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Facilitating or Inhibiting: Digital Transformation and Carbon Emissions of Manufacturing Enterprises

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Abstract: As global attention to the issue of climate change grows, the concepts of carbon peaking and carbon neutrality, proposed by China, have increasingly gained traction. In this international context, digital technology and green development are closely interwoven, carving out a distinct path for countries worldwide to achieve carbon emission reduction goals. This study empirically explores the mechanism of how digital transformation impacted the carbon emissions of Chinese A-share listed manufacturing enterprises from 2007 to 2021. The results indicate a significant inverted U-shaped nonlinear connection between digital transformation and carbon emissions within manufacturing enterprises. Green technology innovation, which is among the crucial driving forces for sustainable development, can act as a mediating factor. External environmental regulations positively moderate the relationship between digital transformation and carbon emissions in manufacturing firms. Furthermore, the heterogeneity analysis reveals that the nonlinear impact of digital transformation on carbon emissions in manufacturing enterprises is particularly significant in western regions, non-resource-based cities, light industry sectors, and large-scale enterprises. This paper innovatively verifies, at the micro level, the inverted U-shaped impact of digital transformation on carbon emissions in manufacturing enterprises, as well as its underlying mechanism. It provides theoretical support and practical guidance for the effective implementation of carbon emission reduction in the manufacturing sector. Meanwhile, it also offers valuable insights for manufacturing enterprises to formulate strategies that take both digital development and sustainable development into account, thereby contributing to the achievement of sustainable development.

Keywords: digital transformation; manufacturing enterprises; carbon emission; green technology innovation; environmental regulation; inverted U-shaped relationship

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1. Introduction

Since China has promoted modernization construction, while China's economy has witnessed rapid development, carbon emissions and energy consumption have been on a continuous upward trend. The contradiction between economic expansion and pollutant discharge as well as energy consumption has become increasingly prominent [1]. Currently, a crucial issue confronting China's development is how to curtail energy consumption and carbon dioxide discharges while propelling the economy towards high quality and sustainable growth. It is not only an immediate necessity for the development of China, but also a significant aspect of responding to the global climate change challenge. On 22 September 2020, the carbon peaking and carbon neutrality (dual carbon) targets advanced by General Secretary Xi Jinping provided directional guidance for the Chinese low-carbon and green development path and also set an significant example for the global carbon emission reduction cause. On 7 September 2023, General Secretary Xi Jinping introduced a brand new concept: new quality productivity. Green productivity, as one of its manifestations, can improve both productivity levels and environmental performance, helping to achieve comprehensive social and economic development. In the fiercely competitive environment created by globalization, China must grasp new development opportunities, take strategic measures to facilitate the rapid development of new quality productive forces, promote the structural upgrading, intelligent transformation, and green transformation of traditional industries, and cultivate green and low-carbon emerging high-end manufacturing industries. According to the data provided by China Statistical Yearbook 2023, coal consumption accounted for 56.2% of total energy consumption throughout the year [2]. Meanwhile, manufacturing carbon emissions constituted 38.18% of the country's total emissions, while the manufacturing industry's added value constituted under 28% of the country's total added value [3]. This series of data clearly shows that the manufacturing industry presents a very obvious pattern of heavy pollution and excessive energy utilization, as well as high input and low efficiency in relation to rough development characteristics. However, precisely for this reason, the manufacturing industry exhibits greater potential for carbon and emission reductions, with a broad space for improvement and value that can be tapped, providing an important focus point and breakthrough direction for realizing the "dual-carbon goal" [4]. Reducing carbon emissions in the manufacturing sector is crucial to the accomplishment of the "dual-carbon" objective. It is vitally important for China to realize green and sustainable development and improve new quality productivity.

At the present stage, the digital economy, being a completely novel economic form, is developing rapidly and vigorously around the world [5]. In China, digital technology continues to inject new vitality into economic advancement. It accelerates the transformation and upgrading of traditional kinetic energy, and also stimulates the growth and expansion of emerging kinetic energy. It is of vital importance in promoting the transformation of old and new kinetic energy. Digital productivity, serving as another manifestation of new quality productivity, is progressively being incorporated into all aspects of economic and social development [6]. "Made in China 2025" advocates for facilitating the deep integration of industrialization and informatization, improving the capacity of industrial manufacturing through digital technology, and achieving green and intelligent development. In the "National 14th Five-Year Plan for Informatization", the Chinese Government emphasizes the necessity of boosting the combination and coordination of intelligence, greening, and digitalization. It also emphasizes the employment of digital technology to drive the conversion of traditional energy-intensive industries into those that are low-carbon and green. Facing the new development environment, the close combination of information technology innovation and traditional industries is becoming a new engine for the manufacturing industry to achieve energy saving initiatives, emission reductions, and efficiency enhancement. Meanwhile, digital transformation is becoming a key driving factor for enterprises to move towards high-quality and green development.

As global environmental issues are becoming increasingly severe, the manufacturing sector, as one of the major sources of carbon emissions, has a key role in achieving the goal of sustainable development through associated energy conservation and emission reductions [7]. At the same time, the wave of digital transformation is spreading across diverse industries all around the world. The manufacturing industry is no exception. Furthermore, the manufacturing industry lies at the core of China's modern economic system. Its digital and green transformations are important means to transform the mode of economic development. China's manufacturing industry has already made certain progress in digital transformation. However, under the constraint of the "dual-carbon" goals, the green transformation of the manufacturing industry still needs to be further promoted. Promoting the digital transformation of the manufacturing industry to achieve carbon emission reduction may be an effective way to accelerate the green transformation of China's manufacturing industry and the realization of "dual-carbon" goals. Moreover, whether digital transformation can empower the green transformation of China's manufacturing industry in the context of the digital revolution has become the focus of academic attention. Although the academic community has conducted relevant studies on the digital transformation of the manufacturing industry and its green transformation in recent years, research on the carbon emission reduction effect of the digital transformation of the manufacturing industry is still relatively insufficient. Therefore, investigating the impact of digital transformation on manufacturing carbon emissions and its underlying action mechanism holds substantial theoretical and practical significance. In light of the requirements stemming from practical challenges and national strategies, this study centers on the influence of digital transformation on carbon emissions in the manufacturing domain. The objective is to probe into the functional mechanism and internal logic through which digital transformation drives carbon emission reduction in manufacturing. This endeavor is intended to furnish theoretical support and practical insights for enhancing the reduction of carbon emissions in the manufacturing industry and accelerating the achievement of "dual-carbon" goals. This article centers on the following crucial questions: (1) Can digital transformation help manufacturing companies reduce carbon emissions? Is there a single linear correlation between the two? (2) Can green technological innovation act as an intermediary in the relationship between digital transformation and manufacturing carbon emissions? (3) Can environmental regulation function as a regulator in the relationship between digital transformation and manufacturing carbon emissions? If so, is it positive or negative? (4) Does the carbon emission reduction effect of digital transformation display heterogeneity due to factors like geographical location, resource endowment, and enterprise size?

