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How the digital economy can contribute to green manufacturing efficiency

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In response to the global call to promote green production and achieve sustainable development, the proper use of the digital economy plays an important role. The deepening development of the digital economy has led to changes in the input of manufacturing factors and the structure of product demand, which in turn has led to corresponding changes in the level of green and sustainable development. This study employs a factor input-output non-expectation SBM-DEM model to assess the green manufacturing efficiency of 273 prefecture-level and higher cities in China. The relationship between the digital economy and green manufacturing efficiency is analyzed based on this model. The rise of the digital economy is found to contribute to the increase in green manufacturing efficiency, albeit with a non-linear "inverted U-shaped" trend. At the same time, the current level of digital economy development is slowly improving but has not yet reached the inflection point of the "inverted U-shaped" curve, and digital economy development still has a positive impact on green manufacturing efficiency at the current level of development. Furthermore, government intervention is critical in moderating the inverted U-shaped link between the digital economy and green manufacturing efficiency, which has a major weakening effect.

KEYWORDS

digital economy, manufacturing industries, green manufacturing efficiency, sustainable development, SBM-DEA

1 Introduction

In recent years, China has been a world leader in adhering to sustainable development and achieving green growth, and has made outstanding contributions. The country had always been committed to working towards solving worldwide environmental problems and endeavouring to develop into a more sustainable economy. In order to realise the ultimate goals of resource conservation, environmental protection and global sustainable development, China, as an important participant in the global sustainable development process, needs to make significant adjustments in the structure of inputs of factors of production and product demand. Industrial production, as an important part of China's economy, needs to take the lead in this shift. In order to achieve high-quality economic development, China's Ministry of Industry and Information Technology (MIIT) has issued the '14th Five-Year Plan for Green Industrial Development', which points out that it is necessary to accelerate the promotion of green and low-carbon transformation of industry. General Secretary Xi Jinping said at the National Conference on Ecological Environmental Protection that the situation facing the construction of China's ecological civilisation is still severe, and that we should continue to adhere to the development concept of 'green

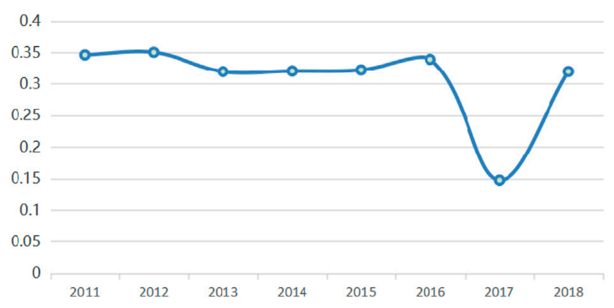

FIGURE 1
China's green manufacturing efficiency development level.

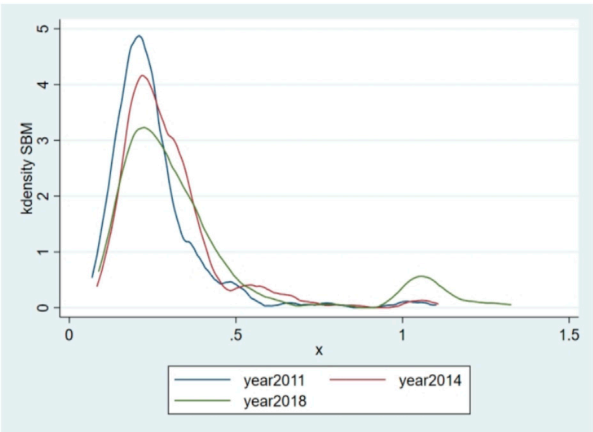

FIGURE 2
Kernel density map of green manufacturing efficiency in China.

mountains are golden mountains' in the future development, and further promote the construction of ecological civilisation in the new era.

However, China's current industrial development has not yet reached a high level of quality, and the quick growth rate is accompanied by a significant degree of pollution. In the 2020 Global Environmental Performance Index ranking, China ranks 120th out of 180 countries (Heet al., 2022), with coal consumption accounting for 56.7% of total energy consumption. While fossil energy continues to dominate overall energy consumption, environmental issues have become an important bottleneck for China's pursuit of high-quality development. The digital economy is a significant tool for reducing the strain on resources and the environment. Digital technologies like the Internet and big data play a crucial and vital role in the process of moving from extensive to intensive development, and many nations view the digital economy as a key strategic development direction. The long-tail effect, economy of scope, and economy of scale are features of the digital economy that can aid in overcoming resource bottlenecks and advancing the green transformation of industrial companies. We can assist industrial industries in developing greener and enhancing sustainable development by integrating the digital economy with green manufacturing, realizing the digitalization and intelligence of green manufacturing, and actively promoting digital green industrialization and industrial green digitalization.

