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Research on Digital Trade Measurement and Green Economy Spatial Econometrics Based on DEA-SBM

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Abstract

In the process of China's economic transformation toward high-quality development, green development has become the core path to breaking through resource constraints and environmental pressures. Against this backdrop, computer technology has demonstrated significant advantages in addressing the complex network data in areas such as digital trade and the efficiency bottlenecks of traditional models in big data scenarios. This study develops a digital trade scale measurement system based on data envelopment analysis (DEA) and slacks-based measure (SBM) in an attempt to investigate the coordinated development path of digital trade and the green economy. Digital trade is measured using the DEA-SBM-GA model embedded with genetic algorithm (GA). Each province's degree of development in digital trade is assessed using the entropy value technique. The level of green economic development is gauged by the super-efficiency SBM model. Spatial spillover effects are examined using the spatial Durbin model. The results indicated that DEA-SBM-GA was significantly more efficient than traditional models $p<0.001$), reducing single iteration time by 87.3%. For every 1-unit increase in artificial intelligence-enabled digital trade, local green economic growth increased by 0.129 ($p<0.05$), with an indirect effect of 0.112 ($p<0.05$) and a total effect of 0.246 ($p<0.05$). Technological innovation had a dual threshold (0.314/0.721), and after crossing the high threshold, the impact coefficient increased from 0.063 to 0.247 ($p<0.01$). There was a positive geographical spillover impact and notable regional heterogeneity. The Moran's I index for the green economy was 0.304, with a Z-value of 4.82 ($p<0.001$), indicating significant spatial clustering. The study addresses the shortcomings of earlier research by offering a theoretical framework and policy suggestions for the coordinated growth of the green economy and digital trade. This work has significant academic and practical value.

Keywords: Green Economy; Digital Trade; DEA-SBM; Spatial Econometrics; Data Envelopment Analysis; Slack Variable Model.

1. Introduction

Green development (GD) is the main strategy for overcoming resource limitations and environmental concerns in China's shift to high-quality economic development (ED) [1]. Nevertheless, the quick growth of digital trade (DT) has also presented new difficulties. Electricity is needed in vast quantities for infrastructure, including data centers. China's energy structure, dominated by thermal power, exacerbates energy consumption (EC) and pollution. It has a complicated effect on the green economy (GE). Through industrial reorganization and technological innovation (TI), it might foster development, but economies of scale could also impede advancement. In this sense, computer technology is essential since it reduces memory usage, speeds up iteration times, and enhances the efficiency of complex network data processing. This provides technical support for balancing the relationship with the GE [2, 3]. Although DT can empower green TI, it also has a "double-edged sword" effect. This is due to issues such as the high EC of data centers and increased

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resource dependence caused by the transformation of the industrial chain's end stages [4]. In terms of measuring DT, Osma et al. proposed a framework for measuring the development of DT in ASEAN. The study identified notable variations in each country's implementation levels by combining quantitative data from 30 DT exporters in six ASEAN countries with qualitative analysis using the Booz Company method. The highest scores were for digital transformation, while the lowest were for sustainable future. This framework provided a reference for academic research and policy-making, filling a gap in relevant measurements in developing regions [5]. In the study of the impact mechanisms of the digital economy (DE) and the GE, Hao et al. used the data envelopment analysis (DEA)-Marquardt index and entropy method to measure the green total factor productivity (GTFP) of the manufacturing sector and the level of the DE from 2011 to 2018. The outcomes revealed that the DE significantly enhanced manufacturing GTFP with a "marginal increase" characteristic, positively influencing current technical efficiency but hindering technological progress [6]. Xu et al. developed an influence factor analysis method based on a gray coordinated development prediction model to gauge the degree of integration between China's DE and real economy. This study offered a theoretical foundation and impartial reference for raising China's degree of convergence [7].