In summary, the marginal contributions of this paper are presented through the following aspects: (1) It compensates for the deficiencies of the extant literature concerning the environmental outcomes of digital transformation, verifies the inverted U-shaped nonlinear connection between digital transformation and carbon emissions of manufacturing enterprises, and offers a theoretical underpinning for manufacturing firms to execute digital transformation strategies; (2) From the intermediary vantage point of green technological innovation, the influence mechanism of digital transformation on manufacturing carbon emissions is lucidly elaborated. This research enriches the research scope of the transmission path within the relationship between the two; (3) It introduces environmental regulation into the theoretical framework of studying the inverted U-shaped effect of digital transformation on manufacturing enterprises' carbon emissions. It innovatively identifies the key boundary conditions affecting the relationship between the two, and enriches the exploration of the application of institutional theories to the situation.

The rest of this study consists of the following parts: the second section presents a comprehensive review of the existing literature and analyzes its shortcomings. The third section investigates the relevant theories and proposes innovative research hypotheses. The fourth section describes the research methodology adopted in this study along with the associated data. The fifth section highlights the results of the empirical research. Section six finally draws the research conclusions and proposes targeted policy suggestions accordingly.

2. Literature Review

Research pertaining to corporate carbon emissions has been progressively evolving into a salient research topic within the academic realm. The extant literature predominantly concentrates on the role of internal and external environmental factors in generating carbon emissions. Several research studies within enterprise have demonstrated that the asset structure represents a crucial factor affecting the carbon emission performance of enterprises in low-carbon sectors. Specifically, the ratio of fixed assets in enterprises exerts an inhibitory effect on the carbon emission efficacy in low-carbon sectors. Moreover, it has been further confirmed that the utilization efficiency of enterprise assets negatively moderates the role of the fixed assets ratio in inhibiting carbon emission efficiency in low-carbon sectors [8]. Wang et al. executed empirical research regarding the factors influencing carbon productivity in Chinese manufacturing firms. The findings indicated that the asset size, age of firm, management level, export intensity, and marketization degree within enterprises all contribute to improving carbon productivity [9]. Enhancing carbon productivity stands as one of the crucial measures to address global climate challenges and achieve conversion to a low-carbon economy [10]. There are significant correlations between business strategies and total carbon emissions, as well as direct carbon emissions. Moreover, the levels of these two types of emissions in prospector enterprises are higher than those in defender enterprises [11]. Meanwhile, the diversification of a company's board of directors also has a certain impact on the sustainable development of the enterprise. For example, companies with female external directors are more likely to achieve lower carbon emissions, while the effect of emission reduction will be weakened when women serve as internal directors [12]. As far as the external environment affecting manufacturing carbon emissions is concerned, Zhang and Wang et al. empirically examined the relationship between the Mandatory Cleaner Production Audit (MCPA) and carbon emissions utilizing the DID model, founded on the PSM model. The findings demonstrated that the MCPA policy can negatively restrain the intensity of enterprises' carbon emissions, presenting the effect of carbon and pollution reduction [13]. From the perspective of externality theory, Song and Cai discussed the negative environmental externalities generated by profitability pressure. They discovered that when facing greater profitability pressure, corporations tend to satisfy short-term interests by diminishing green innovation investment and heightening the degree of financing constraints, thereby causing higher carbon emissions [14]. Other research has shown that within high-polluting industries, the Low Carbon City Pilot (LCCP) policy has been capable of generating carbon emission reductions for enterprises. Moreover, technological innovation and environmental protection input can play an intermediary role in this process [15]. The progress of the Internet is also capable of reducing carbon emissions from industrial enterprises through improving production efficiency, promoting technological innovation, and restructuring the energy mix [16]. Kwilinski et al. utilized the data of EU countries from 2013 to 2020 to verify that there is a significant inverted U-shaped relationship between the development of digital technologies and carbon emissions [17]. Meanwhile, the development of the digital economy can also significantly reduce carbon emissions through approaches such as technological progress, structural optimization, and the enhancement of educational levels [18]. Moreover, previous research has examined the connection between environmental regulation and carbon emissions. Relevant research has shown that environmental regulations from the government can not only decrease the emission of pollutants from industrial enterprises, but also to some extent inhibit the emission of carbon dioxide from industrial enterprises, which can facilitate the sustainable and green development of businesses [19]. Utilizing the SBM model and factor analysis approach, Yang and Zha et al. carried out an empirical examination of the connection between environmental regulation, green technology, and carbon intensity. They discovered that environmental regulation would initially promote and subsequently restrain the development of green technology. Simultaneously, the impact of environmental regulation on carbon intensity is first curbed and then enhanced. Moreover, a monotonically negative correlation exists between green technology and carbon intensity [20]. This indicates that green technology may serve as an intermediary between environmental regulation and carbon intensity.

The advent of digital transformation aims to comply with the latest round of scientific and technological revolutions and industrial alterations. It aims to deeply integrate digital technology with all production aspects of the substantial economy [21], to develop new digital business models, and to help enterprises sustainably gain competitive advantages through data-driven changes in research and development design, production processes, marketing strategy, and other aspects of the enterprise [22]. The extant literature on digital transformation primarily concentrates on its impact. For example, digital transformation eases firms' financing constraints by improving their information transparency, reducing financing costs, and enhancing their innovation capabilities, which in turn improves business performance [23]. Meanwhile, digital transformation exerts a beneficial influence on business total factor productivity [24]. The implementation of digital transformation helps to increase analysts' awareness of the future development of the company, thereby increasing analyst attention. The increased attention of analysts can enhance the enterprises' financial standing and strengthen the enterprises' internal monitoring, thus improving the total factor productivity [25]. Then, there are other studies that show that digital transformation can facilitate the fulfillment of ESG responsibilities by manufacturing companies. The results of the analytical mechanism show the magnitude of the moderating effects of the three moderating variables of Total Factor Productivity > Investor Stickiness > Information Transparency [26]. Digital transformation, as an important impetus for the overall green transition within economic and social systems, lays a firm foundation for achieving China's "dual-carbon" goal. The primary transmission mechanisms by which digital transformation facilitates pollution and emission reduction for enterprises are green technology innovation, factor allocation efficiency improvement, and environmental information disclosure [27]. Of these, the improvement of factor allocation efficiency assumes a particularly crucial part in the reduction of pollutions and emissions. Xu and Yu et al. proposed that digital transformation can foster ecological innovation and thus enhance the sustainable performance of manufacturing firms [28]. In addition, digital transformation provides substantial assistance for enterprises' green technological innovation. For example, digital transformation can establish cross-organizational collaboration platforms and facilitate internal communication and knowledge sharing among enterprises. In the current business environment, knowledge sharing has turned into a crucial support for enterprise development. With an active and effective knowledge-sharing model, enterprises are able to overcome the constraints of their own knowledge stocks and acquire a broader scope of technical knowledge and information. Such knowledge and information act as abundant nourishment, continuously injecting vitality into enterprises' green technological innovation and thereby effectively enhancing its quality [29]. To sum up, from a multi-dimensional perspective, it can be clearly observed that digital transformation performs a critical function in the process of enterprise development. It has an undeniable promoting effect on the business performance of enterprises, whether in terms of revenue growth, cost control, or the improvement of market competitiveness. Meanwhile, it also brings a positive effect to the environmental performance of enterprises, prompting them to continuously optimize in environment related fields such as energy conservation, emission reduction and resource utilization efficiency. In addition, it significantly promotes the progress of green technology, providing solid technical support for enterprises on the path of sustainable development.

