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Research article

Digital economy, spatial spillover and industrial green innovation efficiency: Empirical evidence from China

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ABSTRACT

The digital economy is pushing more efficient and greener production and innovation processes, as well as quickening the mobility of production factors, which would have a critical impact on improving industrial green innovation efficiency. Based on the panel data of 30 Chinese provinces from 2005 to 2019, this study established a comprehensive index system to assess the level of provincial digital economy development, and adopted the SBM-DEA model including non-expected output to evaluate industrial green innovation efficiency, then adopted the *Global Moran's* I and *Local Moran's* I to test whether there is spatial autocorrelation, followed by the spatial Durbin model (SDM) and the mediating effect test model to investigate the direct impact, spatial spillover effect and indirect transmission mechanism of the digital economy on industrial green innovation efficiency. The results show that: both the development level of the digital economy and industrial green innovation efficiency show positive spatial autocorrelation; The digital economy not only has a significant direct role in promoting industrial green innovation efficiency but also has a spatial spillover effect; The digital economy can improve industrial green innovation efficiency by promoting manufacturing structure upgrading and stimulating enterprises' green technology innovation. The findings of this paper are helpful for policymakers to clarify the relationship between the digital economy and industrial green innovation efficiency and provide favorable policy directions for developing the digital economy to promote industrial green innovation efficiency.

1. Introduction

China has been the world's largest industrial producer for 11 consecutive years since it surpassed the United States in 2010 with an industrial output value of 1.96 trillion yuan. However, China's industrial development mode of "high input, high pollution, and low efficiency" has led to increasingly prominent problems such as resource shortage, environmental pollution, and overcapacity. China's total carbon emissions have nearly tripled since 2000, from 3.002 billion tons to 9.899 billion tons in 2020, with total emissions and share of global carbon emissions both peaked in 2013. The share has remained between 25% and 30% since then and exceeded 30% for the first time in 2020. It is urgent to promote the green transformation of China's industrial production. For this, the China National Development and Reform Commission and the Ministry of Science and Technology jointly issued "the guideline on building a market-oriented green technology innovation system" in 2019, calling on industrial enterprises to actively carry out green technology

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innovation and solve deep-seated environmental pollution problems. Unlike traditional pollution control methods, green technology innovation can not only reduce resource waste and environmental pollution, but also enable enterprises to obtain good economic benefits by improving the efficiency of production processes and producing green differentiated products, which gradually becomes an inevitable choice to achieve coordinated development of economy, resources, and environment. According to the purpose of green technology innovation, green innovation efficiency incorporates resource input, green technology innovation revenue, and environmental pollution into a single evaluation framework, which becomes a crucial index for determining the efficiency of green technology innovation activities. Improving the green innovation efficiency in industry has become the focal point of China's modern industrial green development.

In recent years, with the widespread use of the Internet, big data, cloud computing, blockchain, and other emerging digital technologies, the digital economy has emerged and become a new engine of economic development. In 2021, the scale of China's digital economy was 45.5 trillion yuan, representing a nominal growth rate of 16.2% year on year, 3.4% points greater than nominal GDP growth at the same time, and accounting for 39.8% of yearly GDP. "Digital industrialization" and "industrial digitalization" are constantly giving birth to new industries, new forms of business, and new models, and promoting the transformation of production and innovation processes toward network, collaboration, and ecology, which provides new feasible paths for industrial green technology innovation. From the perspective of digital industrialization, the production processes of the emerging digital manufacturing industry are inherently environmentally friendly, which mainly rely on knowledge and information rather than resources. From industrial digitization, the application of digital technology in enterprises improves both innovation efficiency and energy use efficiency by enabling enterprises to execute innovation processes and promote the intelligent transformation of production processes. At the same time, by removing spatial barriers to information transfer, the Internet and various internet-based digital platforms enable green innovation factors to be matched on a larger geographic scale and enhance green technology spillovers across provinces, thus strengthening the linkages between green technology innovation activities in different provinces. Based on the above reality, this paper proposes the following questions: Can the digital economy improve industrial green innovation efficiency directly or indirectly? What are the indirect effect's transmission mechanisms? Is there a spatial spillover effect of the digital economy on industrial green innovation efficiency? We hope to answer the above questions based on provincial-level data in China, providing a policy basis and targeted policy paths to develop the digital economy to promote green development and regional green synergy development for China and developing countries with similar extensive industrial development modes.

This paper utilizes a sample of 30 provinces in China from 2005 to 2019 to study the impact of the digital economy on industrial green innovation efficiency. We firstly construct a comprehensive index evaluation system including "digital industrialization" and "industrial digitization" to assess the level of the digital economy development and use the SBM-DEA model that includes undesired outputs to measure industrial green innovation efficiency. On this basis, we use the *Moran's* I and *Local Moran's* I to conduct static spatial autocorrelation analysis and dynamic spatial-temporal evolution analysis of the digital economy and industrial green innovation efficiency to provide a convincing basis for using spatial econometric analysis, followed by using the spatial Durbin model (SDM) and the mediating effect test model to study the direct impact, spatial spillover effect and indirect transmission mechanisms of the digital economy on industrial green innovation efficiency.

The possible marginal contributions of this paper are as follows: First, this paper constructs two indicator systems to measure the development level of the digital economy and industrial green innovation efficiency, and systematically analyzes the spatial correlation of the two indicators, which can enrich the relevant research on the digital economy and industrial green innovation efficiency; Secondly, this paper uses the spatial econometric model to systematically investigate the direct impact and spatial spillover effect of the digital economy on industrial green innovation efficiency, and clarifies the relationship between the digital economy and industrial green innovation efficiency; Third, the paper proposes and supports the transmission mechanism of "manufacturing structure upgrading" and "green technology innovation", which can help to unfold the "black box" of how the digital economy improves industrial green innovation efficiency and provide policymakers inspiration to combine the digital economy with manufacturing structure upgrading and green technology innovation to improve industrial green innovation efficiency.

The rest of this paper is organized as follows: Section 2 reviews relevant literature and develops research hypotheses; Section 3 describes the sample and sets the econometric model; Section 4 reports the empirical results; Section 5 concludes and proposes policy recommendations.

2. Literature review and research hypothesis

2.1. Literature review

Green innovation efficiency research begins with its measurement. The two most frequently employed efficiency measures are stochastic frontier estimation (SFA) and data envelope analysis (DEA). Compared to the SFA model, the DEA model has two significant advantages: first, it is unnecessary to set the specific form of the production function in advance, thereby avoiding the subjectivity-induced deviation; second, it is possible to evaluate the efficiency of the multi-input-output model. The DEA model can further be divided into the radial model and the non-radial model. The radial model requires input and output to alter proportionally and does not account for slack variables and undesirable outputs, leading to an overestimation of efficiency. In comparison, the non-radial and non-angular SBM-DEA model allows the input and output to alter flexibly and incorporates the undesirable outputs and slack variables simultaneously, leading to more accurate efficiency estimation. Therefore, it has gradually become the standard way for measuring the effectiveness of green innovation. Ren and Wang (2016) compared the green innovation efficiency measured by the two types of DEA models and discovered that the green innovation efficiency measured by the SBM-DEA model decreased significantly compared to that measured by the radial DEA model, indicating that the evaluation of green innovation efficiency should take the environmental undesirable output into account, and the SBM-DEA model increases the precision of the evaluation of green innovation efficiency [1].

Further studies on green innovation efficiency can be divided into two types: One focuses on the spatial correlation, spatial heterogeneity, and spatio-temporal evolution of green innovation efficiency within a certain geographical region; the other focuses on investigating the factors influencing industrial green innovation efficiency. Lian and Du (2019) investigated the spatial characteristics of green innovation efficiency of 281 prefectural cities in China and found that green innovation efficiency exhibited significant positive spatial autocorrelation and significant spatial heterogeneity, with decreasing levels of efficiency from east, central, and west [2]. Incorporating convergence analysis into the spatial econometric model, Zhao et al. (2021) discovered that the spatial difference in green innovation efficiency in China is decreasing year by year, showing σ-convergence and spatial condition β-convergence, which means intra-regional difference has replaced inter-regional difference as the main source of green innovation efficiency difference [3]. From a dynamic spatio-temporal evolutionary perspective, Liu et al. (2021) and Xu et al. (2021) discovered that although overall industrial green innovation efficiency at the provincial level in China increased, it did not increase linearly, but rather exhibited a U-shaped evolution trend of decreasing and then increasing [4,5]. Based on the perspective of the innovation value chain, Du et al. (2019) divided the green technology innovation cycle into two stages: green technology R&D and green technology achievement transformation, and measured the efficiency in the two stages. They found that overall green innovation efficiency at the provincial level in China is low, which is mainly restricted by the green technology R&D stage [6]. Chen et al. (2020) further refined the green technology innovation value chain into three stages: green technology R&D, green technology achievement transformation, and green product industrialization. Based on the phased and integrated measurement results, they concluded that rising achievements transformation efficiency is the main reason for the improvement of integrated green innovation efficiency in Chinese industrial enterprises, while the efficiency difference between the east, middle, and west is mainly caused by the product industrialization stage [7].