Regarding the interaction mechanism between the DE and international trade, and green innovation, Yang et al. discovered that rural revitalization, international trade, and the metaverse are interconnected in complex ways. Traditional international trade presented many challenges, such as complicated market access and information asymmetry. However, the virtual world could use technology, such as blockchain, to create new solutions to these issues. This helped rural areas participate in the global market and sustainable development, acting as a catalyst for change [8]. To investigate the contribution of the DE to the GD of foreign trade, Xu et al. first measured China's digital ED. Then, based on an environmental pollution product list and an extended gravity model, they examined its influence on the export of representative products. The outcomes revealed that green TI was used to produce the DE's notable promotional effect on the GD of international commerce [9]. Ren et al. investigated the effect of DE agglomeration on China's inclusive green growth (GG) and its transmission mechanism. Combining a relaxation-based directed distance function measurement model, the study constructed a measurement system for the level of the DE and used geographic concentration to measure its agglomeration degree. The study found that DE agglomeration positively affected inclusive GG through EC, environmental pollution, and other channels [10]. Using panel data from 278 Chinese cities from 2011 to 2019, Luo et al. calculated the cities' DE using principal component analysis (PCA) and green innovation counted by green patent applications. Green innovation had a spatial spillover effect (SSE), but more developed regions might suppress less developed regions [11].

To explore the spatial impact of the DE and R&D investment on environmental quality and examine the spatial correlation of regional carbon emissions in China, Peng et al. conducted an integrated analysis of spatial and nonlinear effects. They used the entropy weight method to assess the development level of the DE and a partial differential equation to analyze the direct and indirect impacts of the DE and R&D investment. They also constructed an interaction term between DE and R&D investment to assess its moderating effect on R&D investment in reducing carbon dioxide emissions from DE. They found that the increase in R&D investment directly affects the ability of DE to reduce carbon emission intensity at the regional level [12]. Chen et al. used panel data from 285 Chinese prefecture-level cities from 2011 to 2022. They employed the spatial Durbin model (SDM) to capture the spatial effects and used stepwise regression and bootstrap tests to analyze the mediating effects. They also employed the generalized method of moments for systems to solve the endogeneity problem. Finally, they examined the spatial spillover effects and the mediating role of industrial structure (Indstr) in the relationship between the DE and carbon emissions. They found that DE significantly increased carbon emissions and had significant regional spillover effects [13].

Yu et al. used provincial panel data from China from 2011 to 2020 to construct a DE indicator system for the degree of DE agglomeration. They used static and dynamic SDMs and geographically weighted time regression methods to explore the spatial effect and mechanism of DE agglomeration on green economic efficiency. They found that DE agglomeration affected green economic efficiency through green technology innovation and Indstr upgrading [14]. Xiao et al. explored the complex relationship between the DE and agricultural trade efficiency within the framework of the Comprehensive Economic Partnership Agreement, employing an empirical analysis and spatial exploration approach. The results showed that the DE plays a key role in improving agricultural trade efficiency, especially in export trade [15]. To explore the impact of logistics digital transformation on urban innovation, Li & Meng used the dynamic spatial Durbin model as an empirical method for testing. The results showed that logistics digital transformation plays an important role in promoting innovation. This role was reflected in the direct effect of logistics digital transformation itself, as well as the spillover effect from neighboring cities [16].

In summary, existing research has limitations in several aspects. First, methods for measuring DT are limited. Traditional DEA-slacks-based measure (SBM) models are limited by the linear frontier assumption, which makes it challenging to capture the nonlinear network effects of cross-border data flows. Grey models and principal component analysis lack accuracy with high-dimensional, complex data, and most measurement systems lack a green orientation because they do not incorporate undesirable outputs, such as carbon emissions. Second, the analysis of influencing mechanisms is not in-depth enough. Although the role of the DE in the GE is recognized, the unique spatial spillover paths of DT remain unclear, and the threshold effects of variables such as TI and Indstr are overlooked. Discussions of regional heterogeneity are mostly limited to a single scale, lacking a panoramic analysis. Finally, the integration of existing methods is insufficient. The combination of intelligent optimization techniques, such as genetic algorithms (GAs), with spatial econometric models has been ineffective. This results in low efficiency when handling dynamic weight calibration and complex network effect calculations. Consequently, it is difficult to accurately quantify the synergistic relationship between DT and the GE. This study constructs a DEA-SBM-GA model embedded with a GA. Using chromosome encoding relaxes the linear frontier to a non-convex surface and dynamically adjusts indicator weights to adapt to the nonlinear characteristics of DT. Undesirable outputs are also incorporated to reinforce the environmentally friendly orientation. The entropy method is used to objectively assess the development level of DT in each province. A super-efficient SBM model is employed to measure the level of GE. A SDM is used to decompose direct and indirect effects, clarifying the spatial spillover intensity and pathways of DT. A panel threshold model is used to identify the critical values of variables such as TI and Indstr, revealing the non-linear impact patterns. An instrumental variable method is introduced simultaneously to address endogeneity issues. Robustness tests are conducted using geographical adjacency and economic distance matrices to capture regional heterogeneity comprehensively. Through the proposed methods, this study aims to fill gaps in existing literature and provide more precise theoretical support and policy basis for the coordinated development of DT and the GE.