The manufacturing sector is a key driver of economic expansion, but there is currently a conflict between the sector's high pollution levels and undesirable output in China and its ongoing efforts to increase industrial efficiency. In order to advance China's green economy and achieve sustainable development, it is crucial to increase the efficiency of green manufacturing, especially in light of tightening resource limits and environmental pressures. Therefore, it is crucial to investigate the connection between the growth of the digital economy and efficient green manufacturing.

In light of this, this paper uses an overly efficient SBM-DEA model that takes undesirable outputs into account to assess the green manufacturing efficiency of Chinese cities at the prefecture level and higher. A fixed-effects model is used to thoroughly investigate the connection between green manufacturing efficiency and the digital economy. The digital economy is then included as a quadratic factor in the model to see if there is a nonlinear relationship between it and the effectiveness of green manufacturing. In order to examine how government attention influences how the digital economy affects green manufacturing efficiency, it was also added as a moderating variable. The aforementioned conclusions will aid in the formulation of targeted policies by decision-makers in order to fully exploit the positive effects of the digital economy and ultimately help to realize the "double carbon" aim and green and sustainable development.

The marginal contributions of this study are mostly in the following three aspects. Firstly, by incorporating earlier research, this paper creates a more lucid assessment index system for the efficiency of green manufacturing and the digital economy. In particular, when calculating green manufacturing efficiency, industrial value added as well as industrial fixed asset input industry indicators were used in the selection of both input and output variables, focusing the green total factor productivity, which has been widely researched, to an industrial perspective. Secondly, This paper not only focuses on the linear relationship between the digital economy and green manufacturing efficiency, but also pays attention to the non-linear relationship between the two, and finds that there is an 'inverted U-shape' relationship that rises first and then falls. Third, the moderating effect of government attention between the digital economy and green manufacturing efficiency is focused on and found to play an important weakening effect.

2 Literature review

Tapscott (1996) introduced the idea of the "digital economy," which he defined as an economic system that heavily relies on ICT technology and includes infrastructure, e-commerce, and B2B, B2C, and C2C transaction patterns. The term "digital economy" was initially established in the 1998 report "The Emerging Digital Economy" by the U.S. Department of Commerce. A few academics have developed an accounting framework for the digital economy to gauge its size and development (Milosevic et al., 2018; Yang and He, 2022); however, many other studies describe the digital economy using only one variable without performing a thorough analysis of the sector. Numerous studies have been conducted on the digital economy from the angles of digital industrialization as well as the digitalization of industries (Liu, 2009; Wang and Shi, 2021). Chinese research on the digital economy began later than studies from other countries, although the data sources are more varied. The level of development of the digital economy has been assessed by several academics at various scales, including national (Zhang and Shen, 2018), provincial (Zhang and Wu, 2019), city (Liu et al., 2020a), district, and county (Wu and Qin, 2022).