The existing literature mainly discussed the driving factors for green innovation efficiency improving from environmental regulations. Liu et al. (2021), Irfan et al. (2021), and Du et al. (2021) respectively discussed the impact of carbon trading policy, green finance policy, and emission trading policy on enterprises' green technology innovation, and their research results showed that market-oriented environmental regulation policies encourage enterprises to carry out green technology innovation [8–10]. However, Fan et al. (2021) found that integrated environmental regulation has a positive u-shaped nonlinear effect on green innovation efficiency, which first inhibits and then promotes [11]. In addition, some studies showed that foreign direct investment (Liu et al., 2021), public participation constraint (Zhao et al., 2022), and manufacturing intelligent transformation (Yang et al., 2022) all play an important role in improving green innovation efficiency [12–14].

The influence of the digital economy on energy consumption is a double-edged sword. Digital technologies promote the arrival of the era of industry 4.0. In this context, energy digital systems supported by the Internet, cloud computing, and big data analysis can dynamically manage energy consumption by monitoring production, leading to an improvement in energy use efficiency [15]. However, economic growth and expansion of information technology production caused by the development of the digital economy may lead to a further increase in energy consumption, a phenomenon known as the "energy rebound effect" [16]. As for which impact direction is dominant, many scholars' research conclusions are controversial. The empirical results of Ren et al. (2021), Langea et al. (2020), Sadorsky (2012) supported the view that "energy rebound effect" dominates and that the digital economy contributes to the increase of energy consumption [16–18]. While Ishida (2015) confirmed that the "energy efficiency improvement effect" is dominant, and the digital economy has reduced the energy usage intensity of most industries in China [19]. Respectively based on global panel data and China's prefecture-level panel data, Shahbaz et al. (2022), Xue et al. (2022) both concluded that the digital economy has a positive impact on energy transformation, promoting the increase of renewable energy consumption [20,21].

The impact of the digital economy on pollution emissions is also two-sided. As mentioned before, the production processes of the digital industry are inherently environmentally friendly. Meanwhile, as the digital economy develops, digital pollution treatment technologies would gradually enrich and effectively reduce pollution emissions. However, the "energy rebound effect" would aggravate pollution emissions. Based on this, Li et al. (2021) utilized a sample of global panel data including 190 countries, and confirmed the existence of an inverted u-shaped nonlinear relationship between the digital economy and carbon dioxide emissions, which is in line with the EKC hypothesis [22]; Shvakov and Petrova (2019) collected data from the ten most digitized countries, showing that the rapid pace of digitalization has led to an increase in carbon dioxide emissions [23]; The research findings of Yu and Zhu (2022) also showed that by promoting economic expansion, the digital economy greatly increased the carbon emissions of most provinces in China [24]. On the contrary, Chen (2022) found that the digital economy significantly reduced the carbon emissions of most BRICS countries in the short and long run during the sample period from 1990 to 2018 [25]. Taking the spatial effects of the digital economy into account, Liu et al. (2022), Zhu et al. (2022) confirmed that digital technology development not only promotes local carbon reduction but also has a positive impact on the carbon reduction of neighboring cities, but this spatial spillover effect has geographical boundaries [26,27]. Considering the spatial network of the digital economy, Zhong et al. (2022) pointed out that the digital economy development is regional in China, and his empirical results showed that, in the digital economy network composed of various provinces, the carbon emission reduction effect of the core position is greater than that of the peripheral nodes [28].

As for the impact of the digital economy on innovation, although most scholars agree that the digital economy has facilitated innovation in firms, a few scholars still expressed concern about the "information overload" phenomenon that may be caused by the digital economy. Digital technologies promote open innovation of enterprises by improving their ability to acquire, absorb and apply external knowledge [29]. Digital platforms reduce the cost of cross-sectoral interactions between technology R&D and industrial application sectors by facilitating the flow of knowledge and information and improving the synergy of the innovation ecosystem [30]. Digital technologies drive mass customization innovation production by helping companies quickly gather customized preferences and reducing the cost of customized manufacturing through product design modularity and flexible production techniques [31].

Broadband infrastructure accelerates knowledge and technology spillovers in environmental protection between enterprises, which helps to promote green technology innovation of enterprises [32]. Wu et al. (2016) and Dou et al. (2022) pointed out that while promoting innovation, the digital economy will also lead to "information overload" phenomenon, which would increase the difficulty and cost of internal management of enterprises and cause an imbalance in the allocation of limited resources, thus impeding technological innovation [33,34].

Although many scholars have studied the separate impacts of the digital economy on energy, environment, or innovation, however, little literature has focused on the digital economy and green innovation, and there is no literature discussing the relationship between the digital economy and green innovation efficiency. The following studies are most like the topic of this paper: Luo et al. (2022) assessed the direct impact and transmission path of the digital economy on the green development efficiency of the Yangtze River Economic Belt but lacked attention to the spatial spillover effects [35]. Li et al. (2022) and Hu and Guo (2022) respectively studied the direct impact and the spatial spillover effect of the digital economy on green economic efficiency and green total factor productivity. However, neither of them provided a clear explanation of the geographical spillover effect's underlying mechanism nor a test of the transmission mechanism. In addition, green total factor productivity and green economic efficiency are both used to explore the greenness of the entire production activities, unlike green innovation efficiency, which focuses on the greenness of innovation activities barely [36,37]. Wang et al. (2022) studied the nonlinear relationship, transmission mechanism, spatial spillover effect, and policy effect of the Internet on urban green innovation efficiency in prefecture-level cities of China. However, the Internet is simply a sub-dimension of the digital economy. His study doesn't reflect how the integrated digital economy affects green innovation efficiency [38].

2.2. Research hypothesis

2.2.1. The direct impact of the digital economy on industrial green innovation efficiency

The digital economy may directly improve local industrial green innovation efficiency by reducing energy consumption and increasing the efficiency of innovation activities. From the perspective of energy consumption, On the one hand, the digital industry is supported by large amounts of data. The replicability of data enables the digital industry to realize the "positive feedback mechanism" in production, which can achieve a continuous reduction of marginal costs on a larger production scale, thus forming economies of scale and reducing the energy required per unit of product. [36]; On the other hand, the application of the big data in production enables enterprises to collect the energy flow in the production process in real time and intelligently adjust the energy-inefficient parts to reduce unnecessary energy waste [39]. From the perspective of innovation efficiency, the digital economy can simultaneously improve efficiency at three stages of the innovation value chain. Firstly, the Internet carries abundant external knowledge and information and accelerates their flow. While the application of digital technologies empowers enterprises to quickly acquire and integrate external information from the internet and efficiently analyze and apply it internally within the enterprise, which enables them to shift from closed innovation to open innovation, thus enhancing the R&D efficiency of green technology [29]. Secondly, the digital platforms specializing in industry-academia-research cooperation attract multiple innovation departments such as universities, research institutes, governments, and enterprises to settle in, which helps accelerate the connection and collaboration of innovation departments, and reduce the time lag from basic research to applied research on green technology. Thus, the achievements transformation efficiency of green technologies can be improved [30]. Finally, the e-commerce platforms improve the efficiency of matching supply and demand for green products through big data precision marketing, while its cooperative powerful logistics system greatly improves the efficiency of the transaction process [40], which jointly shortens the cycle for enterprises to obtain the sales revenue of green products. Thus, the industrialization efficiency of green technologies can be improved. Given the above analysis, we propose the following hypothesis.

H1. The digital economy can directly improve local industrial green innovation efficiency.

