development, which can forward-look identify and instantly correct potential defects and deficiencies in product design, significantly reduce the risk exposure in the process of technological innovation, and build a more solid foundation for enterprise technological innovation activities, thereby accelerating the pace of technological innovation and improving the overall R&D efficiency (BLOOM, GARICANO, SADUN et al., 2014). Existing studies have shown that enterprise green technology innovation can reduce environmental pollution, improve resource utilization efficiency, and achieve green and sustainable development in which environmental protection and enterprise competitiveness are coordinated (Sun, Liu, & Chen, 2017).

Therefore, this paper proposes a research hypothesis 3: the digital transformation of enterprises can achieve pollution reduction and carbon reduction by promoting green technology innovation.

4. Research Design

4.1 Sample Selection and Data Sources

The A-share listed companies in 2012~2022 were used as the initial sample, and the screening was carried out according to the following criteria: (1) ST or at the end of the year within the exclusion of the samplePT Corporation; (2) exclude companies in the financial sector; (3) Exclude companies with missing data within the sample range. After processing, 12122 sample observations were finally obtained. In addition, in order to avoid the influence of extreme data, all continuous variables are tailed by 1% above and below. Among them, the data used in this paper are from the Guotaian Database (CSMAR), the China Industrial Enterprise Pollution Database, the China Industrial Economic Statistical Yearbook, and the China Energy Statistical Yearbook, and the annual report data of enterprises are from the official websites of the Shenzhen Stock Exchange and the Shanghai Stock Exchange, and some other data are collected manually.

4.2 Definition of Variables

4.2.1 Explanatory Variables

The explanatory variable in this paper is pollution, which is based on Zhao Yanqiao (ZHAO, ZHANG, HE, n.d.) and Guo Jinhua (Guo, Chang, & Guo, 2024) et al., which measure corporate pollution reduction and carbon reduction by corporate carbon emission intensity (Ce) and sulfur dioxide emission intensity (lnSO2). Level.

The total energy consumption data of the industry is from the China Energy Statistical Yearbook, and the operating cost data of the industry is from the China Industrial Economic Statistical Yearbook, and the carbon dioxide conversion coefficient of 1 ton of standard coal is 2.493 according to the carbon dioxide calculation standard of Xiamen Energy Conservation Center.

$$\text{Corporate carbon emission} = \frac{\text{Main business cost} \times \text{Total energy consumption by industry}}{\text{Industry operating cost}} \times \text{Carbon dioxide conversion factor}\#(1)$$

$$\text{Enterprise carbon emission intensity} = \frac{\text{Corporate carbon emission}}{\text{Business income}}\#(2)$$

Total sulphur dioxide emissions are from the China Industrial Enterprise Pollution Database.

$$\text{Sulfur dioxide emission intensity} = \ln\frac{\text{Sulfur dioxide emission}}{\text{Business income}}\#(3)$$

4.2.2 Explanatory Variables

The explanatory variable in this paper is enterprise digital transformation (DCG), drawing on the research of Wu Fei et al. (Wu, Hu, Lin, et al., 2021), from the perspective of artificial intelligence technology (AI), blockchain technology (BD), cloud computing technology (CC), big data technology (DT) and digital technology application (ADT) to build a digital transformation dictionary. Specifically, the jieba library of Python is used for word segmentation, and according to the processing results, the digital transformation word frequency and statistics in the annual report of listed companies are added by 1 for logarithmic processing to obtain the digital transformation indexDCG is used as a metric to measure the digital transformation of enterprises.

$$\text{Digital transformation} = \ln(\text{Digital word frequency totals} + 1)\#(4)$$

4.2.3 Control Variables

Referring to the existing relevant literature and the research of Ma Congwen et al. (Ma & Yang, 2023), the following control variables were set: the age of the enterprise (Age) and the scale of the company's revenue (Sale, logarithmic), cash flow intensity (Cash, the ratio of cash and its cash equivalents to total assets), net profit margin on total assets (ROA, the ratio of net profit to average total assets), book market value ratio (BM, total owner's equity), total asset turnover ratio (ATO, the ratio of operating income to total assets), the asset-liability ratio (Lev, the ratio of total liabilities to total assets). For detailed variable data structures, refer to Table 1.

