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Digital economy and the green transformation of manufacturing industry: evidence from Chinese cities

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The global economy is undergoing a transformative shift propelled by continuous technological advancements. This digital revolution has ushered in a new era characterized by the pervasive influence of the digital economy. Notably, the inherent "green" attributes of the digital economy, such as reduced marginal costs and diminished environmental impact, have injected fresh momentum into the green transformation of the industrial sector. Using spatial econometric model, we examine the impact of the digital economy on the green transformation of the manufacturing industry using panel data for 283 prefecture-level Chinese cities from 2011 to 2019. We first calculate the level of the manufacturing industry's green transformation in this paper according to the Slack-Based Measure model. The green transformation of the industrial sector is facilitated by the digital economy in both the eastern and central regions, as revealed by heterogeneity analysis based on geographical areas. The moderating effect analysis reveals a distinct negative moderating impact of industrial structure upgrading and industrial agglomeration. Additionally, the threshold effect tests indicate significant nonlinear features in the influence of industrial structure upgrading on the green transformation of the manufacturing industry.

KEYWORDS

digital economy, manufacturing industry, green transformation, industrial structure upgrading, industrial agglomeration

1 Introduction

The world's economy nowadays is in the midst of a new era of digital transformation, representing a burgeoning industrial revolution driven by advanced digital technologies that are rapidly expanding worldwide. Specifically, the average score of the Digital Economy Development Index increased from 45.33 in 2013 to 57.01 in 2021, signifying a gain of 26%[1], showing a general upward trend in the global digital economy development since that year. In recent years, China has experienced remarkable development in its digital economy, driven by a combination of favorable government policies, technological innovation, and a large and digitally savvy population. As far as the advantages of the digital economy are

1 Data sources: Global Digital Trade Development Trends Report 2022, Institute of International Trade and Economic Cooperation, Ministry of Commerce, China.

concerned, traditional industries may be successfully empowered by the typical characteristics of the digital economy, which include permeability, platformization, and sharing, boosting the effectiveness of resource utilization and promoting sustainable growth. Leveraging the next-generation of information technology innovation and the availability of data resources, the digital economy can deeply integrate with key emission-intensive sectors such as electricity, construction, and transportation, driving industrial structural upgrades and agglomeration, optimizing energy use and costs in traditional industries, reducing the consumption of energy and lowering carbon emissions intensity (Zhang and Zhao, 2023). Digital technologies also enable intelligent risk prediction, decision control management, and demonstrate high efficiency and feasibility for enterprises. The digital economy simultaneously reduces emission reduction costs and enhances environmental protection benefits, driving the transition from extensive to precise, from mechanization to intelligent transformation and reshaping, and serving as a significant driving force for green transition. For instance, in the steel industry, which accounts for the largest carbon emissions in the industrial sector, digital technology enables deep integration of data elements and modern industry, achieving intelligent control throughout the production line in terms of energy efficiency, quality, and environmental protection. And data modeling may be used to optimize processes using digital technologies like AI and big data, which reduces costs (Lo et al., 2022).

The positive externalities of the digital economy on the green transformation of the manufacturing sector have been especially prominent. Compared with the traditional economy, it is characterized by platformization, openness, and networking. In the meantime, the digital economy utilizes information technologies like the Internet and big data. It forms a model called “data, algorithm, and computing power". With the support of this model, it is possible to balance intermittent renewable energy sources, such as solar and wind power, in real-time while also overcoming geographical and temporal constraints. By facilitating the flow of all kinds of resource elements, the digital economy’s evolution has substantially increased the resource utilization rate and production efficiency. And it helps businesses operate intelligently, improves the efficiency of decision-making, and enables better economic returns. Digital technologies can also assist and guide more capital flow towards enterprises using low-carbon technologies, effectively addressing the financing challenges in green industries. With characteristics such as spillovers and sharing, digital technologies allow companies to overcome temporal and spatial barriers to learn new technologies and knowledge globally, driving technological progress (Lo et al., 2022). Digital technologies optimize established industrial supply networks, value chains, and manufacturing processes, enhancing organizational operational effectiveness and thus driving industrial upgrading. And digital technologies play an essential contribution in improving energy and resource utilization efficiency, promoting the utilization of renewable energy sources, increasing the efficiency of production and distribution of society’s goods, or decreasing the energy and raw material demand for human activities and communication by dematerializing them. For instance, they enable key industries such as electricity, transportation, manufacturing, and construction to implement green supply chain management through cloud computing and intelligent networking, reducing energy consumption in production processes while achieving quality enhancement and efficiency improvement. It may be stated that the digitalization and sustainable growth of the digital economy have profoundly empowered conventional sectors. Smart energy Internet of Things platforms, intelligent energy-saving buildings, and green factories have become key directions for digital enterprises to support environmentally friendly growth.

One key departure from existing research lies in our emphasis on the comprehensive flow of resource elements facilitated by the digital economy’s evolution. This, in turn, significantly amplifies resource utilization rates and production efficiency. The transformative power of the digital economy extends beyond operational enhancements; it enables intelligent business operations, improves decision-making efficiency, and yields superior economic returns. A critical contribution of our study is the identification of the role played by digital technologies in guiding capital flow towards enterprises employing low-carbon technologies, effectively addressing financing challenges in green industries. In essence, our study underscores the profound empowerment of conventional sectors through the industrial structure upgrading and industrial agglomeration. This nuanced perspective distinguishes our research and underscores its importance in understanding the multifaceted contributions of the digital economy to the green transformation of the manufacturing sector.

The following three questions are the focus of this study: Firstly, is the manufacturing sector’s transition to a greener economy being driven by the digital economy? Secondly, upon confirmation of the impact, what are the underlying mechanisms? Lastly, what is the heterogeneity of the digital economy’s influence on the green transition in manufacturing? For the manufacturing industry to fully benefit from the digital economy’s contribution to green transformation and to advance sustainable development, it is crucial to conduct research on these issues. The remainder of this paper is organized as follows. Section 2 is Literature Review and Theoretical Hypotheses. Section 3 presents the Model Construction. Section 4 explains the empirical results, including the benchmark regression results, robustness check, and heterogeneity analysis. Section 5 focuses on the mechanism analysis, and Section 6 concludes the paper.

2 Literature review and theoretical hypotheses

2.1 Digital economy and the green transformation of the manufacturing industry

The majority of the literature currently available on green manufacturing transformation development and the digital economy focuses on determining the level of green manufacturing transformation development from the perspective of green total factor productivity (*GTFP*), green innovation as well as green economic growth. On the basis of the theories of ecological modernization and global value chains, Meng and Zhao (2022) conducted research on the impact of the green economy on China’s

GTFP in the manufacturing sector. The findings indicate that the digital economy has a favorable spatiotemporal influence on *GTFP* and that its embeddedness in the GVC positively modifies this relationship. In Chen et al.'s (2023) investigation of the impact of the digital economy on *GTFP* in the Chinese forestry industry, they employed dynamic panel models, mediation models, and dynamic spatial Durbin models. In their findings, they found that by upgrading the industrial structure and green technology innovation, the digital economy has the ability to enhance the *GTFP* of forestry. Gaglio et al. (2022) conducted research using data from small enterprises in South Africa and found that the digital economy boosts productivity in the manufacturing industry. In their study of the effects of the digital economy on the green transformation of the manufacturing sector, Ran et al. (2023) concentrated on the mechanism of natural resource utilization. The research demonstrated substantial variability in how the use of natural resources and the potential influence of the digital economy on the move towards environmentally friendly development of various industries. Furthermore, the manufacturing sector's green productivity, as well as green economic growth, are both significantly impacted by the digital economy. Evidence from China has been demonstrated that the convergence of the Internet and new energy technologies and digital transformation significantly contribute to green economic development (Wang et al., 2022), and via technological innovation, the digital economy may increase the effectiveness of the sustainable economy (Li et al., 2022). The effectiveness of green development was assessed by Luo et al. (2022) using a random nonparametric data envelopment analysis model, and the effect of the digital economy on the effectiveness of green growth was investigated using a mediation model. They found that the most crucial mechanism factors are the upgrading of the industrial structure, the growth of human capital, and technical innovation. Chen et al. (2015) compared the differences in green development between direct digital manufacturing and other traditional manufacturing paradigms. The research indicated that direct digital manufacturing can reduce energy-intensive raw material usage as well as fuel consumption related to transportation, thus enabling a more effective manufacturing green transformation.