2.2.2. The spatial spillover effect of the digital economy on industrial green innovation

By reducing the spatial and temporal barriers to information transfer and communication, the digital economy exhibits a powerful "connectivity" capability, increasing the breadth and depth of inter-regional linkages in production and innovation activities [41]. Therefore, the digital economy may affect the industrial green innovation efficiency in neighborhoods through the following three paths, displaying spatial spillover effect. Firstly, the digital economy enables enterprises from different regions to easily exchange information via the Internet, which strengthens industrial linkages between regions and gives rise to "virtual agglomeration", i.e., upstream, and downstream enterprises operating physically in different regions are linked in a cross-regional industrial chain [42]. The industry association is the main support of technology spillover between enterprises. Through the upstream-downstream correlation effect, an enterprise's green technologies may spill over to linked firms in other regions or push them to undergo green transformation [43], impacting the industrial green innovation efficiency in neighborhoods. Second, the online platforms for industry-university-research cooperation help innovation institutes from different regions interact and cooperate, thus promoting the cross-regional combination of innovation resources, and making the innovation value chain across geographical boundaries [44]. For example, when two research institutes and enterprises from different regions reach cooperation, the green technology developed in one region may be transformed and applied in the other, thereby improving the industrial green innovation efficiency in that region. Third, by creating a unified online consumption market across the country, the e-commerce platform breaks the segmentation of the spatial market and accelerates market integration, which intensifies the competition among similar industrial enterprises located in different regions [45]. In a broad unified national market, High-productivity industrial firms in one region have lower costs and can offer their products at lower prices, which may “crowd out” industrial enterprises in other provinces that are lagging in production or force them to upgrade their processes or innovate to achieve intensive use of energy [46]. Thus, the industrial green innovation efficiency in other provinces may be affected. Given the above analysis, we propose the following hypothesis.

H2. The digital economy can enhance the industrial green innovation efficiency in neighboring regions, displaying a spatial spillover effect.

2.2.3. The indirect impact of the digital economy on industrial green innovation efficiency

The digital economy may improve industrial green innovation efficiency indirectly through the following two channels.

First, the digital economy can contribute to the upgrading of manufacturing structure, thus indirectly improving industrial green innovation efficiency. Compared with labor-intensive and capital-intensive manufacturing industries, technology-intensive manufacturing industries, with technology as the main input factor, are less dependent on energy and their production process is inherently clean. When the proportion of technology-intensive manufacturing rises and promotes the upgrading of manufacturing structure, it will bring about the reduction of energy inputs and pollution emissions of the whole industrial industry and improve industrial green innovation efficiency. The digital economy can promote the upgrading of manufacturing structure by increasing the scale of technology-intensive manufacturing and reducing the scale of low-end manufacturing. First, from the perspective of “digital industrialization”, many emerging digital industries, such as artificial intelligence, electronic chips, and integrated circuits, are constantly attracting investment inflows with high industry profit margins, promoting the scale expansion of technology-intensive manufacturing [47]. Second, from the perspective of “industrial digitization”, deep integration of digital technologies and traditional manufacturing industry promotes the intelligent transformation of low-end manufacturing industries and increases the proportion of technology factors in their overall factors, thus facilitating the transformation of certain low-end manufacturing industries into technology-intensive manufacturing industries [48]. The application of artificial intelligence in production is a good example; Third, the establishment of online trading systems and information platforms for carbon emission rights and wastewater discharge rights improve the speed of matching supply and demand and reduce transaction costs, which ensures the efficient operation of these two types of markets, enabling clean enterprises to profit by selling corresponding indicators and polluting enterprises to increase costs by purchasing corresponding indicators, thus forcing some low-end manufacturing industries with high emissions and high pollution to exit the market [49].

Second, the digital economy stimulates the enterprises to carry out green innovation, thus improving industrial green innovation efficiency. Green technology innovation has a “double externality” for the improvement of industrial green innovation efficiency. On the one hand, it helps enterprises to innovate production processes to reduce energy consumption and pollution in the production process, which brings about a reduction in resource input and non-desired output; on the other hand, it brings about an increase in desired output through the sale of green differentiated products and the marketing of green technologies. The digital economy can stimulate enterprises to carry out green technology innovation in the following two ways. First, the supply of financial resources is a guarantee for SMEs to carry out green technology innovation activities. Compared with traditional finance, digital finance has the

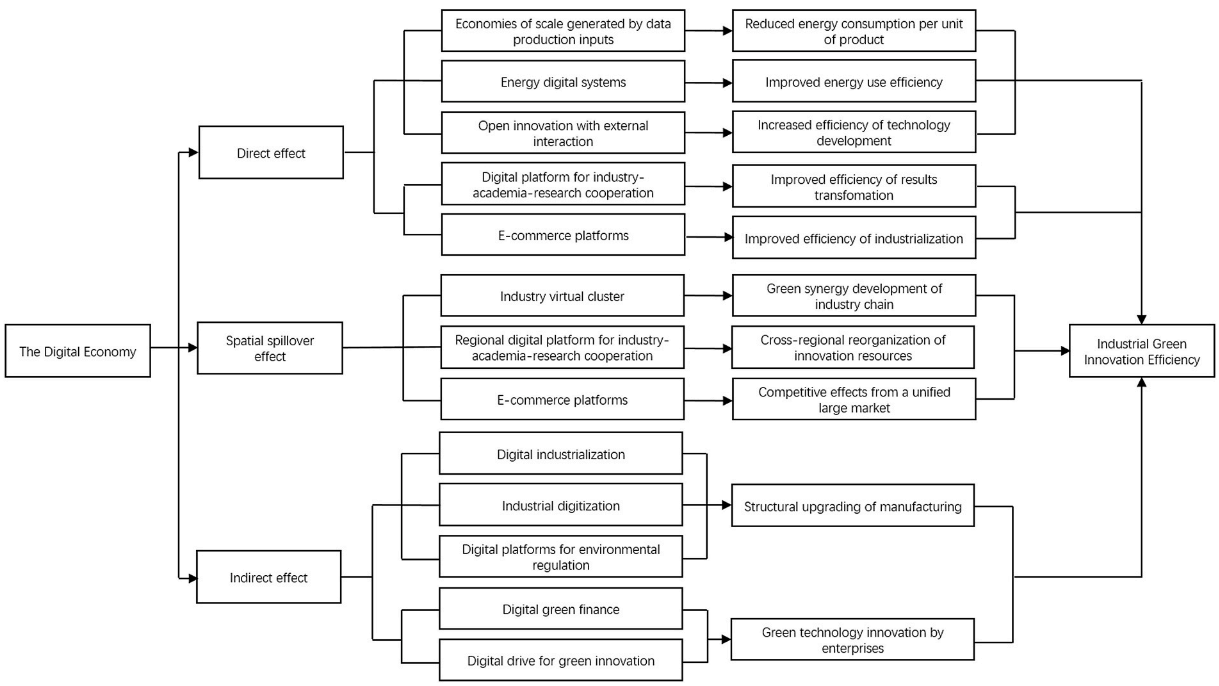

Fig. 1. Influence mechanism of the digital economy on industrial green innovation efficiency.

characteristics of wide coverage, high transparency, and a rich variety of financial products, which can lower the threshold of the credit market and give rise to more green financial products, broadening the financing channels for green innovation activities of SMEs, thus stimulating them to carry out green technology innovation [50]. Second, digital technologies improve the ability of enterprises to interact with users and help to alleviate the information segmentation between the consumer side and the innovation side. The green consumption preference information collected by enterprises with the help of digital technologies can help enterprises determine the direction of green innovation, green innovation potential, and green innovation path, effectively reducing the risk of green innovation and motivating enterprises to carry out green technology innovation [51]. Given the above analysis, we propose the following hypothesis.

H3. The digital economy can indirectly improve industrial green innovation efficiency by promoting the upgrading of manufacturing structure and stimulating enterprises to engage in green technology innovation.

Based on the above analysis, we have made the impact mechanism diagram of the digital economy on industrial green innovation efficiency (see Fig. 1).