4.3 Model Setting

In this paper, a benchmark regression model (5) is constructed to study the impact of enterprise digital transformation on pollution and carbon reduction.

$$\text{Pollution}_{i,t} = \varphi_0 + \varphi_1 \text{DCG}_{i,t} + \varphi_2 \text{Controls} + \alpha_i + \beta_t + \gamma_j + \varepsilon_{i,t}\#(5)$$

In Eq. (4), the explanatory variables are $\text{Pollution}_{i,t}$, including $Ce_{i,t}$ and $\ln SO2_{i,t}$. Among them, $Ce_{i,t}$ indicates the carbon emission intensity of enterprise I in year T, and indicates that $\ln SO2_{i,t}$ enterprise I is inSulphur dioxide emission intensity in year t. The core explanatory variable is $DCG_{i,t}$, which indicates the digital transformation of enterprise i in year t. Controls represents the set of control variables. α_i is the fixed effect of the individual (enterprise) (Firm FE), and the β_t fixed effect of time (Year FE), γ_j is the industry fixed effect (Industry FE), which is the $\varepsilon_{i,t}$ random error term of the model.

5. Analysis of Empirical Results

5.1 Descriptive Statistics

Table 1 shows the descriptive statistical results of the main variables. The minimum and maximum values of lnSO2 were -3.4768 and 10.2758, respectively, and the standard deviation was 1.5327. The results show that there are large differences in sulfur dioxide emission intensity among different enterprises. The minimum and maximum values of CE were 0.0965 and 2.6842, respectively, and the standard deviation was 0.7259, indicating that the carbon emission intensity of different enterprises was 0.7259. Compared with sulfur dioxide, the emission intensity difference is small; Similarly, when analyzed for other variables, the standard deviations of all variables were less than 1, except for sulfur dioxide emission intensity (lnSO2), enterprise digital transformation (DCG), and enterprise revenue scale (Sale). , the data is less dispersed. In addition, the multicollinearity test is also performed for each explanatory variable, and the VIF values are all less than 5, which does not exist in the strict sense.

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Ce	12122	0.6683	0.7259	0.0965	2.6842
lnSO2	12122	3.9993	1.5327	-3.4768	10.2758
DCG	12122	1.2316	1.2540	0	4.7005
Age	12122	2.9321	0.3151	1.9459	3.4965
Sale	12122	22.5080	1.2810	20.1934	26.2723
Cash	12122	0.0556	0.0610	-0.1026	0.2331
ROA	12122	0.0415	0.0553	-0.1560	0.2158
BM	12122	1.0642	0.9862	0.1222	5.7360

ATO	12122	0.6638	0.3881	0.1190	2.3927
Lev	12122	0.4157	0.1854	0.0564	0.8201

5.2 Benchmark Regression

Table 2 shows the baseline regression results, where columns (1) and (2) are the regression results without the addition of control variables, and the regression coefficients for digital transformation (DCG) are respectively-0.0120 and -0.0670 at the 1% significance level; Columns (3) and (4) are the regression results after adding control variables, and the regression coefficients of Digital Transformation (DCG) are -0.0125 and - respectively. 0.0169 and still significant at the 1% significance level. This shows that the higher the degree of enterprise digital transformation, the carbon emission intensity (Ce) and sulfur dioxide emission intensity (lnSO2) of enterprises will be significantly reduced, that is, the improvement of enterprise digital transformation will reduce enterprise carbon emissions and pollutant emission intensity, and enterprise digital transformation can promote enterprise pollution reduction and carbon reduction, assuming that H1 is validated.

Table 2. Baseline Regression Results

Variable	(1) Ce	(2) lnSO2	(3) Ce	(4) lnSO2
DCG	-0.0120***	-0.0670***	-0.0125***	-0.0169***
	(0.0030)	(0.0101)	(0.0030)	(0.0047)
Age			0.1290**	-0.0413
			(0.0605)	(0.0734)
Sale			0.0185*	-0.9254***
			(0.0097)	(0.0171)
Cash			0.0552	-0.1151*
			(0.0339)	(0.0596)
ROA			0.0103	1.1638***
			(0.0558)	(0.1055)
BM			-0.0158**	-0.0035
			(0.0070)	(0.0092)
ATO			-0.0426**	-1.3417***
			(0.0194)	(0.0374)
Lev			-0.0204	-0.1167**
			(0.0324)	(0.0587)
_cons	0.6830***	4.0817***	-0.0602	25.8717***
	(0.0036)	(0.0124)	(0.2630)	(0.4320)
Year FE	YES	YES	YES	YES

Industry FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
N	12122	12122	12122	12122
Adj. R^2	0.9600	0.9213	0.9603	0.9791

Note. (1), **, and * represent 1% respectivelysignificant at the significance levels of 5% and 10%; (2) In parentheses are clustering robust standard errors. The same applies hereinafter.