According to the modern theory of economic growth, production effectiveness and total factor productivity are key factors in economic growth. While total factor productivity is a relatively dynamic analysis, production efficiency is one of them. Due to resource shortages and environmental concerns, academics have increased their focus on high-quality development in recent years. They have also studied the degree of green development by measuring green production efficiency and green total factor productivity. The assessment of green productivity and the factors that affect green productivity are the two main topics of the present study on this topic. Single indicator measures, non-parametric methods employing data envelopment analysis (DEA) (Li, 2014), and parametric methods represented by stochastic frontier analysis (SFA) (Morakinyo and Victor, 2020) are the three primary types of green productivity measurements. The three-stage DEA model combines the basic DEA model and SFA, eliminating the issue of environmental impact and statistical noise (Fried et al., 2002). As a result, the DEA method is more frequently used to evaluate environmental efficiency because it has the advantage of being able to handle multiple inputs and multiple outputs (Liu et al., 2020b). Traditional DEA models, however, struggle to rate the effectiveness of various decision units when it comes to efficiency measurement. Tone (2002) put up the Super-SBM model as a solution to this issue, moving away from the [0,1] range and utilizing a relaxation-based efficiency metric to rank the efficiency and ranking of decision units more logically. The accuracy of the efficiency measure is increased by combining the three-stage DEA model and the SBM model, which further takes into account slackness to more thoroughly minimize interference from outside influences and random mistakes (Chen et al., 2021). Furthermore, Färe et al. (1989) claimed that in order to optimize efficiency while avoiding environmental damage, non-desired outputs need to be taken into account when calculating efficiency. Based on this, Li et al. (2013) took things a step further and coupled the Super-SBM model with the SBM model that took undesirable outputs into account, using the Tobit model to examine the variables affecting environmental efficiency. The investigation was done. The efficiency of green production is influenced by a variety of elements, including economic growth (Halkos et al., 2016), technological advancement (Qu et al., 2022), energy consumption patterns (Zhang et al., 2018), industrial structure, and degree of urbanization (Lu et al., 2020), among others. Studies on green productivity in manufacturing have placed a greater emphasis on the impact of environmental regulation. Tao et al. (2022) measured green manufacturing productivity in Chinese cities using the SBM-DEA model and examined the effects of environmental legislation on green manufacturing productivity and spatial spillover effects. By encouraging technological change, strict implementation of energy efficiency policies can aid in achieving green productivity in manufacturing (Li and Lin, 2016).

Data, a new factor of production, is crucial for increasing production effectiveness, allocating resources optimally, and fostering environmentally friendly and sustainable development (Wang et al., 2022). According to certain research, the growth of the digital economy will boost the effectiveness of green innovation (He et al., 2021). The Internet will have a nonlinear impact on the productivity of green total factors, while human capital will have a threshold effect between the two (Li et al., 2020). Green total factor productivity is significantly positively impacted by the degree of digitization; however, this impact is declining over time (Zhao et al., 2022). Shen (2006) discovered, using the super-efficient SBM model, that the digital economy has a considerable positive impact on ecological performance and that there is a significant spatial spillover effect. However, the majority of current research focuses on the green production efficiency of agriculture (Fu and Zhang, 2022; Yu et al., 2022), with few studies on the production efficiency of other industries. There is very little research that specifically examines the relationship between the digital economy and green industrial efficiency.

Compared with previous studies, the main contributions of this paper are reflected in the following three aspects: Firstly, this paper takes the manufacturing industry as the object of study, and adopts an ultra-efficient SBM-DEA model that takes into account undesirable outputs to quantify the green manufacturing efficiency of prefecture-level and above cities in China. Most of the previous studies have only investigated green total factor productivity, but this paper is more specific, using industrial sector data and focusing on the manufacturing sector. Second, this study empirically examines the relationship between the digital economy and green manufacturing efficiency, focusing on green productivity in the manufacturing sector. In addition, an inverted U-shaped nonlinear trend was found in this association. Finally, this paper focuses on the relationship between the government's attention to the digital economy and green manufacturing efficiency, where previous studies have focused more on market factors and less on the role played by the government, and found that the government plays an important moderating role.

3 Theoretical mechanisms

The traditional approach to economic development has undergone significant change as a result of the growth of the digital economy, which is now gradually emerging as a significant factor behind high-quality economic development. Data and information are the primary resources of the digital economy, in contrast to the traditional development model, since they are more easily replicable and shareable and facilitate information exchange. The sharing economy, platform economy, online office, virtual industrial park, and industrial clusters have evolved into the new business models that are currently thriving under the development mode of the digital economy. By having the flow of resources follow the price signal, the popularity of these new development forms can enable higher resource and equipment sharing and open up the channel for resource allocation. This would enable maximum resource utilization. This improvement in resource allocation effectiveness is crucial for the improvement of production efficiency under the current input scale. The shift in resource use will result in better infrastructure, stronger relationships between firms, and more efficient production. At a given input scale, this improvement in resource allocation efficiency is important for productivity gains. The change in resource use will lead to improved infrastructure, improved inter-firm partnerships, and increased production efficiency. Specifically, the digital economy can achieve green production efficiency through two channels: the substitution effect and the cost effect. The substitution effect means that the virtual products brought by the digital economy will have a substitution effect on the original physical products. The reduction of physical products will directly reduce the consumption of resources and reduce the pollution caused in the production process, thus improving green production efficiency. The cost effect means that the cost of transporting, processing, computing, and storing data will decrease with the development of digital technology. This is partly due to the fact that digital technology will lead to higher processing speeds and higher processing power, resulting in lower unit costs. On the other hand, the integration of digital elements into the production process will result in higher marginal utility and near-zero marginal costs, which will enable significant increases in production capacity without additional inputs and productivity without increasing resource consumption. Thus, in the digital economy, manufacturers are able to use digital resources to obtain greater economic benefits and reduce pollution using fewer natural resources. In particular, manufacturing is an industry with relatively high pollution levels, and the integration of the manufacturing industry with the digital economy will have a more pronounced impact on the improvement of green efficiency. This leads to the hypothesis:

H1a: The digital economy will promote the efficiency of green manufacturing.