3. Econometric models, variables, and data

3.1. Model setting

To test the above theoretical hypotheses, we construct the OLS panel regression model as given in Eq. (1) and the spatial Durbin model (SDM) as given in Eq. (2):

$$indgrinn_{it} = \alpha + \beta digi\_eco_{it} + \gamma X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{1}$$

$$\begin{aligned} indgrinn_{it} &= \alpha + \rho Windgrinn_{it} + \beta digi\_eco_{it} \\ &+ \eta Wdigi\_eco_{it} + \gamma X_{it} + \delta WX_{it} + \mu_i + \nu_t + \varepsilon_{it} \end{aligned} \tag{2}$$

Among them, "*i*" represents the province and "*t*" represents the year. *Indgrinn* denotes industrial green innovation efficiency, *X* denotes the development level of the digital economy. *X* denotes the set of control variables; μ_i and ν_t denotes the province fixed effect and year fixed effect respectively; ε_{it} is the random disturbance term; α, β, γ are the parameters to be estimated, if $\beta > 0$, it means that the digital economy can improve industrial green innovation efficiency. In model (2), *W* is the spatial weight matrix, $Windgrinn_{it}$, $Wdigi\_eco_{it}$ and WX_{it} denotes the spatial lagged terms of industrial green innovation efficiency, the digital economy and control variables respectively, ρ, η, δ are the corresponding coefficients.

3.2. Variables description

3.2.1. Explained variable

We use the SBM-DEA model with variables return to scale and undesirable outputs to measure industrial green innovation efficiency. The input and output indicators included in the industrial green innovation efficiency index system are presented in Table 1.

3.2.2. Core explanatory variable

We examined the digital economy's development level of 30 Chinese provinces by creating a comprehensive index system and utilizing principal component analysis (PCA). The index system has two major indicators, digital industrialization, and industrial digitalization, and contains eight secondary indicators and 31 third-level indicators. Specific indicators are listed in Appendix Table 1.

3.2.3. Control variables

We selected the following control variables: industrial enterprise size (*size*), measured by the average assets of industrial enterprises above the designated size; Nationalization degree of industrial enterprises (*soe*), measured by the state-owned holding enterprises' assets to total assets of industrial enterprises above designated size; Regional openness (*open*), measured by the total imports and

Table 1
Index selection of industrial green innovation efficiency.

Type of Indicators	Selection of indicators	Measurement of indicators
Green Innovation Inputs	Industrial Energy Inputs	Energy consumption of 10,000 Yuan GDP
	Industrial Innovation Human Investment	Industrial R&D personnel full time equivalent
	Industrial Innovation Capital Investment	Internal expenditure on industrial R&D expenses
		Industrial new product development funds
		Industrial technology introduction and transformation funds
Green Expected Outputs	Technology development phase outputs	Number of Green Patents
	Outputs in the transformation phase	New product sales revenue
Green Unexpected Outputs	Industrial waste indicators	Industrial waste gas emissions
		Industrial wastewater discharge
		Industrial solids emissions

exports to GDP; Regional infrastructure status (*base*), measured by the total postal and telecommunications services to GDP; Regional Technology Market activity (*tech*), measured by the technology market turnover to GDP.

3.3. Sources of data and descriptive statistics

The data in this paper are primarily obtained from the China Industrial Economic Statistical Yearbook, the China Environmental Statistical Yearbook, the China Energy Statistical Yearbook, and the China Science and Technology Statistical Yearbook, with any gaps filled in by consulting the provincial statistical yearbooks. After accounting for a substantial number of missing data points for Tibet, Hong Kong, Macao, and Taiwan, the sample is finally determined to be balanced panel data from 30 Chinese provinces from 2005 to 2019. The descriptive statistics for each variable are shown in Table 2.

4. Empirical results and discussion

Based on the variable description and data selection in the previous part, the task of this part is to test the hypotheses empirically. We follow the process below (see Fig. 2): Firstly, The spatial correlation of data is tested to determine whether the spatial econometric model is appropriate; Secondly, the choice of spatial econometric model is tested; Thirdly, The direct effect and spatial spillover effect of the digital economy on industrial green innovation efficiency are examined, as well as the robustness of the conclusions; Finally, the indirect transmission mechanisms of the digital economy on industrial green innovation efficiency is verified.

4.1. Spatial correlation test

4.1.1. Construction of spatial weight matrix

We created three spatial weight matrices based on geographic and economic distances, namely, geographical proximity matrix, inverse geographic distance matrix, and economic anti-geographical matrix, which are expressed in Eq. (3), Eq. (4), and Eq. (5).

1. Geographical proximity matrix

$$W_{ij}{}^{a} = \begin{cases} 0 \text{ , province } i \text{ and province } j \text{ not border, or } i = j \\ 1 \text{ , province } i \text{ and province } j \text{ border} \end{cases} \tag{3}$$

where $i, j = 1, 2 \ldots n$ denote provinces. W_{ij} denotes the location relationship between province i and province j. The value is 1 if province i and province j border, and 0 if they do not border or $i = j$.

2. Inverse geographic distance matrix

$$W_{ij}{}^{b} = \begin{cases} 1/d_{ij}, & i \neq j \\ 0, & i = j \end{cases} \tag{4}$$

where d_{ij} is the geographic distance between provinces i and j, which is calculated using the spherical distance between the two provinces' capitals. The spatial weights are inversely proportional to the geographic distance between two provinces; the greater the geographic distance between the two provinces, the lower the spatial weight.

3 Economic anti-geographical matrix

$$W_{ij}{}^{c} = \begin{cases} \left|\overline{Y_i} - \overline{Y_j}\right| / d_{ij}^2, i \neq j \\ 0, i = j \end{cases} \tag{5}$$

where d_{ij} denotes the geographical distance between provinces i and province j, $\overline{Y_i}$ and $\overline{Y_j}$ denote the average real GDP per capita of province i and province j from 2005 to 2019. The larger the economic discrepancy between two provinces and the shorter their geographical distance, the greater the spatial weight.

Table 2
Descriptive statistics for variables.

Variable Name	Sample size	Mean value	Standard deviation	Minimum value	Maximum value
Industrial Green Innovation Efficiency (*indgrinn*)	450	0.44	0.28	0.08	1.45
The Digital economy development level (*digi_eco*)	450	0.27	0.22	0.00	1.00
Infrastructure Status (*base*)	450	0.06	0.04	0.01	0.24
Technology market activity (*tech*)	450	0.01	0.02	0.00	0.16
Regional openness (*open*)	450	0.55	0.66	0.05	5.79
Size of industrial enterprises (*size*)	450	9.69	1.00	6.67	11.83
Degree of nationalization of industrial enterprises (*soe*)	450	0.51	0.18	0.14	0.84

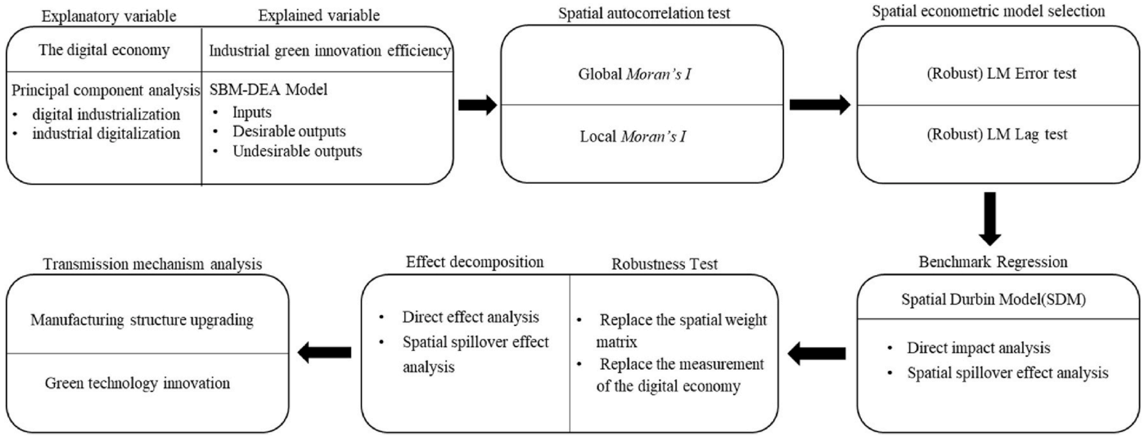

Fig. 2. Flowchart of empirical analysis.

4.1.2. *Spatial correlation test*

We first test the global spatial autocorrelation of the digital economy and industrial green innovation efficiency respectively using *Global Moran's* I. Geographic proximity weight matrix is used for this measuring. Table 3 shows the results. During the sample period, the *Global Moran's* I of the digital economy and industrial green innovation efficiency are both significantly positive at the statistical level of 5%, indicating that both the digital economy and industrial green innovation efficiency exhibit positive spatial autocorrelation, in other words, the spatial agglomeration is dominated by high-high agglomeration and low-low agglomeration. From a spatio-temporal evolution trend standpoint, the *Global Moran's* I of industrial green innovation efficiency exhibited a generally rising trend, from 0.197 in 2005 to 0.494 in 2019, showing that its positive spatial autocorrelation was enhancing. However, the *Global Moran's* I of the digital economy fell from 0.331 in 2005 to 0.154 in 2019, indicating that its positive spatial autocorrelation gradually weakened.