In addition, there are several studies have focused on the effect of digital transformation on green transformation in the manufacturing industry, mainly from the perspective of environmental pollution. Firstly, air pollution including smog and SO2 emissions may be greatly reduced thanks to the expansion of the digital economy (Wan and Shi, 2022), and this impact shows significant regional heterogeneity depending on the level of manufacturing industry agglomeration (Wu et al., 2023). Che and Wang (2022) discovered that by encouraging technology innovation and optimizing resource allocation, the growth of the digital economy could substantially mitigate smog pollution. And the effect of the establishment of an integrated experimental zone with big data on atmospheric pollutants and carbon emissions was empirically analyzed using the difference-in-differences method by Hu (2023). Their findings demonstrate that measures related to the digital economy exhibit an ongoing dampening effect on pollution and carbon emissions. Evidence from heavily polluting manufacturing industries in China suggests that there is a notable U-shaped influence of digital transformation on firms' environmental performance, and it is moderated by environmental information disclosure (Zhang and Zhao, 2023). Secondly, digital finance also performs an essential function in industrial pollution in the manufacturing sector. Qiu et al. (2023), using samples of heavily polluting firms, found that digital finance can effectively make improvements in the environmental behavior of these firms. According to a mechanism study, the impacts of innovation and financing greatly moderate the influence of digital finance on industrial performance in the environment. Research by Du and colleagues (2022) demonstrated that as digital finance improves, it increasingly mitigates local environmental pollution. Through fostering technological innovation, driving industrial upgrades, and encouraging rational industrial structuring, digital finance can help alleviate environmental degradation. Moreover, digital finance can stimulate internal capital flow within enterprises and intensify market competition to promote green investments (Ding et al., 2023).

Hypothesis 1: The digital economy growth in the city follows a "U"-shaped curve relationship on the influence of the green transformation of urban manufacturing. Specifically, the initial increase in digital economy development can negatively affect the green transformation of the manufacturing industry, but once it reaches a certain maturity level, it will begin to support the green transformation.

2.2 Digital economy, industrial structure upgrading and the green transformation of manufacturing industry

Promoting green development is one of the main objectives of upgrading industrial structure, which is a crucial component of this process. By adjusting the industrial structure, an industry upgrade can decrease the proportion of heavily polluting industries and increase the proportion of green industries, reducing energy consumption and environmental contamination and promoting sustainable development (Feng and Yuan, 2016; Pan et al., 2022). The Spatial Durbin Model (SDM) was employed by Su and Fan (2022) to investigate the influence of industrial structure upgrading on environmentally friendly development. The findings demonstrated that although industrial structure upgrading exerts a major negative impact on sustainable growth, rationalizing industrial structure has a considerable beneficial impact. Empirical research from China's agricultural sector suggests that the aggregation of rural industries and upgrading the industrial structure tend to exert a non-linear impact on sustainable agricultural growth, and both exhibit threshold effects (Zhang et al., 2022). According to previous research by Qiu et al. (2023), regional agglomeration and fluctuation tendencies can be seen in both green innovation and industrial structure upgrading. While the indirect and overall impacts of industrial structure overlay are both notably detrimental for green innovation, the direct effect is significantly beneficial.

Digital industrialization and industrial digitalization are two characteristics of the digital economy that support the growth and integration of new and old industries, gradually adjusting the existing industrial structure towards rationalization and sophistication (Carlsson, 2004). The change in the quality of conventional production elements may be facilitated by the digital economy. And conventional sectors often depend on labor as well as capital to be the main production factors, while the digital economy, taking data elements as the primary production factors, incorporates these high-end production factors into various stages of production and consumption, changing and optimizing the input-output structure of the traditional economic system. The new digital information technology significantly promotes information dissemination and innovation, improves the information exchange efficiency of the entire production line, saves production resources, controls innovation costs, facilitates digital management of enterprises, and promotes the transfer of conventional manufacturing elements from the secondary to the tertiary sectors (Teece, 2018). Data from listed manufacturing companies in China demonstrate that the innovation of digital technology contributes to the manufacturing firms' industrial upgrading (Lo et al., 2022). And the digital economy in terms of G7 countries is a vital contributor to technological innovation according to Yuan et al. (2021). The industrial structure upgrading caused by the digital economy is expected to exert a crucial impact on the manufacturing industry's green transformation through channels such as energy consumption and carbon emissions. In the opinion of Xue et al. (2022), the growth of the digital economy encourages a rise in energy consumption, while concurrently enhancing the structure of its use. In the immediate timeframe, the principal factors impacting carbon emissions are the rise in energy usage and technological advancements that do not prioritize environmental sustainability. However, for the long-term perspective, it is the advancements in green technology and transitions in industrial structure that exert a more pronounced influence on carbon emissions. This shift underlines the importance of prioritizing environmentally friendly technologies and industries for long-term carbon emission reduction and sustainable development (Li and Wang, 2022; Yi et al., 2022). In addition, the green digital economy is steadily becoming a vital driver for low-carbon, sustainable growth, as stated by Zhang et al. (2022), who also stressed this point. They identified three key mechanisms that drive this transformation: industrial structure upgrading, technological innovation, and environmental governance.

Hypothesis 2a: Industrial structure upgrading has a "U-shaped" moderating effect in the relationship between the digital economy and the green transformation of the manufacturing industry.

Hypothesis 2b: On the basis of the industrial structure upgrading, the impact of digital economy development on the green transformation of the manufacturing industry exhibits a threshold effect.

2.3 Digital economy, industry agglomeration and the green transformation of manufacturing industry

Industrial agglomeration represents a crucial strategy for achieving regional green development as it integrates regional factors, achieves economies of scale, and generates agglomeration economies, thereby improving regional economic efficiency and pollution control (Wang et al., 2023). Studies already conducted have shown considerable spatial spillover effects between environmental pollution, ecological productivity, and the concentration of industries. Additionally, there is a notable inverted U-shaped association between industrial agglomeration and pollutant emissions as well as a remarkable U-shaped relationship between industrial agglomeration and ecological efficiency (Chen et al., 2020). In the meantime, industrial agglomeration exhibits a significantly inverted "N" shaped effect on air pollution, where air pollution initially decreases, then increases, and eventually decreases again with the deepening of industrial agglomeration (Hao et al., 2022). Furthermore, different levels and modes of agglomeration are likely to be associated with different environmental benefits. As industrial agglomeration continuously evolves, the balance between scale negative externalities (pollution effects) continues to strengthen (Shen and Peng, 2021). Additionally, by enhancing technical effectiveness and promoting technological change, industrial agglomeration might have an impact on the green growth of the manufacturing sector (Cheng and Jin, 2022; Yang et al., 2022).