Promoting digitalization is an essential strategy for the acceleration of the sustainable and green development of the manufacturing sector. With regard to the influence of digital transformation on manufacturing enterprises' carbon emissions, extant studies primarily concentrate on aspects such as the connections between digital transformation and carbon intensity as well as the carbon emission performance of manufacturing firms for a series of explorations. Yang et al. [30] and Liu et al. [31] demonstrated that digital transformation influences carbon emissions by way of three channels: industrial structure, technology innovation, and energy intensity. Yang et al. suggested that digitalization exerts a positive function in significantly decreasing the carbon intensity of manufacturing business, and this effect increases with the degree of digitalization. Further mechanism analysis reveals the mediating effects of the four mediating variables. Among them, the mediating effect of green technological innovation is extremely remarkable, followed by financing constraints, information asymmetry, and finally energy utilization efficiency [32]. Meanwhile, digital transformation exerts a favorable influence on the manufacturing enterprises' carbon performance, and this effect is more pronounced in the face of external scrutiny from government and investors [33]. In addition, regarding digital transformation and carbon performance, other related studies have pointed out the presence of a nonlinear relationship. For instance, Yu et al. revealed that a U-curve relationship exists regarding digital transformation and corporate carbon performance, especially in large-scale firms, enterprises in high-pollution sectors, enterprises with a high intensity of R&D investment, and state-owned enterprises [34].

In conclusion, the existing literature has discussed the function of digitalization in enabling carbon emission abatement in manufacturing enterprises from various perspectives, providing theoretical support for, and enlightening the significance of, the research in this paper. Nevertheless, further investigation is required to determine whether digital transformation can actually reduce manufacturing carbon emissions and to identify the internal logic and transmission paths that underpin this process. Few studies have been conducted that analyze the connection in relation to digital transformation and manufacturing enterprises' carbon emissions from the aspect of environmental regulation. Environmental regulation acts as an invaluable factor in the advancement of sustainable and green development [35], and a significant guarantee for realizing the "dual carbon" goal. Its role in integrating and harmonizing digital transformation and manufacturing carbon emissions deserves attention. What's more, the extant literature primarily analyzes the simple linear correlation between digital transformation and corporate carbon emissions. These studies have not yet revealed the comprehensive and complex relationship between the two. Therefore, using the panel data of China's A-share manufacturing enterprises from 2007 to 2021, our paper empirically studies the nonlinear effects and transmission paths of digital transformation on manufacturing enterprises' carbon emissions.

3. Theoretical Analysis and Research Hypothesis

3.1. The Direct Impact of Digital Transformation on Carbon Emissions of Manufacturing Enterprises

Acting as a vital driver, digital transformation empowers the green transformation of the manufacturing sector and facilitates the high-quality advancement of China's economy [36]. As the manufacturing industry and digital technology are continuously coordinated and integrated, the manufacturing industry's capability for acquiring, storing, analyzing, and applying data during the production and operation processes will be significantly strengthened. On the enterprise level, digital transformation can facilitate manufacturing enterprises to adopt more advanced production technology to replace traditional production methods and promote lean production [37]. This allows production methods to comply with the requirements of sustainable green-oriented development and also raise the economic efficiency of the manufacturing enterprise [38]. This promotes the transformation of manufacturing companies from a rough development mode to an innovation-driven development mode, reduces the pollution-intensive production activities of enterprises, realizes cleaner production, and diminishes the carbon emissions of enterprises. Outside the enterprise, digital transformation can help manufacturing enterprises to obtain market information faster. It enables them to grasp the development status and demand of upstream and downstream of the supply chain in a timely manner, alleviating the production lag brought about by information asymmetry. It also helps them formulate production plans scientifically [39], thus eliminating redundant resources and reducing carbon emissions. Moreover, from the energy conservation perspective, the digital economy breaks regional boundaries and overcomes time constraints. It accelerates the flow of factors and production, saving the energy consumption caused by spatial and temporal factors in production and life. This reduction in energy consumption results in a lower energy loss rate and promotes enhanced energy utilization efficiency, thereby restraining carbon emissions.

Simultaneously, the impacts of digitalization within manufacturing enterprises are not confined to just one dimension of carbon mitigation. The digital transformation process itself will bring massive energy consumption. In accordance with the environmental Kuznets theory, the connection between environmental quality and economic development is not simply linear. Within a specific range or period of time, economic development negatively affects environmental quality. However, after reaching a certain inflection point value, economic development positively contributes to the improvement of environmental quality. Therefore, digital transformation acts as the core stage of the progression from informatization to intelligence while fueling the progress of the economy and society, and its influence on manufacturing carbon emissions perhaps exhibits a nonlinear characteristic. At the beginning of digital transformation, enterprises purchased digital equipment. They invested large amounts of human, material, and financial resources to develop digital technology and promote its application. Additionally, they increased resource extraction and energy consumption to expand the scale, which resulted in an increase in carbon emissions [40]. When digitalization is developed to a certain stage, the enterprise's outputs become stable. The cost of the previous input gradually produces a net effect. The upgrading of production technology and the enhancement of efficiency reduces energy consumption, thereby reducing carbon dioxide emissions and having a dampening impact on carbon emissions, from the perspectives of technology innovation diffusion theory [41] and the learning curve [42]. In the early stage of digital transformation, enterprises are in the phase of exploring and adapting to new technologies. They cannot quite fully leverage the carbon emission reduction advantages brought by digitalization. As enterprises become more familiar with digital technologies, expand innovative applications, and accumulate relevant talents, the carbon emission reduction effects will gradually emerge and exceed the increase in carbon emissions caused by transformation investments in the early stage. Consequently, an inverted U-shaped change in carbon emissions will occur. Accordingly, the following hypothesis is proposed in this study:

Hypothesis 1 (H1). *The influence of digital transformation on carbon emissions of manufacturing enterprises shows an inverted U-shaped characteristic, which firstly promotes and then inhibits carbon emissions.*

3.2. The Mediating Role of Green Technology Innovation

Green technological innovation is a result of the merger of innovation and green development. It incorporates the concepts of resource conservation, environmental pollution reduction, and green sustainable development into the enterprise innovation process. This includes green production processes, the research and development of environmentally friendly materials, and the application of clean energy and other innovations [43]. These play an essential role in promoting enterprises to obtain ecological and economic benefits.

According to the innovation theory proposed by Joseph Alois Schumpeter, green technology innovation is a revolutionary and endogenous innovation that entrepreneurs adjust production methods for the target of sustainable development. Advanced digital technological support for green technology innovation is provided by digital transformation. On the one hand, enterprises can increase the allocation and use efficiencies of production factors through digital transformation. They can also optimize the R&D and innovation process, enhance the quality of supply, and stimulate the potential of green technology innovation through rationally leveraging the advantages of data factors [44]. On the other hand, digital transformation will speed up the information flow within the enterprise. It can alleviate information asymmetry and provide timely market and technology information for enterprises, making them fully understand the market demand [45]. It also reduces the waste of resources in the research process, effectively guarantees the benefits of enterprise green technology innovation, and stimulates their enthusiasm to conduct green technological innovation [46]. Furthermore, as the level of digital transformation improves, the scale effect of the digital industry drives the economic development of regions. The favorable economic benefits facilitate the flow of elements such as talents, technologies, and knowledge within the regions. Enterprises integrate digital resources with their original resources, which is conducive to the implementation of green technology innovation. Regarding green technological innovation itself, it is featured with resource conservation, energy consumption reduction, and preservation of the environment [47]. Green technology innovation activities can directly reduce the pollutant emissions of manufacturing enterprises. This is achieved by thoroughly transforming products and production processes. Furthermore, these activities optimize the paradigm of enterprise pollution control. They also promote the improvement of enterprise energy utilization efficiency and pollution control efficiency, which helps to weaken the negative impact of production and business activities on the environment. Accordingly, our study proposes the following hypothesis:

Hypothesis 2 (H2). *In the relationship between digital transformation and carbon emissions of manufacturing enterprises, green technology innovation acts as an intermediary role.*

3.3. The Moderating Effect of Environmental Regulation

The institutional environment is a crucial determinant in regulating the green behavior of enterprises and endowing them with sustainable competitive advantages. As the contradiction between the ecological environment and economic development becomes increasingly prominent, environmental regulation, which is used to restrain the environmentally destructive behavior of enterprises and better coordinate environmental protection and economic growth, has gradually developed into a crucial element of the institutional environment and performs an essential role in environmental governance system [48]. Environmental regulation from the government, as an important institutional force, can guide and supervise enterprises. It enables them to adopt environmentally friendly behaviors through strict external costs, such as conserving resources, decreasing energy consumption, and reducing the production and emission of pollutants.

This study argues that corporate external environmental regulation can positively modulate the association between digital transformation and manufacturing carbon emissions. It reinforces the inverted U-shaped relationship between the two. Based on institutional theory, organizations that comply with the rules of external institutions are more likely to achieve further development and good competitiveness compared to other organizations. Amidst the strict environmental regulatory regime, the expenditure on environmental pollution control by manufacturing enterprises surpasses that of carbon emission reduction. Subsequently, the external cost pressure shall impel enterprises to adhere to the government's environmental regulations and adopt relevant measures to curtail carbon emissions and engage in cleaner production via the internalization of costs [49]. At this time, the support of digital technology has emerged as a vital factor in facilitating manufacturing companies to reduce carbon emissions to meet government compliance requirements. Through effectuating the digital transformation strategy, enterprises drive the green improvement of the production process. They reduce pollution emissions from the source, thus avoiding environmental penalties and reducing the cost of environmental pollution control for enterprises [50]. For manufacturing enterprises, the inclination and motivation to use digital transformation for carbon reduction will be greatly enhanced. Accordingly, the following hypothesis is put forward in this study:

Hypothesis 3 (H3). *Environmental regulation positively moderates the inverse U-shaped relationship between the digital transformation and carbon emissions of manufacturing enterprises.*

4. Research Design

4.1. Sample Selection and Data Sources

Chinese A-share listed manufacturing enterprises during the period from 2007 to 2021 served as the research sample in our study. After data collection was completed for the sample interval, the obtained raw data were processed as follows: (1) the samples like ST and ST* during the observation period were removed; (2) the samples with significant missing observations for core variables (including digital transformation, carbon emissions of manufacturing firms, etc.) were deleted; and (3) all continuous variables were made to undergo a 1% and 99% shrinkage procedure (Winsorise) to avert the impact of extreme values. Finally, this paper considered 17,875 valid observations. The data of relevant variables were obtained from CSMAR, CNRDS, annual reports of listed companies, the China Statistical Yearbook, and the China Environmental Statistical Yearbook.

4.2. Measurement of Variables

4.2.1. Explained Variable

The explained variable in this study was carbon dioxide emissions (Emissions). This article collected the energy use data of enterprises in reference to the study of Wang Hao [51]. We utilized their annual disclosure of social responsibility reports, sustainable development reports, and environmental reports. Then, we further calculated the carbon emissions of the enterprises. Finally, we took the natural logarithm to deal with the emission figures.

4.2.2. Explanatory Variable

The explanatory variable for this study was digital transformation (DT). The information disclosed by enterprises in their annual reports is crucial for determining their long-term development goals and daily operational activities. When it comes to digital transformation, the mention of relevant keywords can indicate the degree of enterprises' attention and investment in this area. It can reveal the specific performance of their digital transformation. This study, relying on this foundation, adopts the approach of Wu Fei and other scholars [52]. We used Python 3.10 software to systematically collect the sample enterprises' annual reports and calculate the occurrence frequency of keywords connected with digital transformation in these reports. Eventually, we added 1 to undertake logarithmic processing to evaluate the enterprises' digital transformation. Although this method has its limitations and may be influenced by corporate reporting styles and rhetorical strategies, it still provides a useful indicator for measuring the overall trend and awareness of digital transformation within enterprises.

4.2.3. Mediating Variable

The mediating variable for this study is green technology innovation (GTI). Our study adopts the research approach of Wurlod and Noailly [53]. The degree of green technological innovation is measured by computing the natural logarithm after adding 1 to the companies' green invention patent applications quantity. In our study, the number of green invention patent applications, to some degree, mirrors the significance level that enterprises attach to green technology innovation and their actual technical level.

4.2.4. Moderating Variable

The moderating variable in this study was environmental regulation (ER). Drawing on Shen Neng et al. [54], we reflected the stringency of external environmental regulation by computing the ratio of investment in pollution control to its industrial output value in each province. The data of environmental regulation (ER) were sourced from CSMAR and China Environmental Statistics Yearbook published in previous years.

4.2.5. Control Variable

Based on previous research, the control variables in this article comprised gearing ratio (Lev), net profit margin of total assets (ROA), return on equity (ROE), number of directors (Board), accounts receivable percentage (REC), and whether it was loss-making (Loss). The specific definitions of these variables are presented in Table 1.

Table 1. Variables and definitions.

	Symbol	Variable	Definitions
Explained variable	Emissions	Carbon dioxide emissions	Carbon emissions from combustion and escape, emissions in the production process, waste emissions, and land use conversion (from forest to industrial land) are taken as logarithms
Explanatory variable	DT	Digital transformation	Digitize related word frequencies, added by one and then logarithmized
Mediating variable	GTI	Green technology innovation	Number of green invention patent applications, added by one and then logarithmized
Moderating variable	ER	Environmental regulation	Investment in pollution control by province/industrial output value by province
Control variable	Lev	Asset-liability ratio	Total liabilities/total assets
	ROA	Total assets net profit margin	Net profit/average balance of total assets
	ROE	Return on net assets	Net profit/average balance of shareholders' equity
	Board	Number of Directors	Logarithmic number of board members
	REC	Accounts receivable ratio	Net accounts receivable/total assets
	Loss	Loss or not	If the net profit of the year is less than 0, it is 1, otherwise it is 0

4.3. Model Setting

4.3.1. Baseline Regression Model

Drawing on the above theoretical analysis, with the aim of examining the inverted U-shaped effect of digital transformation on carbon emissions of manufacturing enterprises, our article constructs a benchmark regression model as follows:

$$Emissions_{it} = \alpha_0 + \alpha_1 DT_{it} + \alpha_2 DT_{it}^2 + \alpha_3 Z_{it} + Year_{it} + Ind_{it} + \varepsilon_{it} \quad (1)$$

$Emissions_{it}$ denotes the carbon emissions of manufacturing firm i in year t; DT_{it} stands for the level of digital transformation of manufacturing firm i in year t; DT_{it}^2 signifies the squared term of the level of digital transformation; Z_{it} represents the control variable set; $Year_{it}$ and Ind_{it}, respectively, indicate year and industry fixed effect; ε_{it} signifies a random disturbance term; and α_0 is a constant term.