In addition, we further select 2005, 2010, 2015, and 2019 and draw in chronological order the *Local-Moran's* I scatter plots of industrial green innovation efficiency and the digital economy development level to conduct local spatial autocorrelation tests. The *Local-Moran's* I scatter plots of industrial green innovation efficiency are shown in Fig. 3a–d and the *Local-Moran's* I scatter plots of the digital economy development level are shown in Fig. 3e–h. The plot of the two indexes both showed that most provinces fell in the first and third quadrants, exhibiting high-high and low-low local spatial agglomeration with the surrounding areas. The *Local Moran's* I scatter plots of industrial green innovation efficiency show that the number of provinces falling in the first quadrant gradually increases, while the number of provinces falling in the second and fourth quadrants with "low-high" local agglomeration and "high-low" local agglomeration gradually decreases, indicating that its positive spatial autocorrelation gradually enhances, which is consistent with *Moran's* I test. The *Local Moran's* I scatter plots of the digital economy indicates a declining trend in the number of provinces falling in the first quadrant with some provinces moving from the first to the second or third quadrants. This agrees with the *Moran's* I test finding that the digital economy's positive spatial autocorrelation is fading, showing polarization and hollow tendency. Overall, both global and local spatial autocorrelation tests show that using the spatial econometric model is appropriate, while the OLS panel regression model may lead to some deviations in the results.

Table 3
Test results of *Global Moran's I*.

year	Industrial green innovation efficiency			The Digital economy		
	Moran's I	Z	*P*-value	*Moran's* I	Z	*P*-value
2005	0.197	2.497	0.01	0.331	4.408	0.00
2006	0.172	2.216	0.03	0.326	4.350	0.00
2007	0.251	2.680	0.01	0.313	4.216	0.00
2008	0.216	2.420	0.02	0.292	3.996	0.00
2009	0.290	2.950	0.00	0.268	3.711	0.00
2010	0.272	2.799	0.01	0.271	3.730	0.00
2011	0.392	3.422	0.00	0.275	3.770	0.00
2012	0.272	2.515	0.01	0.266	3.654	0.00
2013	0.377	3.395	0.00	0.266	3.644	0.00
2014	0.351	3.163	0.00	0.269	3.675	0.00
2015	0.312	2.813	0.00	0.253	3.489	0.00
2016	0.442	3.826	0.00	0.226	3.177	0.00
2017	0.468	4.014	0.00	0.203	2.910	0.00
2018	0.483	4.164	0.00	0.179	2.638	0.01
2019	0.494	4.282	0.00	0.154	2.334	0.02

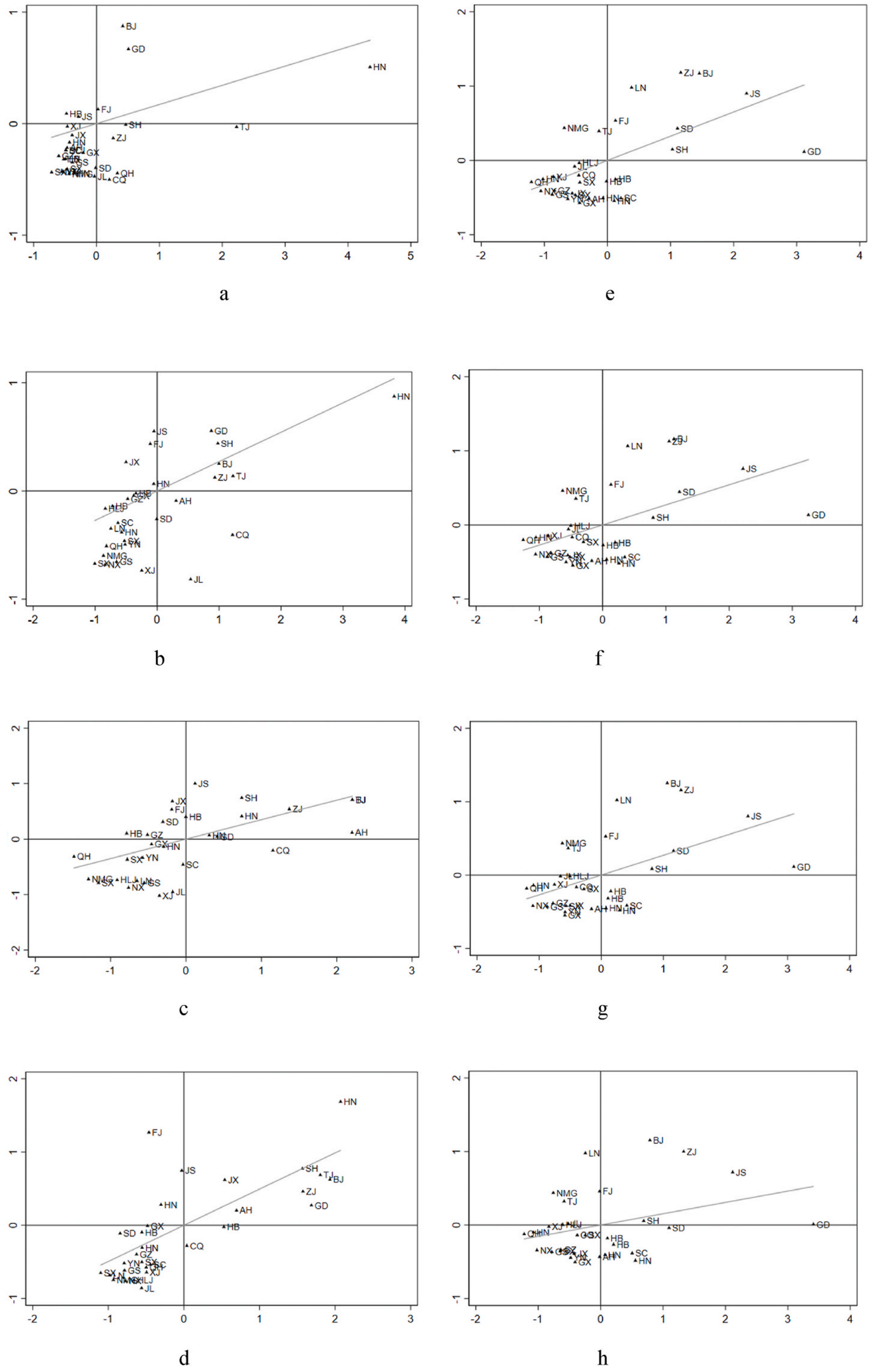

Fig. 3. a) The *Local-Moran's I* scatter plot of industry green innovation efficiency in 2005. b) The Local-Moran's I scatter plot of industry green innovation efficiency in 2010. c) The *Local-Moran's* I scatter plot of industry green innovation efficiency in 2015. d) The *Local-Moran's* I scatter plot of industry green innovation efficiency in 2019. e) The *Local-Moran's I* scatter plot of the digital economy development level in 2005. f) The *Local-Moran's* I scatter plot of the digital economy development level in 2010. g) The *Local-Moran's I* scatter plot of the digital economy development level in 2015. h) The *Local-Moran's* I scatter plot of the digital economy development level in 2019.

Notes: BJ: Beijing; TJ: Tianjin; HB: Hebei; LN: Liaoning; SH: Shanghai; JS: Jiangsu; ZJ: Zhejiang; FJ: Fujian; SD: Shandong; GD: Guangdong; HN: Hainan; SX: Shanxi; JL: Jilin; HLJ: Heilongjiang; AH: Anhui; JX: Jiangxi; HN: Henan; HB: Hubei; HN: Hunan; SC: Sichuan; NMG: Inner Mongolia; GZ: Guizhou; YN: Yunnan; SX: Shaanxi; GS: Gansu; QH: Qinghai; NX: Ningxia; GX: Guangxi; CQ: Chongqing.

4.2. Spatial econometric model selection

According to Table 4, we can make a judgment about the optimal form of the spatial econometric model. The LM and Robust LM tests both significantly reject the original hypothesis under the spatial error model (SEM), the spatial lag model (SAR), and the joint form of the SAR and SEM models, proving that the spatial Durbin model (SDM) is a reasonable choice for this investigation.