The digital economy, facilitated by modern computer networks, exhibits significant innovative characteristics during its development. It can expand knowledge spillovers within and outside industries, drive the progress of technology and optimize the industrial structure, and contribute to the formation of manufacturing industry agglomerations within urban areas (Wang et al., 2022). On one hand, within the agglomeration area, the digital economy may enhance the production scale of large manufacturing enterprises within agglomeration areas, generating significant economies of scale, which in turn attract homogeneous manufacturing enterprises from outside the region to concentrate within the agglomeration area (Cui et al., 2023). The digital economy, on the other hand, also offers new opportunities to small-scale manufacturing enterprises in their initial stages, thus resulting in higher levels of manufacturing agglomeration. As a result, the digital economy growth will further contribute to the manufacturing sector's spatial agglomeration (Chang et al., 2023). And the concentration of manufacturing undermines the carbon reduction benefits of digital trade, according to research by Wang et al. (2023), while agglomeration of productive service industries, manufacturing-productive service industry synergistic agglomeration, in addition to the carbon emissions trading pilot policies further strengthened the carbon emission reduction effect of digital trade. The research of Yan et al. (2023) pointed out that the growth of the digital economy effectively promotes urban and industrial agglomeration, and through harnessing green elements of the digital economy, it can reduce the intensity of carbon emissions and promote the development of green transformation.

Hypothesis 3a: The level of industrial agglomeration negatively moderates the relationship between digital economy development and manufacturing green transformation, following a "U-shaped" pattern.

Hypothesis 3b: Under the influence of industrial agglomeration, the impact of digital economy development on manufacturing green transformation exhibits a threshold effect.

3 Research design

3.1 Model construction

3.1.1 Spatial econometric model

By accounting for the spatial diffusion of undesired output in the dependent variable, the pollutants in an area can be categorized into three components: $Pollution_{ct} = L_{ct} + D_{it}$-$D_{ct}$. In this equation, $Pollution_{ct}$ represents the pollutant observation amount in year t for city c. L_{ct} refers to the actual emissions of pollutants in region c; D_{it} means the pollutants diffused to the local area from other regions; D_{ct} does not directly contribute to the actual emission of pollution in this region because this part of pollutants has diffused to other areas (Shao et al., 2016). According to spatial econometric theory, D_{it} and D_{ct} reflect the spatial dependence of pollution in various cities, indicating that neglecting spatial factors in studying pollution issues may lead to biased results (Cole et al., 2020). Furthermore, economic interconnections among cities have become increasingly close with the continuous improvement of unified markets, agglomeration of cities, and metropolitan areas, especially the continuous improvement of transportation conditions. Therefore, urban economic activities may have noticeable correlation effects in space. Moreover, existing studies also show competitive effects between economic decision-making and production activities in different regions of China, implying that geographically adjacent areas can influence local economic activities (Li and Li, 2020). Additionally, the development of inter-industry linkages and commodity trade has facilitated the free movement of production factors and more convenient trade of goods among regions, promoting spatial spillover effects. And the fact is that the digital economy, being the most dynamic area of economic development in China, has strengthened the interconnections among various economic and social domains across regions, indicating a significant spatial correlation in digital economic growth. Thus, this study utilizes spatial econometric models to analyze how the digital economy influences the industrial sector's transition to a greener economy. Since spatial econometric models can be categorized into spatial Durbin model (SDM), spatial autoregressive model (SAR), and spatial error model (SEM), in this paper, the following spatial econometric models are constructed:

First, this study establishes a spatial error model with spatially correlated error terms:

$$Mgt_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2 sDig_{it} + \alpha_3 X_{it} + \varepsilon_{it} + \lambda W \mu_{it} + \lambda_{it} \tag{1}$$

Second, we build a spatial autoregressive model that incorporates the dependent variable's (Mgt) spatial lag term:

$$Mgt_{it} = \alpha_0 + \delta W Mgt_{it} + \alpha_1 Dig_{it} + \alpha_2 sDig_{it} + \alpha_3 X_{it} + \varepsilon_{it} \tag{2}$$

Lastly, by integrating both the spatial error term and the spatial lag term, this research creates a spatial Durbin model:

$$\begin{aligned} Mgt_{it} = \alpha_0 + \delta W Mgt_{it} + \alpha_1 Dig + \alpha_2 sDig_{it} + \alpha_3 X_{it} + \theta_1 W Dig_{it} \\ + \theta_2 W X_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

In the above Eqs 1–3, Mgt_{it} represents the dependent variable, denoting the level of green transformation in the city i's manufacturing sector in year t. With the aim of evaluating the level of green transformation in the manufacturing sector, this study assesses the efficiency of green production in urban industrial enterprise. The variable "Dig_{it}" represents the growth of the city's digital economy, and the coefficient α_1 reflects its marginal impact on the manufacturing sector's transition to a greener economy. A positive value for α_1 means that the green manufacturing sector transition is supported by the growth of the digital economy; $sDig_{it}$ is the squared term of the digital economy; X_{it} represents a variety of factors under control that might affect how the manufacturing sector becomes green. W signifies the spatial weight matrix, and the disturbance terms μ_{it} and ε_{it} are thought to have independent and homogeneous distributions.

3.1.2 Moderating effect model

Building on the previous moderating effect analysis of industrial structure upgrading and industrial agglomeration level, this study further examines the role of the two in moderating the relationship between the digital economy and the manufacturing industry's green transformation. Therefore, in this investigation, we construct a moderated effects model that incorporates the cross terms of the variables of moderation and the core independent variable of the digital economy. The specific construction model is shown below:

$$\begin{aligned} Mgt_{it} = \alpha_0 + \delta W Dig_{it} + \alpha_1 M + \alpha_2 Dig + \alpha_3 sDig_{it} + \beta_1 Dig_{it}{}^{*} M \\ + \beta_2 sDig_{it}{}^{*} M + \alpha_4 X_{it} + \theta_1 W Dig_{it} + \theta_2 W X_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

In Eq. 4, M is the moderator variable, including the industrial agglomeration level as well as the degree of industrial structure upgrading; $Dig^{*}M$ and $sDig_{it}{}^{*}M$ represent the interaction terms of the independent variable digital economy's primary and quadratic terms of the digital economy and with the moderator variables constructed in this paper, respectively.

3.1.3 Threshold regression model

The digital economy may present a non-linear characteristic on the manufacturing green transformation in China based on the level of upgrading urban industrial structure and industrial agglomeration according to the theoretical analysis in the previous section. In the existing literature, researchers commonly have employed the group model for the purpose of investigating the non-linear association that exists between the two variables. Still, this approach is difficult to identify the process by which the digital economy influences the manufacturing industry's transformation into a greener one. Given this, referring to the threshold regression model which was established by Hansen (1999), this study investigates if the digital economy will generate varying impacts on the manufacturing industry's green transformation under the threshold of various degrees of industrial structure upgrading and industrial agglomeration. This study first sets up the traditional single threshold regression model:

$$Mgt_{it} = \alpha X_{it} + \beta_1 Dig_{it} \times I(T_{it} \le \delta) + \beta_2 Dig_{it} \times I(T_{it} > \delta) + C + \varepsilon_{it} \tag{5}$$

In Equation 5, $I(\cdot)$ states that the indicator function; Mgt_{it} is the status of the manufacturing industry's green transformation in year t for city i, while X stands for the control variable; Dig_{it} characterizes digital economy level, which also serves as the core independent variable in this paper. At the same time, the threshold value is characterized by δ, the control variable coefficient is denoted by α, and T is the threshold variable. In addition, β_1 and β_2 represent the

TABLE 1 Data selection and description.