On the other hand, some regions that have not yet reached the inflection point of the environmental Kuznets curve are likely to increase their consumption of resources and energy in the short term as the digital economy grows rapidly, leading to higher levels of pollution (Adha et al., 2022). In the absence of a high level of growth in desired output levels, a significant increase in the level of pollutants, a type of undesirable output, will directly lead to a decrease in the level of green manufacturing efficiency. In the long run, the impact of the digital economy on green manufacturing efficiency may also encounter a growth bottleneck. As the digital economy crosses the scale threshold, the development dividend of the digital economy will gradually disappear (Liu et al., 2021). When the boundary point of the payoff of scale is exceeded, it will be possible to fall into a growth bottleneck, so that the development of green manufacturing efficiency shifts from increasing payoff of scale to decreasing payoff of scale. In such a situation, further development of the digital economy will negatively affect green manufacturing efficiency. This leads to the competing hypothesis that:

H1b: The digital economy can hinder the efficiency of green manufacturing.

Through the above analysis, we further believe that the impact of the digital economy on green manufacturing efficiency may show a dynamic trend in phases. On the one hand, at the early stage of the development of the digital economy, the transformation of the manufacturing industry to digitalization requires large-scale infrastructure construction, which will bring more carbon emissions, and the increase of non-desired output will cause a decrease in green manufacturing efficiency. With the continuous improvement of digital infrastructure, the level of development and popularity of the digital economy will continue to rise, and the scale effect will be realized, which can also bring stronger externalities. The digital dividend will be further released, and more and more subjects will profit from it, which will also make the marginal income of the manufacturing industry grow geometrically. In turn, the efficiency of green manufacturing shows a trend of decreasing and then increasing. But on the other hand, the existence of the law of diminishing marginal utility means that when the development of the digital economy reaches a critical value, its further development will only achieve a slow increase in productivity or even no increase. Specifically, before reaching the development inflection point, the increase in productivity will be greater than the increase in input level, so that the green manufacturing efficiency will show an upward state. After reaching the development inflection point, the further increase of inputs in the development of the digital economy will lead to non-desired output brought about by the increase of inputs being greater than the desired output brought about by its development, which eventually leads to the decline of green manufacturing efficiency. Therefore, in the absence of more disruptive technological innovations, the development of green manufacturing efficiency is likely to show an upward and then downward trend. This leads to the hypothesis that:

H2: The impact of the digital economy on green manufacturing efficiency shows different trends at different stages.

4 Research design

4.1 Data source

In this paper, 273 cities in China are selected for the study. Considering the availability of data, the time span is selected as 2011–2018. The data used were obtained from the China Statistical Yearbook, the China Regional Statistical Yearbook and the China City Statistical Yearbook. And the missing values of the full panel data were made up by linear interpolation method.

4.2 Variable settings

4.2.1 Independent variable

In this paper, the digital economy is chosen as the main explanatory variable. At present, there is no unified standard for the evaluation index system of the digital economy. Based on the previous definition of the digital economy, this paper constructs a digital economy evaluation index system from four dimensions: infrastructure, industrial development, innovation capability, and financial transactions (Chen and Miao, 2021; Luo and Zhou, 2022). In this case, infrastructure is measured by the number of Internet broadband access subscribers as well as the number of cell phone subscribers. Industry development is measured through telecommunications business revenues. Innovation capacity is measured using the number of people in the information transmission, computer services, and software industries and government science expenditures. The Digital Inclusive Finance Index of Peking University is also introduced to measure the development level of digital finance (Guo et al., 2020). The entropy weighting method is used to assign weights to the indicators, and finally, the comprehensive index of the digital economy is calculated. The specific indicators are shown in Table 1.