This study comprises five sections. The first section outlines the research background, research questions, and significance, reviews the current state of literature in related fields, identifies existing gaps, and clarifies the research's solution path and core content. The second section establishes the theoretical foundation and analytical framework. It also proposes research hypotheses and explains the specific measurement methods for DT and the GE. Additionally, it details the construction logic and parameter settings of the spatial econometric and threshold models. The third section presents the empirical results, which mainly showcase the statistical characteristics of the key variables, comparisons of the model performance, the results of the regression and decomposition of the spatial spillover effects, and the analytical conclusions regarding the nonlinear threshold effects and the regional heterogeneity. The fourth section summarizes the study and proposes targeted policy recommendations based on the research results to promote the coordinated development of DT and the GE.

2. Research Methodology

2.1. System Construction for the Effects of DT on the Green Economy

The GE is central to high-quality development. Ecological economics theory combines ecological engineering and economics, aiming to strengthen ecological civilization while promoting economic growth and achieving harmonious development between the economy and ecology [17, 18]. Sustainable development theory is based on the principles of fairness, commonality, and continuity, pursuing the goals of efficiency, multidimensionality, coordination, comprehensiveness, greenness, and fairness [19]. DT theory starts from environmental protection, emphasizes economic greening in the medium term, and achieves the integrated development of the economy, environment, and society in the long term. Resource recycling is encouraged by the ideas of the circular economy and low-carbon economy, which also change ED models, increase ecological and circular efficiency, and optimize economic gains at the lowest possible environmental cost. Figure 1 shows the GE theoretical framework [20].

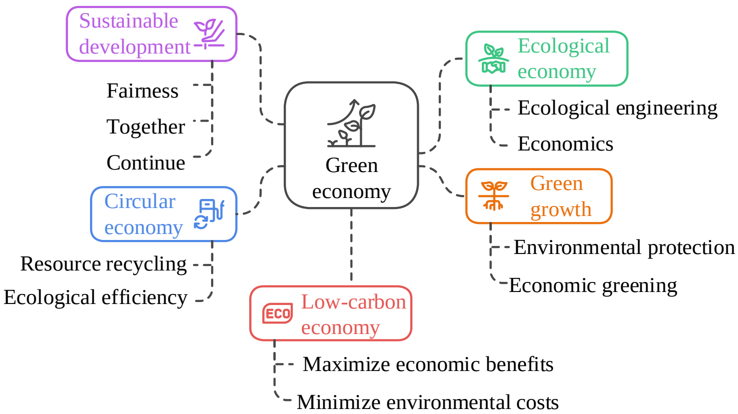


Figure 1. Green economy theory system

Under the impetus of the "dual carbon" strategy, it has become crucial to deeply understand the role of DT in GED [21]. The theory of the environmental effects of international trade covers technological, structural, and scale effects. It has also given rise to the pollution haven hypothesis, the factor endowment hypothesis, and environmental regulation theory [22]. Technological and structural effects contribute to GD. However, economies of scale and the "environmental race to the bottom hypothesis" may hinder the development of a GE. These consequences are reinforced by artificial intelligence (AI), a key enabling technology. On the positive side, AI has improved the environmental compatibility of DT by optimizing energy allocation, accurately predicting carbon emissions, and improving green supply chain management. Moreover, however, the high EC of its computing process cannot be ignored, which highlights the duality and uncertainty of the overall impact mechanism. To present the logical path of AI-enabled DT (AI_DT) influencing the GE more clearly, the study constructs a theoretical analysis framework, as shown in Figure 2.