Index selection	Description	Data source
Resource consumption	Fixed asset investment stock	China City Statistical Yearbook, EPS database (2012–2020)
	Industrial employment	
	Industrial water consumption	
	Industrial electricity consumption	
Undesired output	Industrial sulfur dioxide emissions	
	Industrial wastewater discharge	
	Industrial particulate matter emissions	
Desired output	Total industrial output value	

digital economy's parameters for the influence of the manufacturing industry's green transformation under different threshold levels, and $\varepsilon_{it} \sim (0, \sigma)$ is a random disturbance item. Considering the possibility of the double threshold, we construct a double threshold model. This article will not repeat the triple and above multiple threshold models. The double threshold model is shown in the Eq. 6:

$$Mgt_{it} = \alpha X_{it} + \beta_1 Dig_{it} \times I(T_{it} \le \delta_1) + \beta_2 Dig_{it} \times I(\delta_1 < T_{it} \le \delta_2) + \beta_3 Dig_{it} \times I(T_{it} > \delta_2) + C + \varepsilon_{it} \quad (6)$$

Where δ_1 and δ_2 represent the threshold values; β_1, β_2, and β_3 are the regression coefficients. Additionally, additional variables have identical definitions as in model (5).

3.2 Variable description

3.2.1 Dependent variable: manufacturing green transformation (Mgt)

This paper makes reference to existing studies to represent the status of green transformation at the urban manufacturing sector in terms of industrial green production efficiency. Green transformation typically refers to a fundamental and sustainable shift in economic activities, technologies, and practices toward environmental sustainability and the mitigation of climate change. Traditional data envelopment analysis models ignore the environmental costs of processes in which production takes place, resulting in biased assessments of efficiency. The SBM model constructed by Tone (2001) solved the problem of ignoring the input-output slack from traditional radial DEA models. As a result, in this research, we employ the SBM (Slack-Based Measure) model to assess the green transformation status of urban manufacturing. A selection of indicators for the inputs and outputs of the study can be found in Table 1. Among them, the fixed asset investment stock we have selected has been computed by taking into account the method of perpetual inventory. The required original data is the total investment in urban fixed assets.

3.2.2 Independent variable: digital economy (Dig)

Existing studies frequently utilize individual indicators, such as Internet penetration rate, mobile broadband, telephone usage, and digital financial accounts, to gauge the digital economy level (Asongu and Odhiambo, 2019; Mohd Daud et al., 2021). Nevertheless, the transformation of economic development in the direction of digitalization, being a novel economic form, is characterized by convergence and external economics. This illustrates that the digital economy is capable of influencing various aspects of economic development. Therefore, it is not straightforward to precisely and comprehensively assess the digital economy's level solely through a single indicator or dimension. In summary, this paper considers both the city-level availability of relevant data and the necessity of ensuring a scientifically sound characterization of the digital economy level. And we measure the comprehensive digital economy level in terms of two aspects: digital financial inclusion and Internet development.

Precisely, drawing inspiration from the research concepts of Zhao et al. (2022) and Luo et al. (2022), the present research quantifies the level of Internet development at the city level through the utilization of four indicators: penetration of mobile phones, the Internet, relevant employment, and relevant output. The Internet penetration rate is measured by the number of broadband access subscribers to the Internet for every 100 people. In comparison, the mobile phone penetration rate is defined as the total amount of mobile phone subscribers for every 100 people. The relevant output situation is characterised by total telecommunication services *per capita*, and the relevant employment is represented by the percentage of persons employed in the field of software and computer services to the total employment in the city. As for the level of digital financial development, we adopt the "Peking University Digital Inclusive Finance Index" to measure the level of digital financial development. Additionally, the entropy method is employed in this study to establish a comprehensive indicator of digital economic growth. Furthermore, to make sure that the empirical results are robust, the present research also utilizes principal component analysis as a robustness analysis approach to calculate the digital economic development level.

3.2.3 Moderating and threshold variables: industrial development level

Industrial structure upgrading (*Isu*). The quantitative growth from the primary sector to the secondary and the tertiary sectors is merely one way to illustrate the development of industrial structure to an advanced level (Zhao et al., 2022), but also, more importantly, qualitatively transformed from labor-intensive to capital-intensive and technology-intensive. As a result, measuring the degree of industrial structural upgrading only from the perspective of quantity share would fail to capture the changes in labor productivity. Consequently, it is a "false high-level" (Ren et al., 2023). In view of this, this study comprehensively considers the dynamic changes in the quantitative and qualitative aspects of the process of industrial upgrading. Subsequently, in order to combine the two indications mentioned above into a complete index that measures the industrial structure's level of upgrading, we choose to use the entropy weight approach. In particular, the industrial structure upgrading (*Isu*1) has been quantified through the industrial structure level coefficient, calculated as follows:

$$Isu1_{i,t} = \sum_{m=1}^{3} Y_{i,m,t} \times m, m = 1, 2, 3 \tag{7}$$

In formula (7), $Y_{i,\ m,\ t}$ signifies the percentage of the city *i*'s GDP that was accounted for by industry *m* during period *t*.

Moreover, in this study, the following formula is adopted for the measurement of the quality of industrial structural upgrading (*Isu*2):

$$Isu2_{i,t} = \sum_{m=1}^{3} Y_{i,m,t} \times Lp_{i,m,t}, m = 1, 2, 3 \tag{8}$$

Where $Y_{i,m,t}$ represents the same meaning as Equation 7, and $Lp_{i,\ m,\ t}$ symbolizes the labor productivity of industry *m* in the city *i* in period *t*.

Industrial agglomeration (*Ina*). Existing studies mainly use the, E.G., index, spatial Gini coefficient, Herfindahl index, and location entropy to measure the industrial agglomeration level. Since location entropy can objectively reflect industrial agglomeration level, this paper takes reference from the research method of Wei et al. (2023) and then we choose two indicators, namely, the total amount of employees as well as the total employment within the region. And the industrial agglomeration level is measured by location entropy.

3.2.4 Control variable

In an effort to alleviate the endogenous problems due to omitted variables, this study has controlled other factors which may affect the urban manufacturing sector's green transformation. In accordance with the research conclusions of the existing literature, this paper incorporates six indicators into the model as control variables: technological investment, urbanization, economic development, openness level, government intervention, and environmental regulation.

(1) Technical investment (*Tec*). Indeed, technological progress plays a crucial role in enabling cities to implement the manufacturing sector's green transformation. From the perspective of emission reduction, the increase in urban technology investment contributes to higher levels of technological progress and promote the green transformation of production technology in manufacturing enterprises, thereby reducing energy consumption and pollutant emissions (Omri, 2020; Wei et al., 2023). In the present research, the amount of urban expenditure on science and technology has been adopted as the measurement of the level of technology investment.
(2) Urbanization level (*Urb*). Relevant studies have shown that urbanization is accompanied by the concentration of production factors such as labor and capital (Wang et al., 2022), which will facilitate the sharing of pollution control facilities, education, transportation, and other facilities, thereby improving the environmental governance efficiency of manufacturing enterprises. Therefore, we choose night light data to represent the urbanization level.
(3) Economic development (*Eco*). The economic development status is an essential reflection of the comprehensive development of a city. Areas with high levels of economic growth may perform a dual useful role in facilitating the green transformation of urban manufacturing. They not only offer capital support for this transformation but also attract talent and gather various resources, further accelerating the process of green transformation. Based on the above, GDP *per capita* has been selected in this study as an indicator to measure the level of economic development.
(4) openness level (*Open*). The degree of openness of a region primarily impacts the urban green transformation of the manufacturing sector through two main channels: the technology diffusion effect and the "pollution paradise" hypothesis. One view is that opening to foreign countries is conducive to the introduction of green technology and environmental protection management concepts from developed countries, thereby promoting the country's green transformation (Ning et al., 2016). And yet, there are some researchers who suggest that the entry of foreign polluting enterprises may lead to increased local pollution (Taskin and Zaim, 2001), thereby hindering urban green development. This study utilizes FDI to stand for the level of openness.
(5) Government intervention (*Gi*). Government intervention indeed has an essential effect on influencing the manufacturing sector's green transformation. Specifically speaking, providing financial resources to support green R&D activities by means of fiscal policy can positively affect green innovation in enterprises. It encourages businesses to invest in eco-friendly technologies and practices, leading to more sustainable and environmentally responsible innovations in the manufacturing sector (Srivastava and Gupta, 2023). For this reason, the extent of government intervention has been measured passively via the selection of the ratio of local fiscal expenditure to the GDP of the city.
(6) Environmental regulation (*Er*). "Porter's Hypothesis" believes that environmental regulation is an essential means to motivate enterprises to innovate in environmental technology. Higher environmental regulations are going to result in increased costs of corporate pollution behaviors, forcing companies to increase investment in green innovation, which can achieve urban green development (Li et al., 2019). Therefore, we measure the intensity of environmental regulation by employing the ratio of environmental protection expenditure to Gross Domestic Product (GDP).