The digital economy index was subsequently calculated using the entropy weight method, where the original data matrix was first constructed, and in the second step the original data was normalised using the extreme value method. The third step calculates the weight of each variable V for city m, denoted as

$$P_{mn} = \frac{V'_{mn}}{\sum_{m-1}^{m} V'_{mn}}$$

The fourth step calculates the entropy value of the *n*th indicator with the following formula:

$$E_n = -\frac{1}{\ln 273}\sum_{m-1}^{m}\left(P_{mn}{}^{*}\ln\left(P_{mn}\right)\right)$$

The fifth step calculates the coefficient of variation for the *n*th indicator. For the *n*th indicator, the greater the difference in indicator values, the greater the impact on the results of the evaluation and the smaller the entropy value. The formula is as follows:

$$d_n = 1 - e_n$$

The sixth step calculates the weight value of the *n*th indicator with the following formula:

$$W_n = \frac{d_n}{\sum_{n-1}^{n} d_n}$$

Final calculation of the Digital Economy Index

$$Dig_{mn} = \sum_{n-1}^{n} W_n{}^{*}P_{mn}$$

4.2.2 Dependent variable

In this paper, the green manufacturing efficiency of the considered non-desired output is used as the explanatory variable. In the measurement of green manufacturing efficiency, on the basis of measuring manufacturing efficiency from the input-output perspective, resource consumption and environmental pollution are also fully considered, so as to construct a green manufacturing total factor productivity index system that includes non-desired outputs. Among them, the fixed asset input of the secondary industry, industrial electricity consumption, number of industrial employees, and built-up area are taken as each input factor of the manufacturing industry; industrial output is regarded as the output parameter; and emissions of industrial three wastes are taken as the non-desired output parameter of environmental pollution in the manufacturing industry. In this study, we adopt the perpetual inventory method to obtain the fixed asset input of the secondary industry as fixed asset input, based on the idea of Young (2003), and obtain the real industrial output of each year by deflating the nominal industrial output of each year according to the price index (Huang et al., 2002), with 2011 as the base period.

$$\min \rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1 - \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^+}{y_{rk}} + \sum_{t=1}^{q_2}\frac{s_t^{b-}}{y_{tk}{}^{b}}\right)}, s.t. \begin{cases} \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j + s_i^- = x_{ik} \\ \sum_{j=1, j\neq k}^{n} y_{ij}{}^{b}\lambda_j - s_r^{b+} = y_{rk} \\ \sum_{j=1, j\neq k}^{n} y_{ij}{}^{b}\lambda_j - s_r^{+} = y_{tk}{}^{b} \\ \lambda \geq 0 \\ s^- \geq 0, s^+ \geq 0 \end{cases}$$

where: ρ denotes the measured green manufacturing efficiency; x_{ik} is the input factor, y_{rk} is the desired output, and $y_{tk}{}^{b}$ is the non-desired output, and $s_i{}^{-}, s_r{}^{+}, s_t{}^{b-}$ is the slack variable for the input factor, the desired output and the non-desired output, respectively; and λj is the constraint.

4.2.3 Control variables

In the selection of control variables, drawing on previous studies, the level of economic development (Lanjouw and Mody, 1996), industrial structure, and the level of openness to the outside world (Jaffe and Stavins, 1995) were selected as control variables for the relationship between the digital economy and green manufacturing efficiency. In this case, the level of economic development is measured using real *per capita* GDP. The industrial structure is referred to by Sun et al. (2022), which measures the upgrading between industries using the formula $indus = \sum_{i=1}^{3} X_i{}^{*}i$, where X_i is the share of industry i in GDP. The degree of government intervention is measured using the share of government fiscal expenditure in GDP. The level of external openness is measured by the logarithm of total foreign investment. The descriptive statistics of each variable are shown in Table 2.

4.3 Fixed effects model

The data used in this paper are panel data from 2011 to 2018, and before determining the empirical model, we tested the choice of model to determine whether a mixed OLS, random effects model, or fixed effects model should be used. First, we conducted the test using the F-test, and the results showed that the random effects model was superior to the mixed model. Based on this, we used the Hausman test, and the results showed that the fixed-effects model was better than the random-effects model. Therefore, the fixed-effects model was finally chosen for the empirical analysis, and the following model was constructed to test the relationship between the digital economy and green manufacturing efficiency:

$$Y_{it} = \alpha_0 + \alpha A + \gamma X_i + \mu_i + \eta_t + \delta_{it}$$

Where i represents city, t represents year, Y represents green manufacturing efficiency, A represents the digital economy, and X represents other control variables that will have an impact on green

TABLE 1 Digital economy development evaluation index system.