4.3.2. Mediation Effect Model

The three-step regression method is used in our paper for testing the intermediary role of green technology innovation, based on the study of Wen Zhonglin et al. [55]. First, we examine the influence of digital transformation on the carbon emissions of manufacturing enterprises.

$$Emissions_{it} = \beta_0 + \beta_1 DT_{it} + \beta_2 DT_{it}^2 + \beta_3 Z_{it} + Year_{it} + Ind_{it} + \varepsilon_{it} \quad (2)$$

Second, the impact of digital transformation on green technological innovation is examined.

$$GTI_{it} = \gamma_0 + \gamma_1 DT_{it} + \gamma_2 Z_{it} + Year_{it} + Ind_{it} + \varepsilon_{it} \quad (3)$$

GTI_{it} represents the level of green technology innovation possessed by manufacturing firm i in year t.

Finally, we conduct an examination of the mediating role of green technology innovation:

$$Emissions_{it} = \varphi_0 + \varphi_1 DT_{it} + \varphi_2 DT_{it}^2 + \varphi_3 GTI_{it} + \varphi_4 Z_{it} + Year_{it} + Ind_{it} + \varepsilon_{it} \quad (4)$$

4.3.3. Moderating Effect Model

Considering environmental regulation's moderating effect, we introduce the moderating variable. Based on model (1), we incorporate the multiplication term of environmental regulation (ER_{it}) and digital transformation (DT_{it}), namely, $DT_{it} \times ER_{it}$ Additionally, we add the multiplication term of environmental regulation (ER_{it}) and digital transformation square (DT_{it}^2), which is $DT_{it}^2 \times ER_{it}$. The following model is established:

$$Emissions_{it} = \delta_0 + \delta_1 DT_{it} + \delta_2 DT_{it}^2 + \delta_3 DT_{it} \times ER_{it} + \varphi_4 DT_{it}^2 \times ER_{it} + \delta_5 ER_{it} + Year_{it} + Ind_{it} + \varepsilon_{it} \quad (5)$$

5. Analysis of Empirical Results

5.1. Descriptive Statistics

As presented in Table 2, the descriptive statistics reveal that the average value of carbon emissions (*Emissions*) stands at 13.37, and its standard deviation is 1.376. The minimum value amounts to 10.69, while the maximum value reaches 17.25. This implies that a certain disparity exists in the carbon emissions across different manufacturing enterprises. The digital transformation (*DT*) degree of enterprises ranges from 0 as the minimum value to 4.5 as the maximum value. The average value amounts to merely 0.969, having a standard deviation of 1.21. This implies that, in general, the enterprises' digital transformation degree remains at a relatively low level and presents significant differences. Moreover, the statistical results of other variables are within a sensible range, suggesting the rationality of the data selection.

5.2. Correlation Analysis

In accordance with the outcomes of the correlation analysis presented in Table 3, the coefficients between DT^2 and *Emissions* are significantly positive. However, this is contrary to the conclusion above. This is presumably attributable to the fact that the correlation analysis reflects the relationship between the two variables without taking into account the influence of industry, year, and other factors. Therefore, the results of the correlation analysis are only a preliminary judgment of the relationship between the two, and the specifics of the situation need to be further analyzed in the regression. Furthermore, the correlation between other control variables introduced in the model of this study and carbon emissions are all significant to a certain extent. This indicates that the choice of these control variables affects manufacturing enterprises' carbon emissions, which further illustrates the reasonableness and scientificity of the setting of these variables. The correlation coefficients in the table are predominantly less than 0.5. Moreover, the VIF test values are all below 10, manifesting that there is no significant multicollinearity issue among the variables. In other words, the variables are selected reasonably.

Table 2. Results of descriptive statistics of variables.

Variable	N	Mean	Std	Min	Max
Emissions	17,875	13.37	1.376	10.69	17.25
DT	17,875	0.969	1.210	0	4.500
ER	17,875	0.00200	0.00200	0	0.0280
GTI	17,875	0.415	0.811	0	6.620
Lev	17,875	0.398	0.195	0.0500	0.856
ROA	17,875	0.0510	0.0590	−0.161	0.226
ROE	17,875	0.0780	0.110	−0.455	0.366
Board	17,875	2.134	0.191	1.609	2.639
REC	17,875	0.128	0.0920	0.00100	0.415
Loss	17,875	0.0830	0.275	0	1

Table 3. Results of variable correlation statistics.

Variable	Emissions	DT	DT^2	ER	GTI	Lev	ROA	ROE	Board	REC	Loss
Emissions	1										
DT	0.101 ***	1									
DT^2	0.077 ***	0.938 ***	1								
ER	−0.002	−0.210 ***	−0.185 ***	1							
GTI	0.333 ***	0.273 ***	0.267 ***	−0.108 ***	1						
Lev	0.517 ***	−0.037 ***	−0.030 ***	0.100 ***	0.159 ***	1					
ROA	0.026 ***	0. 031 ***	0.023 ***	−0.065 ***	0.008	−0.421 ***	1				
ROE	0.150 ***	0.030 ***	0.023 ***	−0.050 ***	0.058 ***	−0.219 ***	0.907 ***	1			
Board	0.241 ***	−0.127 ***	−0.117 ***	0.125 ***	0.046 ***	0.173 ***	−0.009	−0.024 ***	1		
REC	−0.123 ***	0.207 ***	0.188 ***	−0.109 ***	0.101 ***	0.054 ***	−0.055 ***	−0.023 ***	−0.084 ***	1	
Loss	−0.047 ***	−0.014 ***	−0.003	0.023 ***	−0.016 ***	0.217 ***	−0.592 ***	−0.668 ***	−0.005	−0.025 ***	1

Note: *** $p < 0.01$.

5.3. Baseline Regression Results

As presented in Table 4, column (1) displays the results of estimating the regression model with DT included. Evidently, the regression coefficient of digital transformation on manufacturing carbon emissions is 0.135 and is significant at the 1% level. This finding indicates that digital transformation is correlated significantly and positively with manufacturing carbon emissions. Column (2) includes the regression results incorporating DT^2. The findings reveal that the DT coefficient is notably affirmative while the DT^2 coefficient is markedly unfavorable. This implies that in the manufacturing industry, digital transformation can initially promote and then inhibit carbon emissions. Thus, H1 is verified. Enterprises' digital transformation mainly depends on digital information technologies, including blockchain, big data, and artificial intelligence. These technologies not only hold the capacity to reduce carbon dioxide emissions but also, during the initial stage of digital transformation in the manufacturing sector, may give rise to an increment in carbon dioxide emissions. However, when the level of digital transformation reaches a certain stage, the initial investment of manpower, resources, and other costs gradually produce a net effect. The traditional production and operation mode of companies is greatly enhanced through digital transformation, thereby achieving an upgrade to the industrial structure and optimization of resource allocation. At this stage, digital transformation has an inhibitory impact on the manufacturing carbon emissions.

Table 4. Baseline regression results.