3.2.5 Spatial weight matrix

The construction of the spatial weight matrix in spatial econometric analysis is fundamental to capturing and reflecting the spatial interactions among the analyzed units or regions. Meanwhile, geographic proximity and economic linkages are

TABLE 2 Data Selection and description.

Variable type	Indicator selection	indicator symbol	Indicator description	Data source
Dependent variable	Manufacturing green transformation	*Mgt*	Industrial green production efficiency	China City Statistical Yearbook, EPS database (2012–2020)
Independent variable	Digital economy	*Dig*	Digital economy comprehensive development index	China City Statistical Yearbook, Digital Finance Research Center of Peking University (2012–2020)
Control variables	Technical investment	*Tec*	Science and technology expenditure amount	China City Statistical Yearbook, EPS database, US National Oceanic and Atmospheric Administration (NOAA) (2012–2020)
	Urbanization level	*Urb*	City night light data	
	Economic development	*Eco*	GDP per capita	
	Openness level	*Open*	FDI	
	Government intervention	*Gi*	Fiscal expenditure/GDP	
	Environmental regulation	*Er*	Environmental protection expenditure/GDP	
Moderating variables and threshold variables	Industrial structure upgrading	*Isu*	Entropy method	China City Statistical Yearbook (2012–2020)
	Industrial agglomeration	*Ina*	Location entropy	

essential factors influencing the digital economy as well as the greening of urban manufacturing. Therefore, this paper simultaneously considers both geographical distance and economic correlation when determining the weight matrix to adequately represent spatial interactions. For this purpose, a geographical distance spatial matrix W_1 is constructed on the basis of the geographical distance between cities. Furthermore, for testing the robustness of the empirical results obtained from the spatial distance weighting matrix, this study also constructs a spatial weighting matrix W_2 with economic characteristics. Specifically, this article uses the reciprocal of the absolute difference in GDP *per capita* corresponding to 283 cities in China to construct an economic distance matrix.

3.3 Data sources

In this research, panel data from 283 prefecture-level cities in 2011–2019 are adopted as the research sample to investigate the influence of the digital economy on the urban manufacturing sector's green transformation. Data sources and descriptions are shown in Table 2.

4 Empirical research

4.1 Benchmark regression results

On the basis of the setup of the models and testing approaches outlined above, this study sequentially applies OLS, fixed effect model, SAR, SEM, and SDM for regression analysis. The results of the regression under the above model setting ideas have been presented in Table 3. Among them, without considering the spatial correlation, the significance level of M1 and M2 is not satisfactory. This suggests that spatial factors should be included in the model when studying the influence that exists between the growth of the digital economy and the manufacturing sector's green transformation. Simultaneously, we use the Wald test to judge if the spatial Durbin model (SDM) can be more reasonable in comparison to the spatial autoregressive model (SAR) and the spatial error model (SEM). As a result, it has been demonstrated that the SDM can not be simplified to either the SAR or SEM. In conclusion, this paper will use the SDM to analyze how the growth of the digital economy has affected the city's manufacturing sector's green transformation. Taking into account the results of the regression, the significantly positive spatial autoregressive coefficient indicates that urban manufacturing's green transformation is accompanied by positive spatial spillover effects. This implies that the urban manufacturing sector's green transformation will contribute dramatically to the manufacturing sector's green transformation in other regions by means of economic or geographical connections. To be precise, the positive spatial spillover effects of the urban manufacturing sector's green transformation can be attributed to the fact that the experience and technology adopted in one region's manufacturing industry act as a catalyst for other regions to learn and adopt advanced practices. Consequently, technology spillovers and information exchanges between regions facilitate the acceleration of the green transformation process, leading to positive outcomes in neighboring areas as well.

The first-order and square-term coefficients of the digital economy have been found to be both statistically significant at the 5% and 1% levels, respectively, and are negative and positive in turn, indicating a significant U-shaped relationship between the digital economy and the green transformation of urban manufacturing. During the early stages of the digital economy

TABLE 3 Benchmark regression results.

Variable	OLS	OLS-FE	SAR	SEM	SDM
	M1	M2	M3	M4	M5
Dig	-0.419* (-1.89)	-0.011 (-1.59)	-0.008** (-1.97)	-0.009** (-2.07)	-0.011** (-2.47)
sDig	0.003* (1.69)	0.000* (1.71)	0.082*** (2.80)	0.041*** (2.81)	0.191*** (2.87)
Tec	0.000 (0.09)	-0.001 (-0.08)	0.001 (0.23)	0.001 (0.16)	0.028** (2.49)
Urb	0.011 (0.82)	-0.032** (-2.20)	-0.020** (-2.06)	-0.020** (-2.11)	-0.019* (-1.94)
Eco	-0.006*** (-7.56)	-0.005*** (-4.26)	0.002*** (2.87)	0.002*** (2.87)	0.002*** (2.94)
Open	0.615*** (9.62)	0.082** (2.04)	0.051** (1.96)	0.050* (1.90)	1.011*** (4.54)
Gi	-0.025*** (-9.32)	-0.050*** (-13.345)	-0.005 (-1.21)	-0.005 (-1.10)	-0.085*** (-2.68)
Er	-0.011* (-1.68)	0.003 (0.76)	-0.001 (-0.376)	-0.001 (-0.36)	0.030** (2.03)
Rho			0.897*** (46.54)	0.937*** (71.68)	0.847*** (27.59)
R^2	0.3639	0.6155	0.4593	0.5695	0.7473
F(Wald test) [P]					326.25 [0.000]
Obs	2,547	2,547	2,547	2,547	2,547

The t statistics are in the brackets; the *P* value is in [ ], and the F value is above; ***, **, and * indicate statistical significance when $p<0.01$, $p<0.05$, and $p<0.1$, respectively. The tables below are the same.

development as a whole, the growth of the digital economy of the city has been found to have significantly impeded urban manufacturing's green transformation. This observation might be attributed to the fact that during this period, it is still at a nascent stage for the progressive implementation of digital technologies to contribute to the manufacturing sector's green transformation. In addition, the limited digital infrastructure and the relatively underdeveloped digital scale of the sector over this period might hinder the full manifestation of the positive externalities of the digital economy. At the same time, in the initial stages of the digital economy's development in terms of scale and technology, there is often a period of rapid economic expansion, which leads to extensive growth and a significant increase in pollution emissions. This could be another factor in acting as an impediment to the urban manufacturing sector's green transformation during this phase. However, the digital economy might initially have a facilitating influence on the urban manufacturing sector's green transformation, which is outweighed by the pollution emission effect resulting in economic activity agglomeration. Therefore, there is an inhibitory role for the digital economy in enabling the urban manufacturing sector to achieve a green transition. As the growth level of the digital economy increases, various positive externalities of the digital economy are coming to occupy a prominent position. On the one hand, the digital economy's emergence and progressive growth has contributed to the diffusion and absorption of technology, which is helpful in enhancing the innovation ability of enterprises. Specifically, digital technology progress in terms of Artificial Intelligence and Big Data along with the development of related industries will notably enhance the efficiency of information collection and integration of enterprises. For this reason, it will be expected to reduce the transmission and sharing costs of information between enterprises, facilitating the accelerated spillover of knowledge and technology, thus offering technological support for manufacturing enterprises to move towards environmentally friendly development. The digital economy, on the other hand, possesses a platform effect. By leveraging digital platforms, enterprises can enhance the matching of supply and demand for production factors and expedite the flow of high-end production factors. This, in turn, guarantees the continuous progress of the digital economy and also allows it to exert positive externalities more effectively.