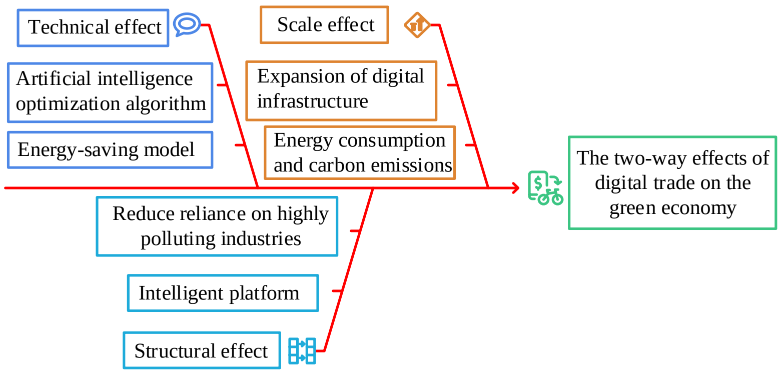


Figure 2. Two-way effects of DT on green economy

Figure 2 illustrates the impact pathways of AI_DT on the GE. In terms of technological effects, AI optimization algorithms build energy-saving models to support GD. Under the scale effect, the expansion of digital infrastructure may lead to increased EC and carbon emissions. In terms of structural effects, intelligent platforms can reduce reliance on high-polluting industries and promote the optimization of Indstr. Green transformation can be facilitated by DT through industrial upgrading and TI. However, it can also increase resource consumption due to infrastructure expansion, exhibiting a significant "double-edged sword" characteristic. The topography of the ways that DT affects GED is intricate and interconnected. Figure 3 outlines the hypothetical conditions for the effect of DT on the GE.

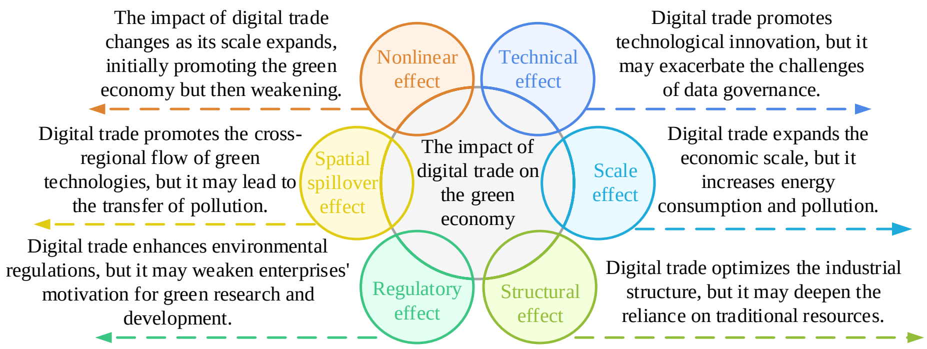


Figure 3. Impacts of DT on green economy assumptions

Figure 3 illustrates the multifaceted and dual nature of the digital technology's effect on GE. At the technological level, big data, AI, and other technologies drive the dissemination of green knowledge and breakthroughs in low-carbon technology. They maximize resource allocation and hasten the shift to knowledge- and technology-intensive sectors in terms of Indstr. However, they may also reinforce traditional structures and impede transformation. Economic growth enhances green investment capacity as economies expand. However, the growth of digital infrastructure raises EC, which intensifies environmental stresses, particularly when thermal power generation makes up a large fraction of the total. In terms of regulation, the internet broadens regulatory channels and enhances governance efficiency, but it may weaken corporate research and development incentives due to rising costs and even trigger a "pollution haven" effect. Spatially, cross-border connectivity promotes the flow of green technologies and equipment, driving regional coordinated development. The overall impact is nonlinear. Initially, technology spillovers and structural optimization play a positive role, but as the scale expands, the positive effects may be weakened by EC and pollution pressures. To confirm its action mechanism and regional heterogeneity, the research puts forth the following hypothesis:

H1: AI_DT promotes GED in this region;

H2: AI_DT has a nonlinear effect on GED, manifesting as a U-shaped or threshold effect (TE);

H3: AI_DT has a SSE on GED;

H4: There are regional variations in how DT affects GE.