Variable	M (1) Emissions	M (2) Emissions
DT	0.135 *** (17.43)	0.226 *** (11.79)
DT^2		−0.027 *** (−5.16)
Lev	3.837 *** (78.89)	3.836 *** (78.93)
ROA	2.450 *** (6.88)	2.428 *** (6.83)
ROE	2.442 *** (12.67)	2.451 *** (12.73)
Board	1.072 *** (26.54)	1.067 *** (26.44)
REC	−1.625 *** (−17.30)	−1.625 *** (−17.32)
Loss	0.056 (1.53)	0.060 * (1.65)
cons	9.307 *** (105.94)	9.294 *** (105.82)
Year	YES	YES
Indu	YES	YES
N	17,875	17,875
R^2	0.4951	0.4972

Note: * $p < 0.1$, *** $p < 0.01$, t-values in parentheses.

5.4. Robustness Tests

Further, to guarantee the dependability of the regression outcomes and address the sample selection bias, we conducted a U-test. Our paper also tested robustness by replacing the explanatory variable, lagging the explanatory variable by one period, and excluding municipalities from the regression. The results are presented in Table 5.

Table 5. Robustness test.

Variable		Emissions	
	M (1)	M (2)	M (3)
DT	0.005 *** (12.45)		0.218 *** (10.75)
DT^2	−0.000 *** (−8.72)		−0.025 *** (−4.48)
L. DT		0.239 *** (11.19)	
L. DT^2		−0.031 *** (−5.17)	
Lev	3.829 *** (82.37)	3.857 *** (73.61)	3.781 *** (74.08)
ROA	2.611 *** (7.60)	3.649 *** (9.28)	2.930 *** (7.90)
ROE	2.466 *** (12.65)	2.299 *** (10.88)	2.052 *** (10.29)
Board	1.015 *** (27.00)	1.090 *** (24.65)	1.003 *** (23.43)
REC	−1.049 *** (−11.92)	−1.703 *** (−16.65)	−1.604 *** (−16.01)
Loss	0.055 * (1.65)	0.123 *** (3.21)	0.025 (0.66)
cons	8.120 *** (98.79)	9.296 *** (96.71)	9.440 *** (101.46)
Year	YES	YES	YES
Indu	YES	YES	YES
N	21,590	14,880	15,349
R^2	0.4524	0.5037	0.5015

Note: * $p < 0.1$, *** $p < 0.01$, t-values in parentheses.

5.4.1. U-Test Test

This study draws on Lind and Mehlum [56]'s methodology to conduct the U-test to probe into whether there exists an inverted U-shaped relationship between the explanatory variable and the explained variable. The test outcomes reveal that the extreme value point is 2.803682, which falls within the value range [0, 417]. At the 1% significance level, this result refutes the null hypothesis. Moreover, the regression fitting slope on the left side of the inflection point is 0.2734049, and that on the right side is −0.1654002. This demonstrates that H1 is robust.

5.4.2. Replacement of Explanatory Variables

In our paper, keywords associated with digital transformation are selected. The "frequency of digital-related words" of each enterprise is sorted out. The "management discussion and analysis" paragraph in the enterprise annual report is chosen for text analysis. Eventually, the frequency of digital transformation-related keywords is obtained, thereby re-evaluating digital transformation (*DT*). As is evident from column (1) in Table 5, the regression outcomes are largely congruent with the prior research conclusions, so the results of H1 are robust.

5.4.3. Explanatory Variables Lagged One Period

This study conducted a regression estimation on the explanatory variable, digital transformation (*DT*), with a one-stage lag. The reason for this approach is that the impact of digital transformation on manufacturing carbon emissions may have a definite lag effect. The model is as follows:

$$Emissions_{it} = \alpha_0 + \alpha_1 L.DT_{it} + \alpha_2 L.DT_{it}^2 + \alpha_3 Z_{it} + Year_{it} + Ind_{it} + \varepsilon_{it} \tag{6}$$

where $L.DT$ is the digital transformation with a one-period lag and $L.DT^2$ stands for its squared term. The regression results in column (2) of Table 5 are consistent with the previous conclusion, indicating that the original conclusions are relatively robust.

5.4.4. Excluding Municipalities

Since the economic development level of centrally-administered municipalities is higher compared to other cities, they have greater advantages in digital transformation, innovation, carbon emission reduction, and other aspects [57]. This may affect the test results. In order to prove the robustness of the results, the four centrally-administered municipalities (Beijing, Shanghai, Tianjin, and Chongqing) were removed from the samples and regression estimation was conducted. It is demonstrated in column (3) of Table 5 that the outcomes are in accordance with the above, denoting that the empirical results preserve their stability after excluding municipalities.

5.5. Heterogeneity Analysis

5.5.1. Based on the Geographic Location Perspective

Given the substantial disparities in the establishment and utilization of digital infrastructure as well as the development level of the manufacturing industry in different territorial areas, it is likely that the impact of digital transformation on the carbon emissions of manufacturing enterprises will show regional differences. Therefore, in our article, the full sample is partitioned into western, central, and eastern sub-samples to carry out regression analysis. As shown in Table 6, in all three regions, there is a nonlinear reversed U-curve relationship between digital transformation and manufacturing enterprises' carbon emissions. In terms of the size of the marginal emission reduction effect of digital transformation, the order is as follows: western > central > eastern. The probable explanation for this phenomenon is that in the western region, which has a relatively lower extent of economic development, the resource allocation capacity of manufacturing enterprises and production capacity are weaker. Consequently, digital transformation can be more effective in reducing their production costs and improving production efficiency. Therefore, digital transformation exhibits a more significant marginal emission reduction effect on manufacturing enterprises in the western region. Given the advanced stage of economic development and science and technology in the eastern region, the marginal impact of digital development on decreasing manufacturing carbon emissions has begun to diminish. In contrast, the central region is undergoing a crucial phase of digital transformation, resulting in a relatively stronger marginal effect on carbon emission reductions within manufacturing enterprises.

Table 6. Heterogeneity at the regional level.

Variable	Emissions		
	Eastern Region	**Central Region**	**Western Region**
DT	0.196 ***	0.247 ***	0.405 ***
	(8.87)	(5.20)	(6.45)
DT^2	−0.017 ***	−0.053 ***	−0.063 ***
	(−2.95)	(−3.90)	(−3.15)
cons	9.283 ***	9.968 ***	8.458 ***
	(89.24)	(48.67)	(31.70)
Controlled	YES	YES	YES
Year	YES	YES	YES
Indu	YES	YES	YES
N	12,255	3185	2345
R^2	0.4928	0.5641	0.5541

Note: *** $p < 0.01$, t-values in parentheses.

5.5.2. Based on the Resource Endowment Perspective

There exists a remarkable relationship between the development pattern of enterprises and the resource endowment of the region where they are located. In regions with significant energy resource endowments, the proportion of resource-dependent industries tends to be higher. This phenomenon leads to enterprises generally encountering greater pressure to lower emissions in the development journey. In accordance with the classification of resource cities outlined in the National Sustainable Development Plan for Resource Cities (2013–2020), we categorized the research sample into two distinct groups: resource-based cities and non-resource-based cities. The findings presented in Table 7 reveal that digital transformation has a significant non-linear influence on carbon emissions from manufacturing enterprises in non-resource-based cities. In contrast, in resource-based cities, it exhibits a monotonous promoting effect. Specifically, in resource-based cities over the long haul, the elevation of the digital transformation level causes a continuous rise in carbon emissions from manufacturing enterprises. The possible reasons for this phenomenon are as follows. First, the green technological level is comparatively low in resource-based cities. Meanwhile, the cycle of technology research, promotion, and application is prolonged. This situation has hindered manufacturing enterprises in resource-based cities from achieving rapid carbon reduction effects through digital transformation. Additionally, the elevation of the digital transformation level can offer adequate technical backing for resource-based cities, thereby facilitating manufacturing enterprises in resource-based cities to expand their production capacity. As resource-based cities have a relatively large share of resource-intensive industries, this results in an increase in their carbon emissions.