As far as the control variables are concerned, the estimated coefficient of the technological investment level has a positive and statistically significant coefficient, suggesting that technological progress performs a vital function in contributing to the urban manufacturing sector's green transformation. Additionally, at the 10% level of significance, urbanization implies a deterrent effect on the manufacturing sector's transition to green production, which proves that urbanization will generate congestion effects and scale effects, which are not conducive to the manufacturing sector's transition to green. Moreover, the impact coefficient of economic growth on the manufacturing sector's transition to green is positive and statistically significant at the 1% level in this research, which demonstrates that an improvement in economic development level can lead to various positive externalities. Furthermore, the coefficient of openness level on the manufacturing green transition is 1.011 and satisfies the significance level test of 1%, implying that foreign direct investment (FDI) in manufacturing is capable of accelerating the spillover of foreign advanced green technologies. In the meantime, the significance and positive value of the coefficient for government intervention suggests that bolstering government intervention can play a role in accelerating the transition towards green manufacturing. In the end, the coefficient for environmental regulation passes the significance level test at the 5% level. A positive coefficient suggests that environmental regulation is conducive to motivating

TABLE 4 Robustness test.

Variable	Instrumental variable method	Replace independent variable	Dynamic SDM	Replace spatial weight
	(1)	(2)	(3)	(4)
$W*Mgt_{t-1}$			0.444*** (16.74)	
Dig	-0.312*** (-7.10)	-0.1332*** (-9.12)	-0.008* (-1.83)	-0.041** (-2.37)
sDig	0.017*** (3.70)	0.0037*** (4.90)	0.000** (2.11)	0.003*** (2.59)
Tec	0.026*** (9.31)	0.0848*** (3.13)	0.003 (0.33)	0.062*** (15.20)
Urb	-0.153*** (-4.24)	0.1667*** (5.25)	-0.013 (-1.28)	-0.005*** (-3.14)
Eco	0.004** (2.22)	0.0142*** (4.88)	0.002** (2.33)	0.120*** (13.06)
Open	0.851*** (3.66)	0.3151*** (3.63)	0.069** (2.50)	0.060*** (4.91)
Gi	-0.0454*** (-4.30)	-0.0485*** (-2.97)	-0.006 (-1.18)	-0.008*** (-2.71)
Er	2.683*** (4.29)	0.0439*** (4.39)	0.001 (0.57)	0.024*** (8.43)
Time fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Rho	1.083*** (15.80)	0.0435*** (25.50)	1.403*** (38.86)	1.484*** (13.93)
R^2	0.5219	0.4562	0.6124	0.6251
Obs	2,547	2,547	2,547	2,547

The t statistics are in the brackets; the *P* value is in [ ], and the F value is above; ***, **, and * indicate statistical significance when $p<0.01$, $p<0.05$, and $p<0.1$, respectively. The tables below are the same.

manufacturing firms to engage in technological innovations in a green way, thereby promoting green transformation.

4.2 Robustness check

With the purpose of further guarantee the robustness of the above findings, this study employs the robustness test by adopting the following four approaches.

The first is a test that considers endogeneity issues. Potential missing variables may exist between the digital economy's development and urban manufacturing's green transformation. For the purpose of ensuring the reliability of the findings, in this paper, the instrumental variable approach has been introduced to correct for possible bias. On the basis of principles that have implications for the digital economy development but not to the urban manufacturing green transformation, this paper uses urban slope as an instrumental variable. The sizeable urban slope leads to a relatively lagging infrastructure because the large slope increases the difficulty and cost of infrastructure construction. However, good urban infrastructure is essential for developing the digital economy, so the urban slope meets the instrumental variable correlation conditions. Meanwhile, the urban slope as a natural geographical environment, having no direct correlation with the current manufacturing industry's green transformation. And it satisfies the exogenous conditions required for the instrumental variable. The second method involves substituting the independent variable and utilizing the principal component analysis, an approach that intends to take advantage of the ideology of dimensionality reduction to assess the digital economy's development level, and the dynamic Spatial Durbin model is again chosen to conduct the regression. Finally, the spatial weight matrix is replaced. Such an approach is chosen for the reason that the spatial weight matrix is crucial for capturing the spatial effects between variables. To address this, we reconstruct the spatial weight matrix W_2 with economic characteristics to better represent the spatial interactions in the analysis. Table 4 in the following section presents the results of the robustness estimation. The regression findings show that the digital economy development as the independent variable of this study exhibits a U-shaped relationship with the manufacturing industry's green transformation, which suggests that there is a first inhibiting and then increasing influence between the two. Therefore, the robustness test results align with the core conclusions of this study, reinforcing Hypothesis 1.

4.3 Heterogeneity test

China's vast territory contributes to considerable variations in natural resource endowments, technical conditions, economic development levels, and regional development policies among different regions. Thus, it is essential to investigate further whether regional heterogeneity exists in the above conclusions. In this paper, the sample cities are categorized into three main regions based on factors such as economic development status, namely, the East, the center, and the West, and then perform group regression. It can be seen from the regression results in Table 5 that both the eastern and central regions have shown a contribution to the transition to a greener manufacturing sector, regardless of whether it is the primary item or the secondary item of digital economy development. In contrast, the digital economy development has demonstrated a notable adverse influence on

TABLE 5 Heterogeneity regression results.

Variable	Regional heterogeneity			Urban density heterogeneity	
	East region	Central region	Western region	Low density city	High density city
	(1)	(2)	(3)	(4)	(5)
Dig	0.008* (1.74)	0.028*** (2.66)	-0.022*** (-4.96)	-0.016 (-1.05)	0.827*** (8.14)
sDig	0.035*** (4.29)	0.002** (1.96)	0.002 (1.29)	0.019*** (5.10)	-0.008* (-1.93)
Control	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Rho	0.003*** (13.34)	0.001*** (14.37)	0.002*** (15.39)	0.003*** (20.70)	0.001*** (12.72)
R^2	0.2328	0.7509	0.6597	0.3121	0.7169
Obs	909	900	738	828	1719

The t statistics are in the brackets; the *P* value is in [ ], and the F value is above; ***, **, and * indicate statistical significance when $p<0.01$, $p<0.05$, and $p<0.1$, respectively. The tables below are the same.

the green transition for the manufacturing sector in the western region. The reason for this is that the eastern region, being the pioneer of China's economic development, has taken the lead in pushing forward the digital economy through fully leveraging the advantages of the agglomeration of resources such as capital, labor, and innovation factors. Therefore, the digital economy at the current time represents the leading position in the country in comparison to other regions. Moreover, in this region, there is a proactive effort towards driving deep integration of digital technologies with traditional manufacturing industries, which, in turn, contributes to manufacturing upgrading and transformation, thereby facilitating its trend to environmentally friendly development. And the manufacturing sector in the central region has greater potential for improvement in green transformation in comparison with the eastern region of the country. As a result, developing the digital economy can bring extraordinary bonuses to manufacturing companies in the central region compared to other regions. Furthermore, the information infrastructure in the Western region remains comparatively weak. These reasons we mentioned above lead to a lack of capacity to influence manufacturing's green transformation in the Western region. Apart from these factors, the high proportion of traditional industries in this region restricts the manufacturing sector's green transformation.