Variable name	Variable interpretation	Mean	Variance
Infrastructure	Number of Internet broadband access subscribers	92.8593	113.311
	Number of cell phone subscribers	458.0863	494.3472
Industrial development	Revenue from telecommunication business	435883.9	728179.2
Innovation capability	Number of people in the information transmission computer services and software industry	12260.78	48307.34
	Government science expenditures	101262.3	334568
Financial transactions	Digital Inclusive Finance Index	155.9187	61.9673

TABLE 2 Descriptive analysis.

Variable category	Variable name	Variable interpretation	Mean	Variance
Independent variable	Green Manufacturing Efficiency	Green Manufacturing Efficiency Value	0.3022	0.1377
Dependent variable	Digital Economy	Digital Economy Development Level	0.0561	0.0877
	Digital Economy Square Item	—	0.0108	0.0631
Control variable	Industry Structure	Industrial Structure Upgrade Index	2.2942	0.1578
	Economic Development Level	Logarithm of GDP *per capita*	10.6813	0.5666
	External Opening Level	Logarithm of total foreign investment	10.1746	1.8035
Moderating variable	Government Attention	Weight of word frequency	0.1929	0.0941

TABLE 3 The impact of the digital economy on green manufacturing efficiency.

Variable name	Model 1	Model 2	Model 3	Model 4
Digital Economy	0.5281***	.7796***	1.2754***	1.2425***
Digital Economy Square Item			−0.6692***	−0.5937***
Industry Structure		−.0921**		−0.1149***
Economic Development Level		.05415***		0.0483***
Openness to the outside world		−.0028		−0.0065**

*, ** and *** are respectively significance level of 10%, 5% and 1%.

manufacturing efficiency. μ represents province-fixed effects, η represents time-fixed effects, and δ represents a random disturbance term.

Considering that the relationship between green manufacturing efficiency and the digital economy may show a non-linear trend, this paper adds a squared term to the model with the following equation:

$$Y_{it} = \alpha_0 + \alpha_1 A + \alpha_2 A^2 + \gamma X_i + \mu_i + \eta_t + \delta_{it}$$

5 Analysis of empirical results

5.1 Basic status of green manufacturing efficiency

As can be seen from the Figure 1, since 2011 to 2018, China's green manufacturing efficiency hovered around 0.35, did not show a clear upward trend, but instead showed a trend of decline rather than rise, and in 2017 there was a precipitous decline. Therefore, on the whole, China's green manufacturing efficiency cannot be considered to be in a favourable development trend, but instead has regressed.

As can be seen from the Figure 2, from 2011 to 2018, the green manufacturing efficiency kernel density curves of Chinese cities basically remained stable, and their peak inflection points were all below 0.5 of green manufacturing efficiency, while the kernel density values of cities with green manufacturing efficiency greater than one kept increasing, which means that China's green manufacturing level keeps improving and the manufacturing industry is changing from a crude and inefficient condition to an intensive and efficient condition. At the same time, the wave height decreases over time, indicating a balanced development trend of green manufacturing efficiency in China, regional disparities are narrowing. And also indicating that China's resource-saving and environment-friendly development model does help to promote green manufacturing efficiency.

TABLE 4 Robustness test results.

Variable name	Model 1	Model 2	Model 3	Model 4
Digital Economy			0.7238***	1.0461***
Digital Economy Squared Items				−0.4198***
Lagged digital economy	0.8311***	1.3406***		
Squared lagged digital economy		−0.6496***		
Industry Structure	−0.1048**	−0.1290***	−0.0401	−0.0499
Economic Development Level	0.0543***	0.0468***	0.0682***	0.0647***
Openness to the outside world	−0.0011	−0.0049	−0.0060**	−0.0088**

*, ** and *** are respectively significance level of 10%, 5% and 1%.

TABLE 5 Robustness test results.

Variable name	Model 1	Model 2
Digital Economy	1.2425***	1.4348***
Digital economy squared term	−0.5937***	−1.9759***
Government Intervention*Digital Economy Squared		5.2769**
Industry Structure	−0.1149***	−0.1184***
Economic Development Level	0.0483***	0.0502***
Level of openness to the outside world	−0.0065**	−0.0076**

*, ** and *** are respectively significance level of 10%, 5% and 1%.