5.3 Robustness Test

5.3.1 Lag Regression of Core Explanatory Variables

Considering that it may take a certain time lag for the impact of enterprise digital transformation on enterprise pollution and carbon reduction, this paper treats the core explanatory variable digital transformation (DCG) with a lag of one period, two lags, and then regression. In this way, it can not only take into account the possibility of transmission time in the actual situation, but also avoid the problem of endogenous interference of reverse cause and effect as much as possible. The results of columns (1) and (2) in Table 3 show that the regression coefficients of enterprise digital transformation (L1.DCG) are both in the lag period Significantly negative at the significance level of 1%; The results of columns (3) and (4) show that the regression coefficient of enterprise digital transformation (L2.DCG) is still significantly negative at the significance level of 1%. Therefore, it can be stated that the hypothesis H1 results are robust.

Table 3. Robustness Test: Lagged Regression of Core Explanatory Variables

Variable	Lag one-period regression of core explanatory variables		Two-period lagged regression of core explanatory variables	
	(1)	(2)	(3)	(4)
	Ce	lnSO2	Ce	lnSO2
L1.DCG	-0.0139*** (0.0032)	-0.0208*** (0.0046)		
L2.DCG			-0.0144*** (0.0033)	-0.0193*** (0.0046)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
_cons	-0.2262 (0.2827)	25.8767*** (0.4778)	-0.3912 （0.3069）	25.9574*** （0.5480）
N	11020	11020	9918	9918

Adj. R^2	0.9625	0.9793	0.9642	0.9798

5.3.2 Re-select the Sample Range

The first is to exclude the impact of China's stock market crash. Drawing on Wu Fei's (Wu, Hu, Lin, et al., 2021) research, the pollution and carbon reduction of enterprises is affected by their business activities and production methods, while the level of digital transformation of enterprises and other economic indicators are affected by major financial shocks, such as enterprise digitalization The transition process may face obstacles, so in order to prevent possible endogenous interference, this paper discusses the financial shock factors in the robustness test. In the sample data time series of this paper (2012~2022), in 2015, China's stock market crash was voiced, in order to exclude the impact of China's stock market crash financial shock, this paper excludes the data sample in 2015, and in order to prevent the aftereffect of China's stock market crash, The 2016 data sample was further excluded and the regression test was re-performed. Columns (1) and (2) in Table 4 show that after excluding the impact of China's stock market crash, enterprise digital transformation (DCG) still has a significant impact on corporate carbon intensity (Ce) and sulfur dioxide emission intensity (lnSO2) have significant negative effects at the significance level of 1%.

The second is to eliminate the impact of data on the digital transformation of zero, and draw on the research of Yang Fengyu (Yang, Jia, Guo et al., 2024) and others to reduce the digital transformation of enterprises to zero The sample data were eliminated and the baseline regression estimate was re-performed. The results of columns (3) and (4) of Table 4 show that the digital transformation of enterprises (DCG) is eliminated in the following areas) is 0, and the impact of enterprise digital transformation (DCG) is still on the carbon emission intensity (Ce) and sulfur dioxide emission intensity (lnSO2) of enterprises) has a significant negative effect at a significance level of 1%.

The third is to exclude the sample of municipalities directly under the central government. Compared with other provinces, municipalities have greater economic and political particularities (Wu, Hu, Lin et al., 2021), and there may be great differences in the digital transformation of enterprises and the reduction of pollution and carbon emissions. Therefore, in this paper, the sample of municipalities directly under the central government is excluded and then the benchmark regression analysis is performed again. The results of columns (5) and (6) in Table 4 show that after excluding the impact of the sample data of municipalities, the digital transformation of enterprises (DCG) still has a significant negative impact on corporate carbon emission intensity (Ce) and sulfur dioxide emission intensity (lnSO2) at the significance level of 1%.