In the meantime, a reasonable and orderly urban spatial structure is the source of power for the improvement of the urban green economy efficiency. Moreover, urban density is an essential aspect of urban spatial structure. So, in cities with different densities, is there any heterogeneity in terms of the digital economy's influence on the green transformation with respect to urban manufacturing? For the purpose of exploring the above interesting issues, the present research takes reference from the research results of Fan et al. (2023) to measure urban density. Furthermore, to investigate the heterogeneous impact of the digital economy, the core variable of this research, and its heterogeneous impact on the manufacturing sector's green transition, the urban sample is divided into low-density and high-density cities in accordance with the median annual density among all cities. This grouping allows for a comparative analysis of the ways in which the digital economy affects green transition outcomes in urban areas with different population densities. The findings suggest that the digital economy development first exerts a non-significant negative influence on the transition to a greener manufacturing sector in low-density cities. With the improvement of the digital economy level, it has played an increasingly prominent position in promoting the manufacturing industry's green transformation. As far as high-density cities are concerned, the digital economy's gradual progression has presented an inverted U-shaped relationship with the manufacturing sector's transition towards greening, where it initially promotes the transformation, but later inhibits it. The reason is that the urban density and scale in the initial stage of urban sprawl have not yet reached the ideal level. And the disorderly spread will weaken the economic agglomeration level and the economies of scale effect, which will not be detrimental to developing the digital economy and suppress its ability to bring about positive externalities, thus impeding the manufacturing sector's green transition. When the digital economy reaches a certain level of growth, positive external effects such as resource allocation optimization and technological innovation become more prominent. These effects subsequently play a critical function in driving the transition to a greener manufacturing sector. With regard to high-density cities, the monocentric urban development model will promote urban concentration. This will help break market segmentation and improve regional economic efficiency so as to expedite the manufacturing sector's green transition. Nevertheless, excessive urban clustering may also have adverse effects, such as congestion effects and reduced energy efficiency, which is going to exert a dampening influence on the digital economy development and manufacturing industry's green transformation.

5 Mechanism analysis

5.1 Moderating effects regression results

Table 6 reports the regression findings regarding the moderating effect of the digital economy growth with respect to the manufacturing industry's green transition. In the table, Columns (3) and (4) draw on

TABLE 6 Moderating effects regression results.

Variable	Entropy Method		Principal Component Analysis	
	(1):Isu	(2):Ina	(3):Isu	(4):Ina
Dig	-0.239*** (-2.99)	-0.195*** (-3.66)	-0.052*** (-2.85)	-0.059*** (-3.07)
sDig	0.013** (2.04)	0.563*** (4.33)	0.009* (1.93)	0.207*** (3.35)
Isu	0.034** (2.03)		0.141* (1.68)	
*Dig*Isu*	-0.038*** (-3.13)		-0.001*** (-3.58)	
*sDig*Isu*	0.028*** (3.16)		0.002** (2.31)	
Ina		0.527** (2.27)		0.197*** (3.25)
*Dig*Ina*		-0.019*** (-3.61)		-0.103*** (-2.86)
*sDig*Ina*		-0.001*** (-3.06)		-0.054*** (-4.92)
Control	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
R^2	0.5348	0.5982	0.6293	0.6066
Obs	2547	2547	2547	2547

The t statistics are in the brackets; the *P* value is in [ ], and the F value is above; ***, **, and * indicate statistical significance when $p<0.01$, $p<0.05$, and $p<0.1$, respectively. The tables below are the same.

the idea of replacing the independent variable to test the regression results' robustness. And principal component analysis proposed in the previous section is utilized to calculate the digital economy level. The regression coefficients of the interaction term between the digital economy's development as the research's core explanatory variable and the industrial structure upgrading are −0.038 and −0.001, respectively. Moreover, all of the coefficients have passed the 1% significance level test, which demonstrates a significantly adverse moderating impact that industrial structure upgrading exerts between the digital economy development and the manufacturing industry's transition to green. Meanwhile, the interaction coefficient obtained from the square term for the digital economy constructed in this study and the industrial structure upgrading are 0.028 and 0.002. Furthermore, the two coefficients have been found to be statistically significant at 1% and 5% levels respectively, which suggests in the first place that industrial structure upgrading undermines the inhibitory influence exerted by the growth of the digital economy on the transition to greening of the manufacturing sector. With the gradual progress of the digital economy and the improvement of its level, the industrial structure upgrading will enhance the positive effect brought about by the digital economy development on the manufacturing sector's green transition. The reason is that the industrial structure upgrading promotes the evolution of traditional industries to emerging industries such as technology-intensive and capital-intensive industries. Such a process will lead to a rapid concentration of capital, technology, and other factors of production in fields and regions with a new industrial structure. Accordingly, urban industrial structure upgrading can not only provide financial and talent to support the digital economy development but also contribute to the elimination of backward industries, thus pushing the industry to green.

The digital economy, as the core explanatory variable in this paper, has an interaction term coefficient of −0.019 and −0.103 for its primary term and the industrial agglomeration level, respectively. Moreover, the coefficients of the squared term of the digital economy and the interaction term with the level of industrial agglomeration are −0.001 and −0.054. And all are significant at the 1% level. The findings mentioned above suggests that the a further increase in industrial agglomeration level weakens the negative impact of the digital economy growth with regard to the manufacturing sector's transition to greening when the digital economy development is at a relatively low level. As the development level of the digital economy increases, the strengthening of industrial agglomeration is expected to inhibit the facilitating effect of the green transition for the manufacturing sector in the digital economy. This may be because industrial agglomeration can speed up the diffusion to the agglomeration area of technology and knowledge during its initial stage of the digital economy's development, and it is beneficial to reduce the search cost of innovative information and knowledge for firms, which contributes to the promotion of innovative technological spillovers among firms and the realization of economies of scale. In this process, the digital economy is able to further expedite the spillover and absorption of innovative knowledge and technology, drive digital technological advances, and then realize the sustainable green transformation of manufacturing industries in cities. However, as the industrial agglomeration level continuously keeps increasing, this results in the positive externalities of industrial agglomeration being progressively weakened. And excessive agglomeration, in turn, has been associated with a shortage of resources, rising production costs, and vicious competition among enterprises. These adverse effects will significantly undermine the digital

TABLE 7 Threshold model regression.

Variable	Isu	Ina	Isu	Ina
	(1)	(2)	(3)	(4)
Single threshold test	15.244* [0.097]	27.191* [0.085]	24.508*** [0.007]	30.901*** [0.000]
Double threshold test	11.564** [0.031]	31.282** [0.022]	37.725*** [0.000]	45.005*** [0.000]
Triple threshold test	33.152 [0.629]	12.531 [0.846]	29.379 [0.157]	6.992 [0.881]
Threshold estimate 1	1.849	0.941	1.828	0.857
Threshold estimate 2	1.962	1.990	1.964	1.991
$T<\delta1$	-0.630*** (-15.12)	0.192*** (4.25)	-0.045** (-2.28)	0.001** (2.19)
$\delta1<T<\delta2$	0.309 (0.48)	0.054 (1.72)	0.135* (1.68)	0.065* (1.78)
$T>\delta2$	0.041*** (2.96)	-0.0523*** (-5.43)	0.151*** (6.26)	-0.004*** (-3.59)
Control	Yes	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Constant	6.501*** (23.65)	2.998*** (20.88)	8.522*** (33.25)	3.166*** (18.10)
R^2	0.4050	0.3862	0.782	0.6683
Obs	2547	2547	2547	2547

The t statistics are in the brackets; the *P* value is in [ ], and the F value is above; ***, **, and * indicate statistical significance when $p<0.01$, $p<0.05$, and $p<0.1$, respectively. The tables below are the same.

economy's potential role in promoting the green transition for the manufacturing sector.