5.2 Impact of the digital economy on the efficiency of green manufacturing

5.2.1 Fixed effects model

The relationship between the digital economy and green manufacturing efficiency was analyzed by regression using a fixed-effects model. The results are shown in Table 3, where Model one is the result without adding control variables and Model 2 is the result after adding control variables. Models 3 and 4 are the regression results with the addition of the squared term.

In Model 1, the effect of the digital economy on green manufacturing efficiency is significant at the 1% statistical level. After adding control variables such as industrial structure and economic development level, it still passed the significance test at the 1% level. In both Model one and Model 2, the coefficients of the digital economy are positive, indicating that there is a significant positive influence of the digital economy on green manufacturing efficiency, and with the improvement of the digital economy level, green manufacturing efficiency will improve accordingly. Model 3 adds the squared term of digital economy on the basis of Model one in an attempt to test the nonlinear relationship between digital economy and green manufacturing efficiency. The results show that both the primary and secondary terms of the digital economy are significant at the 1% statistical level, and the coefficient of the primary term is positive and the coefficient of the secondary term is negative, indicating that the impact of the digital economy on green manufacturing efficiency shows an inverted U-shaped trend of rising and then falling. Model 4 adds control variables to Model 3, and the results show that the primary and secondary terms of the digital economy are still significant at the 1% statistical level. Therefore, it can be concluded that the digital economy will have a significant positive effect on green manufacturing efficiency in the early stages of its development, while with the further development of the digital economy, it will have a negative effect on green manufacturing efficiency. In addition, the level of economic development and the level of openness to the outside world pass the significance test at the 1% and 5% levels, respectively, and the coefficients are positive, implying that they will also have a significant contribution to green manufacturing efficiency. However, the inflection point of the inverted U-shaped curve is calculated on this basis, and it is found that the curve reaches the inflection point only when the level of the digital economy reaches 1.0462. In the descriptive statistics in Table 2, the mean value of the digital economy is 0.0561 and the maximum value is only 0.9398, which is still some distance away from the inflection point. Therefore, it can be considered that at the current stage, the development of the digital economy only plays the role of promoting green manufacturing efficiency but has not yet reached the stage of hindering the improvement of green manufacturing efficiency.

5.2.2 Robustness analysis

5.2.2.1 One-period lag

Considering that there may be a lagged effect of the digital economy on green manufacturing efficiency, we will examine the relationship between the digital economy and green manufacturing efficiency using the digital economy with a one-period lag as the independent variable. In Table 4, Model one shows that there is a promotion effect of the increase in the level of the digital economy on green manufacturing efficiency, and it passes the significance test at the 1% level. Model 2 shows that both the primary and secondary terms of the digital economy pass the significance test at the 1% level, and the coefficient of the primary term is positive and the coefficient of the secondary term is negative, indicating that there is an inverted U-shaped correlation between the digital economy and green manufacturing efficiency. The conclusions in the above section are verified.

5.2.2.2 Model replacement

Since the explanatory variables are efficiency values, they are re-estimated using the Tobit model, and the results are shown in the table below. The digital economy in Model 3 passed the significance test at the 1% level, and both the primary and secondary terms of the digital economy in Model 4 passed the significance test at the 1% level, and the sign of the coefficients did not change. Therefore, the regression results of the Tobit model again validate the findings of the benchmark estimation and represent a robust result.

5.2.3 Moderating effect of government attention

The degree of government attention to green development has a significant impact on green productivity. Therefore, this paper argues that the degree of government attention can play a moderating role between the digital economy and green manufacturing efficiency. Thus, this paper constructs the following model to test the moderating role of government attention between the digital economy and green manufacturing efficiency:

$$Y_{it} = \alpha_0 + \alpha_1 A + \alpha_2 A^2 + \alpha_3 A^{2}{*}B + \beta X_i + \mu_i + \eta_t + \delta_{it}$$

Where i represents province, t represents year, Y represents urban-rural income disparity, A represents digital economy, B represents government concern, and X represents other control variables that would have an impact on green manufacturing efficiency. μrepresents province fixed effects, η represents time fixed effects, and δ represents random disturbance terms.