In summary, after excluding the impact of China's stock market crash and the sample with 0 digital transformation and the sample directly under the central government, the benchmark regression results of the sample range were re-selected, and the regression coefficient of enterprise digital transformation (DCG) was 1%.was significantly negative at the level of significance. Therefore, it can be stated that the assumption that the H1 result is robust.

Table 4. Reselects the Sample Range

Variable	Excluding the impact of China's stock market crash		Eliminate digital transformation as 0		Municipalities are excluded	
	(1) Ce	(2) lnSO2	(3) Ce	(4) lnSO2	(5) Ce	(6) lnSO2
DCG	-0.0127*** （0.0034）	-0.0151*** (0.0050)	-0.0098*** (0.0032)	-0.0192*** (0.0060)	-0.0134*** (0.0034)	-0.0189*** (0.0051)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
_cons	0.0300 (0.2671)	26.1219*** (0.4166)	0.2875 (0.2345)	26.0337*** (0.5608)	-0.0813 (0.2866)	25.6727*** (0.4328)
N	9918	9918	7597	7597	9878	9878
Adj. R^2	0.9593	0.9802	0.9694	0.9820	0.9600	0.9772

5.3.3 Decomposition and Regression of Enterprise Digital Transformation

The empirical results show that in Table 5 and Table 6, except for the impact of blockchain (BD) on the sulfur dioxide emission intensity of enterprises in the sub-index of enterprise digital transformation, it is not unexpected. The regression coefficients of all the other digital transformation sub-indicators are statistically significantly negative at the significance level of 1%, which is very consistent with the hypothesis H1 of this paper, and also indicates that the benchmark regression results of this paper have high stability. On the whole, artificial intelligence (AI) has a relatively high regression coefficient for inhibiting corporate carbon emission intensity (Ce) and sulfur dioxide emission intensity (lnSO2), indicating that AI technology is promoting enterprise reductionGeneral Secretary Xi Jinping stressed the need to "take the new generation of artificial intelligence as a driving force to promote the leapfrog development of science and technology, industrial optimization and upgrading, and the overall leap in productivity, and strive to achieve high-quality development." "Considering the strategic significance of artificial intelligence in China, the above empirical results provide more perspectives and perspectives for understanding and further studying the structure of enterprise digital transformation.

Table 5. Decomposition Regression (CE) Based on Enterprise Digital Transformation

Variable	(1) Ce	(2) Ce	(3) Ce	(4) Ce	(5) Ce
AI	-0.0234*** (0.0039)				

BD		-0.0270***			
		(0.0070)			
CC			-0.0142***		
			(0.0038)		
DT				-0.0159***	
				(0.0038)	
ADT					-0.0060***
					(0.0030)
Indicator characteristics	artificial intelligence	Blockchain	cloud computing	Big data	Digital applications
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
_cons	-0.1118	-0.0366	-0.0706	-0.0625	-0.0364
	(0.2650)	(0.2636)	(0.2641)	(0.2638)	(0.2636)
N	12122	12122	12122	12122	12122
Adj. R^2	0.9603	0.9602	0.9602	0.9603	0.9602

Table 6. Decomposition Regression based on Enterprise Digital Transformation (lnSO2)

Variable	(1) lnSO2	(2) lnSO2	(3) lnSO2	(4) lnSO2	(5) lnSO2
AI	-0.0331***				
	(0.0080)				
BD		-0.0107			
		(0.0184)			
CC			-0.0180***		
			(0.0067)		
DT				-0.0189***	
				(0.0062)	
ADT					-0.0151***
					(0.0050)
Indicator characteristics	artificial intelligence	Blockchain	cloud computing	Big data	Digital applications
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Industry FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
_cons	25.7965***	25.9101***	25.8609***	25.8740***	25.8963***
	(0.4275)	(0.4298)	(0.4278)	(0.4313_	(0.4312)
N	12122	12122	12122	12122	12122
Adj. R^2	0.9791	0.9790	0.9791	0.9791	0.9791