4.3. Benchmark regression results

We estimate the impact of the digital economy on industrial green innovation efficiency and its spatial spillover effect according to Model (2). The control for fixed effects takes three forms: individual fixed-effect controlled, time fixed-effect controlled, and individual and time fixed-effects double controlled. Also, for comparison of the results, we provide regression results for the OLS regression model, the individual time effect double fixed SAR model, and SEM model.

Table 5 shows that no matter what forms of regression models are used, the coefficient of the digital economy is significantly positive at the statistical level of 5%, indicating that the digital economy improves local industrial green innovation efficiency, which verifies H1. Data-driven economies of scale and the use of energy digital systems can promote the intensive consumption of energy, while the application of digital technologies, the digital platforms of industry-academia-research, and the e-commerce platforms enables enterprises to improve the innovation efficiency at all stages of the innovation value chain, which constitutes a direct impetus to the improvement of industrial green innovation efficiency. This is consistent with the findings of Wang et al. (2022) [38], who suggested that the Internet directly enhances industrial green innovation efficiency by promoting energy intensification and open innovation in the firms. We further deepen and expand his view.

The estimation results of the SAR model, individual fixed-effect controlled and individual and time fixed-effect double controlled SDM models all show that the coefficient of the spatial lag term (*W*indgrinn*) of industrial green innovation efficiency is significantly positive, which again indicates a positive spatial autocorrelation of industrial green innovation efficiency. When estimated using the SDM model with time fixed-effect controlled, the coefficient of *W*digi_eco* is highly significantly positive at the 1% statistical level, demonstrating the digital economy's positive spatial spillover effect on industrial green innovation efficiency, which verifies H2. The digital economy accelerates cross-regional cooperation of innovation factors and cross-regional spillover of green technologies and promotes collaborative green development of enterprises in the industrial chain across regions. It also intensifies competition among similar industrial enterprises located in different regions by breaking down market segmentation, thus forcing enterprises with low production efficiency and serious pollution emissions to undergo green transformation. Therefore, while the digital economy has a direct positive impact on local industrial green innovation efficiency, it can also drive the improvement of industrial green innovation efficiency in the surrounding areas. This agrees with the findings of Zhao et al. (2022), Hu and Guo (2022), and Fang et al. (2022) [37,44,52]. Zhao et al. (2022) and Hu and Guo (2022) discovered that the digital economy has a spatial spillover effect on green total factor energy efficiency and green total factor productivity respectively [37,52], while Fang et al. (2022) confirmed that the Internet development has a spatial spillover effect on green innovation efficiency [44].

According to the regression results of the SDM model with individual and time fixed-effects double controlled, the coefficient of *open* is statistically significantly positive. In open provinces, market competition is severe and technological spillover is higher so that enterprises have the intrinsic motivation and external conditions to improve production technology, resulting in a faster increase in industrial green innovation efficiency; The coefficient of *W*base* is significantly positive. The improved infrastructure in adjacent provinces facilitates inter-regional resource mobility and green technology diffusion between industrial firms, which has a beneficial effect on the industrial green innovation efficiency improvement in local industries; the coefficient of *W*tech* is significantly positive. The active technology market in surrounding provinces accelerates technology diffusion, which benefits local absorption of green technology spillover from neighboring provinces; the coefficient of *W*open* is significantly negative. Neighboring provinces compete for foreign investment, and if high-quality FDI is concentrated in nearby provinces, local industrial green innovation efficiency would suffer; the coefficient of *W*soe* is also significantly negative. Generally speaking, the two neighboring provinces have a competitive relationship in green innovation. Since SOEs face less competition in the market and are less motivated to innovate, a neighboring province with a higher share of SOEs will discourage local green innovation, thus negatively affecting local industrial green innovation efficiency.

4.4. Robustness test

We adopted two methods to test the robustness of the benchmark regression results: replacing the spatial weight matrix and replacing the measures of the digital economy. Based on the spatial Durbin model in column 6 of Table 5, column (1) and column (2) of Table 6 show the estimation results of replacing the geographic proximity matrix with the inverse geographic distance matrix and the

Table 4
LM test results.

SEM model		SAR model		Joint form of SAR model and SEM model	
LM test	4118.821 ($p = 0.000$)	LM test	83.832 ($p = 0.000$)	Robust LM Err + LM Lag	373.253 ($p = 0.000$)
Robust LM test	289.422 ($p = 0.000$)	Robust LM test	254.432 ($p = 0.000$)		

Table 5
Benchmark regression results.

Explanatory variables	Explained variable: *Indgrinn*					
	Individual-time fixed	Individual-time fixed	Individual-time fixed	Individual fixed	Time fixed	Individual-time fixed
	OLS	SAR	SEM	SDM	SDM	SDM
	(1)	(2)	(3)	(4)	(5)	(6)
W*indgrinn Or γ		0.215*** (0.059)	0.217*** (0.060)	0.337*** (0.051)	0.018 (0.069)	0.180*** (0.060)
digi_eco	0.819** (0.327)	0.701** (0.304)	0.746** (0.306)	0.746** (0.321)	0.327*** (0.107)	0.689** (0.328)
base	0.408 (0.508)	0.425 (0.470)	0.342 (0.489)	0.072 (0.486)	0.897 (0.547)	0.464 (0.483)
tech	1.939** (0.900)	1.950** (0.832)	1.736** (0.833)	1.264 (0.843)	3.860*** (0.502)	1.136 (0.835)
open	0.035* (0.020)	0.045** (0.018)	0.051*** (0.019)	0.057*** (0.018)	0.023 (0.018)	0.048*** (0.018)
size	−0.012 (0.063)	0.005 (0.058)	0.022 (0.059)	0.036 (0.058)	−0.100*** (0.025)	0.027 (0.060)
soe	−0.148 (0.167)	−0.124 (0.155)	−0.047 (0.158)	0.068 (0.155)	−0.288*** (0.097)	−0.021 (0.149)
*W*digi_eco*				−0.369 (0.467)	0.910*** (0.192)	−0.491 (0.572)
*W*base*				0.108 (0.510)	−1.749* (1.018)	1.627** (0.799)
*W*tech*				4.821*** (1.772)	6.743*** (0.999)	5.115*** (1.892)
*W*open*				−0.185*** (0.053)	−0.052 (0.053)	−0.255*** (0.060)
*W*size*				−0.037 (0.064)	−0.210*** (0.046)	−0.126 (0.123)
*W*soe*				−1.358*** (0.355)	−0.350* (0.189)	−2.063*** (0.362)
N	450	450	450	450	450	450
R^2	0.583	0.204	0.129	0.298	0.159	0.190

Notes: (i) The standard errors of robustness are in brackets; (ii) * Significant at 10% level, ** Significant at 5% level, *** Significant at 1% level.

economic inverse geographic matrix respectively. Columns (3) and (4) show the estimation results of using the first principal component *digi_eco2* to measure the digital economy's development level while replacing the spatial weight matrix.

All four columns of results show that the digital economy significantly enhances local industrial green innovation efficiency, demonstrating the robustness of the benchmark regression results. Columns (1) and (3) show that the coefficients of *W*digi_eco* and *W*digi_eco2* are significantly positive, while columns (2) and (4) show that the coefficients of *W*digi_eco* are significantly negative and the coefficients of *W*digi_eco2* are negative but not significant. It indicates that the positive spatial spillover effect of the digital economy on industrial green innovation efficiency is more likely to occur among regions with close geographic proximity and relatively different economic development levels. The digital economy exerts positive spatial spillover effects through three mechanisms: first, it facilitates cross-regional cooperation of innovation factors between upstream and downstream of the industrial chain; second, it accelerates cross-regional spillover of green technologies between upstream and downstream of the industrial chain; third, it intensifies cross-regional competition among industrial enterprises and pushes industrial enterprises with backward production

Table 6
Robustness test results.