Table 7. Heterogeneity at the resource endowment level.

Variable	Emissions	
	Resource-Based Cities	Non-Resource-Based Cities
DT	0.267 ***	0.212 ***
	(4.17)	(10.50)
DT^2	−0.020	−0.025 ***
	(−0.91)	(−4.54)
cons	9.961 ***	9.192 ***
	(41.20)	(97.80)
Controlled	YES	YES
Year	YES	YES
Indu	YES	YES
N	2066	15,809
R^2	0.6240	0.4867

Note: *** $p < 0.01$, t-values in parentheses.

5.5.3. Based on the Industry Perspective

Due to pronounced disparities in process intricacy, energy consumption structure and intensity, and digital technology integration between heavy and light industries, the effect of digital transformation on carbon emissions in manufacturing enterprises may display industry variances. Consequently, this study partitions the entire sample into heavy and light industry sub-samples for regression analysis. The outcomes are illustrated in Table 8. The results demonstrate that, regardless of whether it is in heavy industries or light industries, there exists a non-linear inverted U-shaped curve relationship between the digital transformation and carbon emissions of manufacturing enterprises. In terms of the size of the marginal emission reduction effect of digital transformation, it is found that the effect in light industries is greater than that in heavy industries. The possible reason lies in the fact that heavy industries are energy-intensive ones with a high reliance on traditional energy sources like coal and oil. They consume a huge amount of energy and have a relatively rigid energy structure. Although digital transformation can reduce material waste and energy consumption to some extent, it is difficult to break through the emission reduction bottleneck formed by the original production model in the short term, thus limiting the marginal effect of emission reduction. In contrast, light industries have lower energy consumption and a more diversified energy mix. Some sectors rely more on clean energy such as electricity. Light industries also possess simpler production processes and greater flexibility. This allows them to rapidly adopt and utilize digital production technologies and green innovation outcomes, leading to more significant carbon emission reductions.

Table 8. Heterogeneity at the industry level.

Variable	Emissions	
	Heavy Industries	Light Industries
DT	0.174 ***	0.299 ***
	(7.06)	(7.28)
DT^2	−0.021 ***	−0.068 ***
	(−3.22)	(−4.90)
cons	8.713 ***	10.422 ***
	(73.15)	(65.72)
Controlled	YES	YES
Year	YES	YES
Indu	YES	YES
N	11,221	4696
R^2	0.4833	0.3743

Note: *** $p < 0.01$, t-values in parentheses.

5.5.4. Based on the Enterprise Size Perspective

Enterprise scale is the crucial index for measuring the comprehensive development level of enterprises. Larger companies generally tend to represent a more mature stage of development. They possess a stronger ability to take on innovative risks and can leverage the economies of scale of digital technology applications more effectively. In this study, the total amount of enterprise assets is employed to measure the scale of enterprises. Enterprises with total assets ranking in the top 50% are grouped into large-scale enterprises. The findings presented in Table 9 suggest that digital transformation generates a nonlinear influence regarding the carbon emissions of large-scale manufacturing enterprises. In contrast, the effect of digital transformation on the carbon emissions of small-scale manufacturing enterprises is not significant. The possible cause lies in the fact that small-scale enterprises frequently lack the capacity to effectively integrate digital technologies into existing production procedures. Consequently, they are unable to fully leverage the function of digital technologies in elevating energy efficiency and lowering carbon emissions. On the other hand, small-scale enterprises may focus more on short-term market demands and survival challenges instead of long-term sustainable development goals. This leads to resource allocation focused on short-term benefits, so small-scale enterprises are more inclined to utilize digital transformation for capacity expansion. In contrast, digital transformation, while promoting large-scale enterprise capacity expansion, also contributes to technological innovation and thus its emission reduction effect.

Table 9. Heterogeneity at the enterprise size level.

Variable	Emissions	
	Large-Scale Enterprises	**Small-Scale Enterprises**
DT	0.203 ***	0.020
	(8.39)	(1.11)
DT^2	−0.026 ***	0.002
	(−3.94)	(0.32)
cons	11.026 ***	10.568 ***
	(92.37)	(129.25)
Controlled	YES	YES
Year	YES	YES
Indu	YES	YES
N	8938	8937
R^2	0.3855	0.2646

Note: *** $p < 0.01$, t-values in parentheses.

5.6. Mediation Effect Test

Our paper employs the stepwise multiple regression approach to examine the mediating function of green technology innovation. The results are presented in Table 10 In column (1), we can notice that digital transformation exerts a notable inverted U-shaped influence on manufacturing carbon emissions, which is in line with the baseline regression outcomes. Column (2) reveals that digital transformation positively affects the green technology innovation level and passes the significance level test at 1%. Column (3) demonstrates the mediating role of green technology innovation. To be specific, digital transformation exerts an inverted U-shaped nonlinear influence on manufacturing carbon emissions by affecting green technology innovation. H2 is verified.

However, the regression coefficient of GTI regarding emissions is notably positive, signifying that with the development of green technology innovation, carbon emissions from manufacturing enterprises increase accordingly. This may be because of the "energy rebound effect" elicited by green technology innovation, and this further leads to the "rebound effect" of carbon emissions [58]. Green technological innovation improves the energy utilization efficiency, lowers the cost of production inputs, and aids in expanding the output scale of enterprises. This, in turn, leads to an augmentation of energy consumption and carbon emissions. When the rebound amount of carbon emissions in the manufacturing industry exceeds the reduction amount, the "rebound effect" of carbon emissions emerges.

Table 10. Mediation effect test.

Variable	M (1)	M (2)	M (3)
	Emissions	**GTI**	**Emissions**
DT	0.2258 ***	0.1129 ***	0.2205 ***
	(11.7861)	(19.3711)	(11.8971)
DT^2	−0.0269 ***		−0.0368 ***
	(−5.1573)		(−7.2676)
GTI			0.3394 ***
			(35.0939)
Lev	3.8361 ***	0.6646 ***	3.6102 ***
	(78.9302)	(18.2289)	(76.0950)
ROA	2.4279 ***	−0.1500	2.4707 ***
	(6.8251)	(−0.5621)	(7.1813)
ROE	2.4515 ***	0.9267 ***	2.1405 ***
	(12.7322)	(6.4163)	(11.4814)
Board	1.0672 ***	0.2980 ***	0.9645 ***
	(26.4433)	(9.8451)	(24.6401)
REC	−1.6248 ***	−0.2037 ***	−1.5558 ***
	(−17.3184)	(−2.8938)	(−17.1413)
Loss	0.0600 *	0.0632 **	0.0401
	(1.6509)	(2.3192)	(1.1410)
cons	9.2941 ***	−0.6395 ***	9.5063 ***
	(105.8215)	(−9.7102)	(111.6292)
Year	YES	YES	YES
Indu	YES	YES	YES
N	17,875	17,875	17,875
R^2	0.4972	0.1841	0.5297

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, t-values in parentheses.