5.4 Endogeneity Test

In view of the possible endogeneity problem, the endogeneity problem has been tested to a certain extent by regressing the core explanatory variable Digital Transformation (DCG) after one and two lags, and the regression results still significantly support the hypothesis H1. Furthermore, drawing on the research of Huang et al. [19], this paper selects the number of post offices in prefecture-level cities in 1984 as a tool variable for enterprise digital transformation (IV). In 1984, the number of post offices in each prefecture-level city represented the previous level of informatization development of the city to a certain extent, and also included the closeness of information exchange to a certain extent, which met the requirements of the relevance of instrumental variables. In addition, as an information transmission agency, the post office has no direct relationship with the level of pollution reduction and carbon reduction of enterprises in theory, which meets the requirements of exogenity of tool variables. Specifically, the carbon emission level (Ce) and sulfur dioxide emission level (lnSO2) of enterprises were regressed in two stages. Table 7 of the test results shows that the F-statistic is greater than 10 and significant, and it can be judged that the instrumental variable selected in this paper is not a weak instrument Variable; The Wald test is significant, and it can be considered that the instrumental variables have certain explanatory power. In the first stage of regression, the regression coefficients of the instrumental variable (IV) were all significantly positive at the significance level of 1%, indicating that the instrumental variable (IV) was significantly positive at the significance level of 1%, indicating that the instrumental variable (IV) was significantly different from the explanatory variable Digital Transformation (DCG).) was significantly positively correlated; In the second stage of regression, the regression coefficients of Digital Transformation (DCG) are significantly negative at the significance levels of 1% and 5%, respectively, which is consistent with the results of the previous test, which indicates that the conclusions of this paper are still robust after controlling for endogeneity.

Table 7. Endogeneity Test: Instrumental Variable Method

Variable	(1)	(2)	(3)	(4)
	Ce		lnSO2	
	Phase 1	Phase 2	Phase 1	Phase 2
IV	0.0005***		0.0005***	

	(0.0001)		(0.0001)	
DCG		-0.4976***		-0.0999**
		(0.0895)		(0.0478)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
_cons	-0.5343*	0.1738	-0.5343*	27.2231***
	(0.3115)	(0.1977)	(0.3115)	(0.0684)
F Value	53.2401***		53.2401***	
Wald chi2		15.0207***		4.1665**
N	10109	10109	10109	10109

6. Mechanism Inspection

This paper conducts multi-level empirical research, but only focuses on the overall impact of enterprise digital transformation (DCG) on corporate pollution reduction, and has not yet explored the impact mechanism. Therefore, this paper further examines the influencing mechanism between the two. In this paper, two intermediary variables of "enterprise energy efficiency (TFP)" and "enterprise green technology innovation (Zls)" are selected for verification. In order to study the mechanism and path of enterprise digital transformation (DCG) affecting enterprise pollution and carbon reduction, this paper draws on Wen Zhonglin et al. (Wen & Ye, 2014), construct a model of mediating effects and test it.

$$\mathrm{Pollution}_{i,t} = \varphi_0 + \varphi_1 \mathrm{DCG}_{i,t} + \varphi_2 \mathrm{Controls} + \alpha_i + \beta_t + \gamma_j + \varepsilon_{i,t} \#(6)$$

$$\mathrm{Mediator}_{i,t} = \theta_0 + \theta_1 \mathrm{DCG}_{i,t} + \theta_2 \mathrm{Controls} + \alpha_i + \beta_t + \gamma_j + \omega_{i,t} \#(7)$$

$$\mathrm{Pollution}_{i,t} = \mu_0 + \mu_1 \mathrm{DCG}_{i,t} + \mu_2 \mathrm{Mediator}_{i,t} + \mu_3 \mathrm{Controls} + \alpha_i + \beta_t + \gamma_j + \rho_{i,t} \#(8)$$

In this paper, the energy utilization efficiency (TFP) measured by enterprise total factor productivity was selected as the mediating variable. The logarithmic measurement of green technology innovation (Zls) is measured by adding 1 to the total number of green patents filed by enterprises, as another mediating variable. The remaining variables were consistent with the previous review.