5.2 Threshold effect regression results

In order to test the heterogeneous impact of the development of the digital economy on the manufacturing industry's green transformation under different levels of industrial development, this study selects industrial structure upgrading and industrial agglomeration as proxy variables for the level of industrial development. We refer to Hansen's (1999) method and use triple threshold regression to judge the existence and number of thresholds. In the meantime, the Bootstrap method is employed to perform 300 samples, enabling the calculation of the threshold value, F value, and *p*-value for the threshold effect test. We can conclude from the regression results in Table 7 that under the double fixation of time and city, the F value of the double threshold model is the highest when industrial structure upgrading and industrial agglomeration are used as threshold variables. Therefore, this paper chooses the double threshold model for analysis.

Specifically, under different levels of industrial structure upgrading, the core explanatory variable of the digital economy constructed in this research presents various impacts on the urban manufacturing green transition. When Isu<1.828, the influence coefficient of the further growth of the digital economy in this paper on the green transition of the manufacturing sector is −0.045 as well as has been tested for significance at the 5% level; when 1.828<Isu<1.964, the regression coefficient becomes 0.135, and it is significant at the 10% level; when Isu>1.964, the impact coefficient becomes 0.151 and is statistically significant at the 1% level. To sum up, along with the continuously increasing industrial structure upgrading level, the digital economy has also been steadily developing in high quality at this time, and its impact on the manufacturing industry's transition to green demonstrates the role of restraint first and then promotion, and the promotion role is gradually enhanced. This shows that the impact of the industrial structure upgrading, which is the moderating variable in this study, on the manufacturing industry's green transformation has staged characteristics. In the initial stage of industrial structure upgrading, emerging advanced industries have not yet fully developed, while traditional industries remain dominant. Typical characteristics of traditional businesses include high levels of energy use and pollution, causing significant negative consequences for the sustainable transformation of the manufacturing sector. Once the industrial structure upgrading is up to a particular level, it will help coordinate economic development and environmental pollution, and fundamentally promote the manufacturing industry's green transformation. In practice, industries that have high levels of technological content and value-address, such as new energy and next-generation information technology, have become new engines to promote economic development, thus effectively solving the problem of environmental degradation.

For the other aspect, under the threshold constraints of industrial agglomeration, the digital economy's contribution to the green transition of the manufacturing sector presents nonlinear characteristics. When the industrial agglomeration level, the moderating variable of this research, is below 0.857, the elasticity coefficient becomes 0.001, which is statistically positive at the 1% level of significance. After crossing this threshold, its elasticity coefficient with respect to the manufacturing green transition is 0.065, and the digital economy, the core explanatory variable, has significantly facilitated the green transition of the manufacturing sector in the city, but such promotion effect has decreased; When the industrial agglomeration level crosses the second threshold, the digital economy's influence of the present research on the manufacturing sector's transition to green changes from positive to negative, with a corresponding regression coefficient of −0.004. Therefore, with the continuous increase of industrial agglomeration level, the digital economy's effects in the study on the transition towards greening of the manufacturing sector show the role of promoting first and then inhibiting. On the one hand, the agglomeration of an industry in a particular region is beneficial for manufacturing enterprises to implement the scale effect of pollution control. This is possible to decrease the pollution control costs for enterprises and enhance the technical level of pollution treatment through information and technology exchanges between enterprises. On the other hand, excessive industrial agglomeration reduces the profit margin of enterprises and hinders the entry and growth of innovative enterprises. Meanwhile, this is not conducive to the region's attraction of high-quality labor and the entry of new technologies, so the industrial agglomeration's influence on the manufacturing industry's transition to green is manifested as an inhibitory effect.

6 Discussion

The findings of this study contribute novel perspectives to the existing literature by providing a comprehensive assessment of the digital economy's impact on the green transformation of the manufacturing industry. The nuanced regional variations, moderating effects, and nonlinear relationships identified in our research underscore the complexity of these dynamics and emphasize the importance of context-specific analyses in advancing our understanding of the interconnection between the digital economy and sustainability in manufacturing. In contrast to prior research, our empirical framework, tailored to the specific context of this study, substantiates the non-linear influence of the digital economy on driving the manufacturing industry's transition to green. This finding is different from the research conclusion of Luo et al. (2022), who believe that the digital economy simply promotes green development. According to the theory of technological evolution, digital technology innovation is the driving force for the development of digital technology, and the diffusion and adoption of technology are key links in its evolution. In the early stages of digital economy development, the diffusion method, speed and extent of technological innovation will be restricted by market, policy, social and economic factors (Saviotti, 1996). Therefore, it is difficult for the digital economy to fully exert its positive externality effect at this time. The robustness tests conducted in our study serve to enhance the credibility of our empirical findings, ensuring the reliability of the observed effects. Delving into moderation effects, our study unveils the adverse moderating impact of industrial upgrading and industrial agglomeration on the relationship between digital economy development and green transition in manufacturing. This finding underscores the importance of considering industrial structural dynamics in assessing the efficacy of the digital economy in promoting sustainability within the manufacturing sector. Furthermore, our threshold effect analysis exposes a significant nonlinear relationship between the moderating variable of industry upgrading and manufacturing green transformation. This nonlinear dynamic suggests that the impact of industrial structure upgrading on the green transition is contingent on certain threshold conditions, necessitating a more nuanced understanding of the intricate interplay between these variables.

7 Conclusion

Using 283 Chinese prefecture-level cities over the period from 2011 to 2019, this study examines the effect of the digital economy, the explanatory variable of this paper, on the manufacturing industry's transition to green. In this research paper, we first calculate the level of manufacturing green transformation using the SBM mode and constructs a detailed empirical framework following the research ideas in this paper to evaluate the influence of the digital economy on the manufacturing industry's transition to green so as to confirm that the digital economy has been able to effectively drive the manufacturing industry's transition to green. Subsequently, a number of robustness tests have been conducted in the present paper to confirm the accuracy of the empirical results. Based on regional heterogeneity analysis, both the eastern and central regions in China, as delineated in this study, demonstrate the facilitating impact that the digital economy has on the manufacturing industry's transition to green, while the western region's digital economy development growth exhibits a notable negative influence on the manufacturing industry's transition to green. Further exploration of moderation effects reveals that industrial upgrading and industrial agglomeration have remarkable adverse moderating effects on the relationship between the independent variable of the present study, digital economy development, and green transition in manufacturing. Threshold effect analysis indicates a notable nonlinear relationship between the moderating variable of industry upgrading and manufacturing green transformation.

In summary, according to the above research findings, this paper proposes the following policy recommendations. First of all, prioritize digital economy development, including promoting new infrastructure like AI and 5G to enhance the digital economy. Encourage traditional industries to integrate digital technology for improved efficiency, resource optimization, and sustainability. Secondly, address regional disparities in digital economy development. Invest in underdeveloped regions to bridge the "digital division," fostering connectivity, cooperation, and knowledge exchange among regions to promote catch-up growth. Thirdly, promote digital industrialization by supporting innovation, addressing technology challenges, and encouraging the growth of digital industry clusters in key sectors. Foster emerging digital technologies and global competitiveness. In summary, focus on digital economy growth, reduce regional disparities, and advance digital industrialization for a more robust and inclusive economic landscape.

Finally, due to limitations in data availability, this paper only studies the impact of digital economic policies on the green transformation of manufacturing at the city level in China. Industry-level and firm-level discussions can complement city-level studies. Therefore, further discussion could focus on industry or company data.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: All the dataset is allowed to use only with permission. Requests to access these datasets should be directed to Han Wang, hanwang@whut.edu.cn.

Author contributions

HW: Conceptualization, Data curation, Methodology, Software, Writing–original draft, Writing–review and editing. CK: Project administration, Writing–original draft, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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