5.7. Moderating Effect Test

Environmental regulation, as a kind of institutional environment, may exhibit certain disparities in the influence of digital transformation on manufacturing enterprises' carbon emissions at different levels. Regressions are performed based on the previous moderated effects model and panel data. The regression outcomes (Table 11 present that the interaction coefficient of environmental regulation and the first-order term of digital transformation is 0.0578, and that the second-order term is −0.0119. This implies that environmental regulation makes the inverted U-shaped curve of the impact of digital transformation on manufacturing carbon emissions more pronounced. In other words, environmental regulation can strengthen the relationship between them. Thus, H3 is verified. Specifically, on the one hand, prior to reaching the inflection point value with digital transformation, manufacturing enterprises may engage in disorderly expansion, increasing output capacity and production scale. This leads to higher consumption and demand for energy sources like fossil fuels, and in turn, causes carbon emissions to rise. Meanwhile, strict environmental regulation requires enterprises to consider the external cost of carbon emissions. Enterprises must invest significant amounts of capital to meet the government's requirements for clean production and energy conservation. Due to cost considerations, some manufacturing enterprises may continue to adopt less environmentally friendly modes of production. Therefore, instead of weakening the unfavorable impacts of digital transformation on manufacturing carbon emissions, environmental regulations will reinforce these negative impacts. On the other hand, when the degree of digital transformation exceeds the inflection point, enterprises do not need to invest a substantial amount of resources in digital infrastructure. They have more abundant funds to invest in the improvement of products, processes, and procedures, and environmental regulations help to incentivize enterprises to reduce carbon emissions. Therefore, when the digital transformation level exceeds the inflection point value, digital transformation and environmental regulations play a synergistic role in emissions reduction.

Table 11. Moderating effects test.

Variable	M (1)
	Emissions
DT	0.6020 ***
	(3.9781)
DT^2	−0.1049 **
	(−2.4019)
DT × ER	0.0578 **
	(2.5566)
DT^2 ×ER	−0.0119 *
	(−1.8706)
ER	−0.0655 ***
	(−4.3828)
Lev	3.8469 ***
	(79.0851)
ROA	2.4330 ***
	(6.8425)
ROE	2.4342 ***
	(12.6453)
Board	1.0743 ***
	(26.5893)
REC	−1.6366 ***
	(−17.4392)
Loss	0.0557
	(1.5333)
cons	8.8570 ***
	(66.5966)
Year	YES
Indu	YES
N	17,875
R^2	0.4977

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, t-values in parentheses.

6. Conclusions and Implications of the Study

6.1. Conclusions of the Study

Our paper carries out an empirical exploration of the impact mechanism of digital transformation on carbon emissions of manufacturing enterprises by utilizing the panel data of A-share Chinese manufacturing enterprises from 2007 to 2021. First, we construct a benchmark regression model to empirically verify the inverted U-shaped association between them. Second, we formulate a mediation model to empirically examine the mediation effect exerted by green technology innovation within the relationship between the two. Finally, a moderating model is set up to empirically research the impact of external environmental regulation as a boundary condition on the relationship between the two. The following main conclusions were drawn:

First, the effect exerted by digital transformation on the carbon emissions of manufacturing enterprises exhibits an inverted U-shaped nonlinear feature, initially promoting and subsequently inhibiting emissions. At the nascent stage of digital progress, digital transformation exerts a positive role in increasing manufacturing carbon emissions. When enterprises reach a certain stage of digital development, digital transformation is conducive to a decrease in manufacturing carbon emissions.

Second, digital transformation can enhance the efficiency of enterprise production factors and optimize the R&D process, thus providing support for green technology innovation within manufacturing firms and facilitating them to strengthen such innovation. However, the advancement of green technology innovation may boost manufacturing enterprises' carbon emissions. This can be explained by the fact that green technological innovation triggers the "energy rebound effect", which in turn gives rise to the "rebound effect" of carbon emissions.

Third, environmental regulation can strengthen the inverted U-shaped relationship of digital transformation with manufacturing carbon emissions. At the early stages of digital development, manufacturing industries may invest significant resources in digital transformation. Under strict environmental regulation, when considering costs, enterprises might still be environmentally unfriendly, which intensifies the negative impact of digital transformation. After digital transformation has developed to a certain degree, enterprises obtain funds for environmental protection improvement, and then environmental regulations and digital transformation jointly exert a synergistic emission-reduction effect.

6.2. Management Inspiration

First, accelerating the process of digital development is an inevitable trend for manufacturing enterprises to propel low-carbon and green evolution. Given that digital transformation first promotes and then inhibits carbon emissions in the manufacturing industry, enterprises should highly value the building of digital transformation capacity and deepen digital development for energy conservation, emission reduction, and carbon efficiency improvement. An essential precondition for digital transformation lies in improving digital infrastructure within the enterprise. Enterprises need to comprehensively upgrade traditional infrastructure and promote the research, development, and employment of digital technologies including big data and artificial intelligence. Concurrently, during the course of digital transformation, firms need to construct a solid carbon emission accounting system to prevent excessive energy consumption during digital development and avoid the "rebound effect" of carbon emissions.

Second, there exists an "energy rebound effect" in relation to green technology innovation. In the short term, although the reduction in carbon emissions achieved through green technological innovation will be partially offset by the rebound effect, green technological innovation remains a key means to refine the energy structure and reduce carbon emissions for enterprises. Manufacturing enterprises should expedite the formation of digital productivity and green productivity, enhance energy utilization with renewable energy, and realize low-carbon and green transformation. This not only aids in mitigating the energy rebound effect from the source, but also brings long-term economic and ecological benefits to enterprises.

Third, the government is supposed to reinforce the institutional function of environmental regulation. It should also comprehensively understand the function of environmental regulation, as a policy tool, in promoting the digital transformation of manufacturing enterprises to attain green, low-carbon, and sustainable development in a dialectical and comprehensive manner. Environmental regulation stands as a crucial means of coordinating ecological environmental protection and economic development. The government should formulate regulations scientifically and clarify the environmental responsibilities of enterprises in all aspects of digital production. In terms of law enforcement, it should standardize the criteria and refine the monitoring and judgment rules. Meanwhile, the construction of the law enforcement team should be strengthened to improve the professional quality and equipment level of the personnel, so as to achieve precise and effective environmental supervision over enterprises. Moreover, it is necessary to ensure the effective implementation of environmental regulation policies, establish a supervision and evaluation mechanism, and optimize and adjust them according to the results. In addition, efforts should be made to promote the coordination between environmental regulation and fiscal, industrial, financial, and other policies to form a joint force and contribute to the green transformation of the manufacturing industry.

6.3. Research Limitations and Perspectives

The measurement of digital transformation in this study relied on the frequency of the use of the term "digital transformation" in corporate annual reports. This method has certain limitations. Although widely adopted in previous literature, it is highly subjective and cannot fully and objectively measure the true extent and maturity of enterprise digital transformation. Future research could focus on developing more objective and comprehensive indicators for digital transformation to achieve more accurate assessments. Future research work could also adopt more detailed empirical methods to accurately quantify the relationship between digital transformation and carbon emissions in manufacturing enterprises, thereby enhancing the practical significance and value of research findings. In addition, the data used in this study were from 2007 to 2021. Given the rapid and continuous development of digital technologies and transformation trends, this period may not cover the latest and most influential developments. Future research could consider the latest digital trends, continuously collect and analyze the most up-to-date data, and enhance the understanding of its impact on carbon emissions in the manufacturing industry.

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