6.1 Energy Efficiency

Energy efficiency is a key factor in the evaluation of corporate pollution and carbon reduction. Since it is difficult to significantly improve the substitution of clean energy and energy consumption structure in a certain period of time, energy efficiency is the key for enterprises to consume less resources under the same resources, so improving energy utilization efficiency (TFP) through enterprise digital transformation (DCG) can reduce the carbon emission intensity and sulfur dioxide emission intensity of enterprises. Promote pollution reduction and carbon reduction (Zhong & Ma, 2022). In this paper, total factor productivity is used as an indicator of energy utilization efficiency (TFP), and an intermediary effect model is established for analysis. The results in Table 8 show that, consistent with the previous results, enterprise digital transformation (DCG) has an impact on enterprise carbon emission intensity (Ce) and sulfur dioxide emission intensity (lnSO2). was significantly negative at the significance level of 1%. Enterprise digital transformation (DCG) has a significant positive impact on energy efficiency (TFP) at a significance level of 10%, while energy efficiency has a significant impact on enterprise carbon emission intensity (Ce) and sulfur dioxide emission intensity (lnSO2) were significantly negative at the significance levels of 5% and 1%, respectively. This shows that the digital transformation of enterprises positively promotes the improvement of energy utilization efficiency, and inhibits the carbon emissions and sulfur dioxide emissions of enterprises through the improvement of energy utilization efficiency, thereby promoting the reduction of pollution and carbon emissions of enterprises, forming a positive path of "enterprise digital transformation → (promoting) energy utilization efficiency → (promoting) enterprise pollution reduction and carbon reduction".

Table 8. Identification of the Mechanism of Enterprise Digital Transformation Affecting Pollution and Carbon Reduction: Energy Efficiency

Variable	DCG→TFP→Ce			DCG→TFP→lnSO2		
	Ce	TFP	Ce	lnSO2	TFP	lnSO2
DCG	-0.0129^{***}	0.0082^{*}	-0.0125^{***}	-0.0192^{***}	0.0082^{*}	-0.0108^{**}
	(0.0031)	(0.0032)	(0.0031)	(0.0048)	(0.0032)	(0.0033)
TEP			-0.0518^{**}			-1.036^{***}
			(0.0160)			(0.3187)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
_cons	-0.0849	-8.409^{***}	-0.521	25.9641^{***}	-8.4093^{***}	17.2496^{***}
	(0.2638)	(0.3091)	(0.2896)	(0.4376)	(0.3091)	(0.3187)
N	11359	11359	11359	11359	11359	11359
Adj. R^2	0.9606	0.9878	0.9607	0.9792	0.9878	0.9888

6.2 Green Technology Innovation

Drawing on the research of Zhong et al., 2022, the digital transformation of enterprises has a positive improvement in the efficiency of information transmission and information acquisition, and the acceleration of information flow enables enterprises to exchange knowledge, information and other data resources in a more timely manner from various aspects. Thus promoting the increase of green technology innovation. In this paper, the total number of green patent applications of enterprises plus 1 is logarithmic as a measure of green technology innovation level (Zls), and an intermediary effect model is constructed for analysis. The results of Table 9 show that the digital transformation of enterprises has a significant positive impact on green technology innovation (ZLS) at the significance level of 1%, and green technology innovation has a significant impact on carbon emission intensity (Ce) had a significant negative effect at the significance level of 5%, but had a negative but not significant effect on sulfur dioxide emission intensity (lnSO2) (p=0.107). However, in general, it has promoted the reduction of pollution and carbon emissions by inhibiting the carbon emission intensity of enterprises, forming a positive path of "digital transformation of enterprises→ (promoting) green technology innovation→ (promoting) corporate pollution reduction and carbon reduction".

Table 9. Identification of the Mechanism of Enterprise Digital Transformation Affecting Pollution and Carbon Reduction: Green Technology Innovation

Variable	DCG→Zls→Ce			DCG→Zls→lnSO2		
	Ce	TFP	Ce	lnSO2	TFP	lnSO2
DCG	-0.0129***	0.0453***	-0.0124***	-0.0192***	0.0453***	-0.0189***
	(0.0031)	(0.0106)	(0.0031)	(0.0048)	(0.0106)	(0.0048)
Zls			-0.0122**			-0.0077
			(0.0043)			(0.0047)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
_cons	-0.0849	-0.9099	-0.0960	25.9641***	-0.9099	25.9571***
	(0.2638)	(0.8456)	(0.2630)	(0.4376)	(0.8456)	(0.4387)
N	11359	11359	11359	11359	11359	11359
Adj. R^2	0.9606	0.7060	0.9607	0.9792	0.7060	0.9792