Explanatory variables	Explained variable: *indgrinn*			
	Inverse geographic distance matrix	Economic Inverse geographical matrix	Inverse geographic distance matrix	Economic Inverse geographical matrix
	(1)	(2)	(3)	(4)
*W*indgrinn*	0.146 (0.136)	−0.289*** (0.101)	0.139 (0.136)	−0.289*** (0.101)
digi_eco	1.001*** (0.333)	0.663** (0.311)		
digi_eco2			0.955*** (0.358)	0.604* (0.333)
base	0.058 (0.531)	0.397 (0.482)	0.189 (0.532)	0.456 (0.481)
tech	3.331*** (0.856)	1.590* (0.881)	3.315*** (0.855)	1.429 (0.884)
open	0.026 (0.018)	0.025 (0.018)	0.028 (0.018)	0.025 (0.018)
size	−0.052 (0.059)	0.075 (0.056)	−0.062 (0.061)	0.074 (0.058)
soe	−0.232 (0.156)	−0.280* (0.154)	−0.240 (0.157)	−0.285* (0.154)
*W*digi_eco*	6.388*** (1.688)	−1.334* (0.783)		
*W*digi_eco2*			7.422*** (1.843)	−1.149 (0.853)
*W*base*	4.583* (2.376)	1.270 (1.374)	3.959 (2.407)	1.119 (1.410)
*W*tech*	20.741*** (5.004)	9.081*** (2.719)	20.721*** (4.995)	9.362*** (2.724)
*W*open*	−0.528*** (0.134)	−0.247*** (0.060)	−0.499*** (0.134)	−0.244*** (0.060)
*W*size*	−0.898*** (0.319)	0.145 (0.163)	−1.049*** (0.334)	0.122 (0.169)
*W*soe*	−3.915*** (1.011)	1.155** (0.490)	−4.036*** (1.010)	1.140** (0.497)
N	450	450	450	450

Notes: (i) The standard errors of robustness are in brackets; (ii) * Significant at 10% level, ** Significant at 5% level, *** Significant at 1% level.

technologies to undergo green transformation. The closer geographical distance makes the connection between the two regions in the industrial chain closer, which provides favorable conditions for the first two mechanisms; at the same time, the "reverse incentive mechanism" means that the green technologies tend to be transferred down the gradient from the developed regions to the backward regions.

4.5. Effect decomposition

To explore the impact of the digital economy on industrial green innovation efficiency more accurately, we employ the spatial effects decomposition method of the spatial econometric model to divide the overall effect into direct and indirect effect. The direct effect is used to examine the effect of the digital economy on local industrial green innovation efficiency, while the indirect effect, also known as the spatial spillover effect, is used to examine the impact of the digital economy on the industrial green innovation efficiency in neighboring provinces.

Table 7 shows the effect decomposition results of the estimation in column (6) of Table 5. As can be seen, the direct effect is significantly positive, indicating that the digital economy is an important force to improve local industrial green innovation efficiency, which is consistent with previous estimation results. The indirect effect results suggest that, according to the results of using geographic distance as the spatial weight, the digital economy has a significant positive spatial spillover effect on industrial green innovation efficiency, Instead, the spatial impact of the digital economy on industrial green innovation efficiency becomes a negative spillover when the combination of economic distance and geographical distance is used as the spatial weight. It also supports the previous estimates, that is, the positive spatial spillover effect is more likely to occur between developed and backward provinces with close geographical proximity. By comparing the coefficients, it can be further concluded that the spatial spillover effect of the digital economy on industrial green innovation efficiency is greater than the direct effect. It indicates that it is not enough to enhance industrial green innovation efficiency directly by developing local digital economy, but absorbing green technology spillovers from surrounding areas and actively participating in the nationwide competition for green development are the keys to improving industrial green innovation efficiency.

4.6. Mechanism analysis

Combining the above analyses, we can conclude that the digital economy significantly contributes to industrial green innovation efficiency in the local and surrounding provinces. In this part, we construct the following set of mediating effect test models based on Eq. (2) to examine the indirect transmission mechanism of the digital economy on local industrial green innovation efficiency, which is to testify H2 and H3:

$$tech\_str_{it} = \alpha + \lambda_1 Wtech\_str_{it} + \beta_1 digi\_eco_{it} \\ + \eta Wdigi\_eco_{it} + \gamma X_{it} + \delta WX_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{6}$$

$$lnpatent_{it} = \alpha + \lambda_2 W\ ln\ patent_{it} + \beta_2 digi\_eco_{it} \\ + \eta Wdigi\_eco_{it} + \gamma X_{it} + \delta WX_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{7}$$

$$indgrinn_{it} = \alpha + \rho Windgrinn_{it} + \beta_1{}' digi\_eco_{it} \\ + \eta Wdigi\_eco + \varphi_1 tech\_str_{it} + \gamma X_{it} + \delta WX_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{8}$$

$$indgrinn_{it} = \alpha + \rho Windgrinn_{it} + \beta_2{}' digi\_eco_{it} \\ + \eta Wdigi\_eco_{it} + \varphi_2 lnpatent_{it} + \gamma X_{it} + \delta WX_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{9}$$

Among Eq. (6), Eq. (7), Eq. (8), and Eq. (9), *tech_str* is the mediating variable "manufacturing structure upgrading", measured by the share of production scale of technology-intensive enterprises in provincial manufacturing production scale. *Lnpatent* is the mediating variable "green technology innovation scale", measured by three indicators: *lnpat_Sum* (the natural logarithm of the total number of green patents), *lnpat_inv* (the natural logarithm of the number of green invention patents) and *lnpat_pra* (the natural logarithm of the number of new green utility patents). The meanings of other variables are consistent with Eq. (2).

Table 7
Spatial effects decomposition results.

Explanatory variables	Inverse geographic distance matrix		
	Direct effect	Indirect effect	Total effect
digi_eco	1.078*** (0.349)	7.762*** (2.269)	8.840*** (2.394)
base	0.077 (0.511)	5.363* (2.759)	5.440** (2.596)
tech	3.643*** (0.843)	25.694*** (7.527)	29.337*** (7.867)
open	0.021 (0.017)	−0.620*** (0.190)	−0.599*** (0.194)
size	−0.061 (0.056)	−1.068*** (0.399)	−1.129*** (0.402)
soe	−0.263* (0.158)	−4.576*** (1.401)	−4.839*** (1.466)

Notes: (i) The standard errors of robustness are in brackets; (ii) * Significant at 10% level, ** Significant at 5% level, *** Significant at 1% level.

Based on Eq. (2), Eq. (6), and Eq. (7) replaced the explained variable with two mediating variables for estimation to test the impact of the digital economy on manufacturing structure upgrading and green technology innovation, and Eq. (8) and Eq. (9) add two mediating variables as explanatory variables to observe the direct impact of the digital economy on industrial green innovation efficiency after excluding the possible indirect impact through two transmission mechanisms. As a group, Eq. (2), Eq. (6), and Eq. (8) are used to investigate the mediating effect of the "manufacturing structure upgrading". The results are presented in Table 8 respectively. Similarly, Eq. (2), Eq. (7), and Eq. (9) are used as a group to investigate the mediating effect of "green technology innovation". The results are presented in Table 9.

The results in column (2) of Table 8 show that the coefficient of *digi_eco* is significantly positive, indicating that the digital economy can promote the upgrading of manufacturing structure; The results in column (3) show that the coefficient of *tech_str* is significantly positive, indicating that the upgrading of manufacturing structure has a significant positive impact on industrial green innovation efficiency, while the coefficient of *digi_eco* is still significantly positive, but it is reduced compared with the coefficient in column (1). Therefore, we can judge that manufacturing structure upgrading plays a partial mediating role in the process of the digital economy influencing industrial green innovation efficiency. The digital economy can indirectly improve local industrial green innovation efficiency by upgrading manufacturing structure, which verifies the first channel proposed in H3. By accelerating the pace of digital industrialization and industrial digitization, while providing technical support for the implementation of various environmental regulation policies through digital platforms to ensure a good incentive or spur effect on industrial enterprises' green transformation, the digital economy can effectively enhance industrial green innovation efficiency. This is like the finding of Luo et al. (2022) [35]. He found that overall industrial structural upgrading plays a significant mediating role in the process of the digital economy impacting green development efficiency, while we focus our attention on the structural upgrading of manufacturing.