The degree of government concern was measured using text analysis. The annual work reports of the government were analyzed by using the following keywords: environmental protection, pollution, energy consumption, emission reduction, emissions, ecology, green, low carbon, air, chemical oxygen demand, sulfur dioxide, carbon dioxide, PM10, and PM2.5. The annual work reports of each prefecture-level city were first crawled using Python, and the total word count of the work reports and the word frequency of the keywords were counted using words count software to count the total word count of the work reports and the word frequency of keywords, and use the proportion of the word frequency of green development keywords to the full report word count as a proxy variable for the government's attention to green development. The specific results are shown in Table 5.

Model 1 shows the regression results without adding the cross-product term, and Model 2 shows the regression results with the addition of the cross-product term. After adding the interaction variables of the degree of government intervention and the squared term of the digital economy, the digital economy, the squared term of the digital economy, and the cross product pass the significance test, which is significant at the 1% and 5% levels, respectively. The coefficient of the digital economy is positive, and the coefficient of the quadratic term of the digital economy is negative, indicating that there is an inverted U-shaped effect of the digital economy on green manufacturing efficiency. And the coefficient of the interaction term between the degree of government intervention and the squared term of the digital economy is positive, indicating that there is a weakening effect of government attention on the inverted U-shaped trend. When the inverted U-shaped inflection point is not reached, the increase in government concern will reduce the contribution of the digital economy to green manufacturing efficiency. After crossing the inflection point, the increase in the level of government concern will suppress the inhibitory effect of the digital economy on green manufacturing efficiency.

6 Research conclusions and recommendations

6.1 Conclusion and discussion

This paper empirically analyzes the relationship between the digital economy and green manufacturing efficiency using panel data for 273 cities in China from 2011 to 2018. Previous studies have not adequately investigated the digital economy for green manufacturing efficiency, so this paper investigates this issue in more depth. It is found that, first, the kernel density analysis of green manufacturing efficiency in Chinese cities shows that the current level of green manufacturing efficiency is in a period of slow improvement from crude inefficiency to intensive and efficient transformation, and the balance of the national development has been improving, and the differences between regions are shrinking, showing a dynamic convergence. Second, this paper finds that the impact of the digital economy on green manufacturing efficiency is not a simple linear trend but shows a non-linear inverted U-shaped trend. That is, at the early stage of development, the enhancement of the digital economy will improve green manufacturing efficiency, while with the further development of the digital economy, it will gradually inhibit the enhancement of green manufacturing efficiency. And by calculating the inflection point of the inverted U-shaped trend, it is found that the current level of digital economy development is still at a low level and still on the left side of the inflection point. This indicates that the current stage of the digital economy promoting green manufacturing efficiency is underway. Thirdly, government attention plays an important moderating role, and there is an obvious weakening effect on the inverted U-shaped relationship between the digital economy and green manufacturing efficiency.

This study, to a certain extent, adds to and advances the research in the areas of the digital economy and environmentally friendly industrial efficiency. This study does, however, have certain drawbacks. Since there are statistics available, the years 2011–2018 are used. To ensure timeliness, the years of data should be stretched further in the upcoming study. The relationship between the digital economy and green manufacturing efficiency is also only examined holistically in this paper; the influencing mechanisms are not examined in detail. Therefore, future studies should conduct a more thorough analysis of the mechanism.

6.2 Recommendations

Based on the above research, this paper obtains the following policy insights. First, at the current stage, it is necessary to more actively promote the development of the digital economy, build digital infrastructure, develop digital industry, enhance the degree of digital innovation, increase the development of digital finance, and improve the overall level of the digital economy to enhance the efficiency of green manufacturing. Although the results of the study show that the current level of development of the digital economy has not yet reached the inflection point, and it is not yet able to play a role in promoting green manufacturing efficiency. However, in the long term, the impact of the digital economy on green manufacturing efficiency shows a U-shaped trend of first decline and then rise, so it should always be determined to develop the digital economy, and closely observe the development of the digital economy, as soon as possible to change its negative impact on green manufacturing efficiency, and give full play to the role of the digital economy on the promotion of green manufacturing efficiency. Second, the role of government should be fully played. The government needs to pay more attention to green development and formulate more policies that are conducive to green production. Especially when the digital economy has reached the inflection point of an inverted U-shaped trend, it is necessary to enhance the role of the government to delay the problem of declining marginal effects caused by the law of diminishing marginal utility in order to achieve the purpose of suppressing the negative impact of the digital economy on green manufacturing efficiency.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

XS: Writing–original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal Analysis, Data curation, Conceptualization. WZ: Writing–review and editing. XK: Writing–review and editing, Supervision.

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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.

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