7. Conclusions of the Study

As a global leader in energy production, consumption and carbon emissions, China shoulders a great responsibility and historical mission to achieve low-carbon development and promote energy transition. In particular, on September 22, 2020, President Xi Jinping was in the 75thAt the general debate of the United Nations General Assembly, China announced its commitment to achieve "carbon neutrality" by 2060. This paper takes A-share listed companies from 2012~2022 as the main research object, and studies the impact of enterprise digital transformation on carbon emissions from two aspects: theoretical and empirical. The results show that: (1) The higher the degree of digital transformation of enterprises, the carbon emission intensity and sulfur dioxide emission intensity of enterprises will be significantly reduced, thereby promoting the reduction of pollution and carbon emissions. (2) The digital transformation of enterprises promotes the improvement of energy efficiency, and it is concluded that the digital transformation of enterprises promotes the increase of green innovative technologies under the construction of the intermediary effect model, which generally plays a certain role in inhibiting the carbon emissions of enterprises and promotes the realization of pollution reduction and carbon reduction of enterprise

8. Policy Recommendations

Based on the above conclusions, the following policy suggestions are put forward: (1). Increase policy support and build a platform for transformation and development. The government and relevant departments will thoroughly implement the digital transformation project of enterprises, study and formulate relevant support policies for the development and utilization of enterprise data resources, continue to optimize the environment for the development of the digital economy, promote the optimal allocation of data element markets, improve the efficiency of enterprise resource utilization, and achieve the role of reducing costs and increasing efficiency. At the same time, the digital transformation of enterprises will be regarded as an important technical strategy for enterprise development, enhance the power of data empowerment, and accelerate the pace of transformation in key areas. Improve the service platform in each industrial chain of the enterprise, strengthen the service supply and solutions, prioritize resource sharing, and establish an industrial platform, so that the application scope of digital transformation can be further expanded, and at the same time, by relying on the platform empowerment, it will bring more opportunities for the digital transformation of multiple industries. (2) Implement differentiated support policies, implement targeted measures for different enterprises, and improve the construction of the digital transformation system. Small and medium-sized enterprises are facing problems such as insufficient funds and technology in the digital transformation, so it is necessary to increase support for the transformation of small and medium-sized enterprises, formulate action plans for the digital transformation of small and medium-sized enterprises, and provide financial support and corresponding preferential tax policies for the promotion of core technology research and technological achievements in the digital transformation of small and medium-sized enterprises, and explore the formation of a long-term mechanism to promote the digital transformation of small and medium-sized enterprises. In addition, for state-owned enterprises, it is necessary to accelerate the digital transformation of state-owned enterprises, optimize the safety management and technical empowerment of state-owned enterprises, improve the capacity of industrial infrastructure construction and the modernization level of the industrial chain, and enhance the competitiveness, influence and anti-risk ability of state-owned enterprises after digital transformation. (3) Relying on artificial intelligence technology, clarify the path of digital transformation. Governments at all levels should actively introduce artificial intelligence technology to add impetus to the digital transformation of enterprises, promote enterprises to reform traditional production methods and energy utilization methods, accelerate the construction of domestic high-level artificial intelligence technology platforms, strengthen the enabling role of intelligent technology, and promote the role of enterprises in reducing pollution and carbon emissions after digital transformation. At the same time, governments at all levels encourage enterprises to clarify their development positioning and development path based on their own advantages, enhance the matching degree of supply and demand in the transformation process, strengthen transformation guidance, and enhance the joint force of digital transformation. (4) Build a platform for technical exchanges, give full play to the effect of green technology, and break technical bottlenecks. The government should actively promote exchanges between enterprises, build communication platforms with relevant universities and scientific research institutions, promote the sharing of data resources, and enhance the transformation advantages of enterprises. At the same time, enterprises should accelerate the development of green technologies, improve the endogenous effects of digitalization, continue to play the role of digital transformation in reducing pollution and carbon emissions, and provide technical support for breaking technical bottlenecks.

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