Similarly, according to the results in Table 9, green technology innovation also plays a significant mediating role. The digital economy can indirectly improve local industrial green innovation efficiency by encouraging enterprises to carry out green technology innovation, which verifies the second channel proposed in H3. By providing financial support for SMEs' green technology innovation through digital green finance and using digital technologies to transform green technology innovation from experience-driven to data-driven, the digital economy can effectively stimulate enterprises to carry out green technology innovation and thus improving industrial green innovation efficiency. This is consistent with Li et al. (2022). He observed that technical innovation is a key way the digital economy enhances green economy efficiency [36]. However, the mediating effects plays by the three types of green technology innovation differ. The estimation results in columns (5) and (6) show that the coefficient of *digi_eco* is still positive, but no longer significant, indicating that both comprehensive green technology innovation and green invention patent innovation play a full mediating effect. The estimation results in column (7) show that the coefficient of *digi_eco* is still significantly positive and only decreases compared to the coefficient in column (1), indicating that the green utility patent innovation only plays a partial mediating effect. The possible reason is that, compared with the green invention patent, the green utility patent is the re-optimized design of the existing green technology, whose technical content and innovation value are smaller, and the transformation of achievements is more difficult, which has little influence on industrial green innovation efficiency.

5. Conclusions and policy suggestions

5.1. Conclusions

The digital economy plays an important role in promoting green technology innovation and the spillover of green technologies in industrial enterprises. Based on the panel data of 30 provinces in China from 2005 to 2019, we firstly established a comprehensive index system to evaluate the development level of the digital economy and used the SBM-DEA model to measure industrial green innovation efficiency. Then, we systematically studied the spatial autocorrelation of the digital economy and industrial green innovation efficiency, the direct effect, spatial spillover effect, and indirect transmission mechanism of the digital economy on industrial green innovation efficiency. The findings are as follows: (i) The spatial autocorrelation analysis based on *global Moran's* I and *local Moran's* I show that the digital economy and industrial green innovation efficiency show significant positive spatial autocorrelation, with an obvious agglomeration of high-high and low-low; The positive spatial autocorrelation of industrial green innovation efficiency gradually enhanced, while the positive spatial autocorrelation of the digital economy gradually weakened, showing a trend toward

Table 8
The mediation effect test of manufacturing structure upgrading.

Explanatory variables	Explained variable		
	indgrinn	tech_str	indgrinn
	(1)	(2)	(3)
*W*indgrinn*	0.180*** (0.060)	−0.085 (0.074)	0.170*** (0.062)
digi_eco	0.689** (0.328)	0.248* (0.128)	0.591* (0.326)
tech_str			0.387*** (0.119)
N	450	450	450
R^2	0.190	0.508	0.141

Notes: All models control for all control variables and spatial lag terms, and are estimated using the SDM model with individual and time fixed-effects double controlled.

Table 9
The mediation effect test of green technology innovation.

Explanatory variables	Explained variables						
	indgrinn	lnpat_sum	lnpat_inv	lnpa_pra	indgrinn	indgrinn	indgrinn
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
*W*indgrinn*	0.180*** (0.060)	0.182*** (0.064)	0.012 (0.069)	0.287*** (0.064)	0.057 (0.065)	0.074 (0.064)	0.126** (0.063)
digi_eco	0.689** (0.328)	2.376*** (0.556)	2.727*** (0.704)	1.928*** (0.660)	0.318 (0.322)	0.305 (0.321)	0.605* (0.328)
lnpat_sum					0.132*** (0.027)		
lnpat_inv						0.117*** (0.021)	
lnpat_pra							0.048** (0.024)
N	450	450	450	450	450	450	450
R^2	0.190	0.785	0.807	0.638	0.332	0.298	0.263

Notes: All models control for all control variables and spatial lag terms, and are estimated using the SDM model with individual and time fixed-effects double controlled.

polarization and hollowing out. (ii) The regression results of the Spatial Durbin Model (SDM) show that: The digital economy not only has a significant direct positive impact on the improvement of local industrial green innovation efficiency but also plays a positive spatial spillover effect, driving the improvement of industrial green innovation efficiency in the surrounding provinces. However, this positive spatial spillover effect only occurs among provinces with close geographic proximity and relatively different economic development levels. (iii) The results of mediating effect show that: The digital economy indirectly improves local industrial green innovation efficiency by promoting the upgrading of manufacturing structure and stimulating enterprises' green technology innovation. Compared with the green utility patent innovation, the meditating effect plays by green invention patent innovation is greater.

5.2. Policy suggestions

This study uses a variety of methods to examine the direct impact, spatial spillover effect, and indirect mechanisms of the digital economy on industrial green innovation efficiency. The empirical test results support the theoretical hypotheses. Based on the research conclusions of this paper, we propose the following policies: First, all countries in the world, as well as local governments, should eliminate the technical barriers in the digital transformation of enterprises and promote the all-round development of industrial digitalization. Specifically, they should explore and formulate a standard framework for enterprise digital transformation, including general technical standards, data element standards, digital tools standards, digital enterprise operation standards, etc., to provide reference implementation plans for enterprise digital transformation and reduce its difficulty. Second, governments should give full play to the spatial spillover effect of the digital economy to promote the joint development of the digital economy among provinces and promote the coordinated development of industrial green innovation efficiency. The government can delimit different green coordinated development regions nationwide and establish a digital platform for green technology cooperation in each region, speeding up cross-provincial docking of green innovation factors and encouraging developed provinces to radiate point-to-point to backward provinces and promote green technology. Third, the government should combine digital finance and green finance policies to improve the coverage of green finance in enterprises, thus promoting the green transformation of enterprises. Specifically, the government should establish a digital platform for green finance that incorporates green projects, green credit, green funds, and green bonds, facilitating green project investment and financing docking.

5.3. Limitations and future research directions

There are some limitations to this study: First, the sample of this paper is limited to the provincial level; if data are available, future research can be extended to the prefecture-level city or provincial-industry level. Secondly, this paper only focuses on China in the past 15 years; If we can expand the research to the *trans*-national level, it may be more instructive to the world. Third, limited by the availability of data, the index system for measuring the development level of the digital economy and industrial green innovation efficiency in this paper is not perfect; future research can further strengthen the improvement of the index system.

Author contribution statement

Guangqin Li: Conceived and designed the experiments; Performed the experiments.
Xiaoge LI: Analyzed and interpreted the data; Wrote the paper.
Lingzhi Huo: Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interest's statement

The authors declare no competing interests.

Appendix Table 1

Evaluation index system and data source of digital economy

Objectives	First-class index	Secondary index	Variable selection	Data source
Development level of digital economy	Digital industrialization	Scale and output of main products of electronic information manufacturing industry	Main business income of communication equipment, computer, and other electronic equipment manufacturing industry	Statistical Yearbook of China's Industrial Economy
			Mobile phone production	National Bureau of Statistics
			Integrated circuit output	
			Output of microcomputer equipment	
		Scale, Communication Capability and Service Level of Telecom Industry	Total telecommunication service	
			Year-end users of mobile phones	
			Internet broadband access port	
			Mobile telephone exchange capacity	
			Long distance optical cable line length	
		Scale of software and information technology service industry, scale and development status of Internet and related service industry	Software business income	Statistical Yearbook of China Electronic Information Industry
			Number of enterprises	
			Income from information technology services	
			Employees in information transmission, computer services and software industry	Urban Statistical Yearbook of China
	Industrial digitalizaion	Industry	Industrial added value	National Bureau of Statistics
			The ratio of the number of national patent applications authorized to the total equivalent of R&D personnel in industrial enterprises above designated size	
			The proportion of new product sales income of industrial enterprises above designated size to the main business income of industrial enterprises	
			Expenditure on technical transformation of industrial enterprises above designated size	China Science and Technology Statistical Yearbook
			Expenditure on technology introduction of industrial enterprises above designated size	
		Tertiary industry	Added value of tertiary industry	National Bureau of Statistics
			Original insurance premium income	
			Number of theaters and cinemas	Urban Statistical Yearbook of China
			Number of Internet users	National Bureau of Statistics
			Total retail sales of social consumer goods	
			Quantity of express delivery	
			Per capita transportation and communication consumption expenditure	
			Per capita consumption of culture, education, and entertainment	
		Agriculture	Added value of agriculture, forestry, animal husbandry and fishery	
			Rural electricity consumption	
		Infrastructure investment	Production and supply of electricity, gas and water, transportation, warehousing and postal services, information transmission, computer services and software industry, water conservancy, environment and public facilities	

(continued on next page)

(*continued*)

Objectives	First-class index	Secondary index	Variable selection	Data source
			management, health, and social work.	
			Investment in fixed assets of the whole society	
		Digital talents	Number of ordinary colleges and universities	
			Number of degrees awarded by this college in ordinary colleges and universities	

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