2.2. DT Measurement System and Measurement Methods Based on DEA-SBM

As a new kind of international commerce model in the DE era, DT is strongly tied to how international trade affects the environment. To build a thorough assessment method for DT's developmental stage, this study consults pertinent [23, 24]. Based on DT's traits, meaning, and development patterns, the study creates a thorough measurement index system. This system is organized around four dimensions: DT potential, structure, technical level, and environmental status. The specific details are shown in Figure 4.

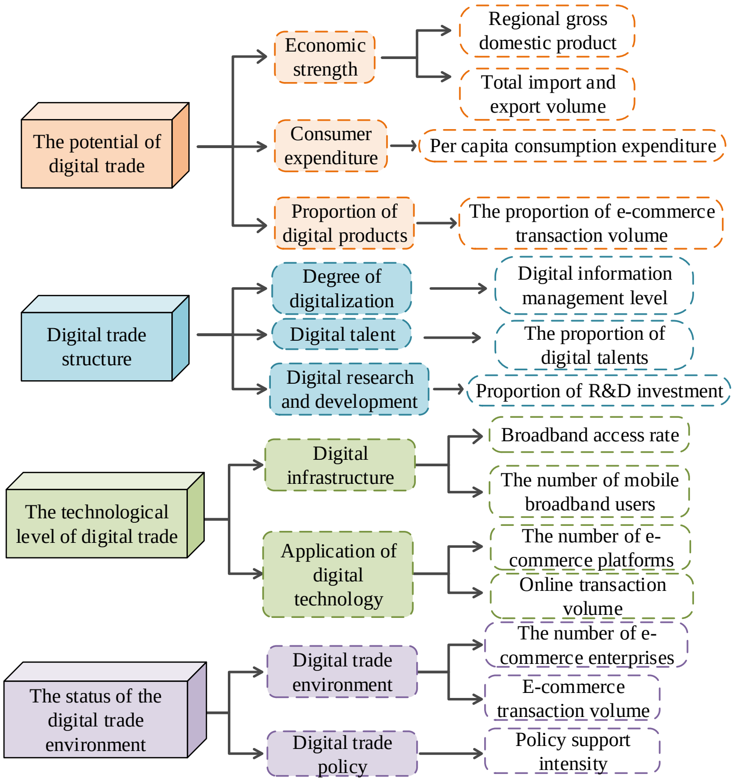


Figure 4. Comprehensive measurement index system of DT

In Figure 4, economic strength and consumer spending reflect the economic foundation and consumption capacity of a region, which are the cornerstones of DT development. The proportion of digital products and the degree of digitization directly measure the weight and prevalence of the DE in the overall economy. Digital talent and research and development investment are key factors driving innovation and technological progress in DT. The technical underpinnings for DT's operations are provided by digital infrastructure, which includes broadband penetration rates and the quantity of mobile broadband users. The number of e-commerce platforms and online transaction volumes reflect the market activity and transaction scale of DT. The DT environment involves the number of e-commerce enterprises and transaction volumes, reflecting the market scale and development potential of DT. The intensity of policy support measures the government's level of support for the development of DT and influences its long-term development. Using the entropy approach to establish the weights of each indicator and standardizing the data to the 0-1 range, the study measures the development status of DT objectively throughout China's provinces [25]. Meanwhile, a distinction is made between positive indicator x_{ij}^* and negative indicator y_{ij}^*, as shown in Equation 1.

$$\begin{cases} x_{ij}^* = \dfrac{-x_{j\min} + x_{ij}}{-x_{j\min} + x_{j\max}} \\ y_{ij}^* = \dfrac{-y_{ij} + y_{j\max}}{y_{j\max} - y_{j\min}} \end{cases} \tag{1}$$

In Equation 1, x_{ij} and y_{ij} display the original values of the jth indicator in the ith year. Among them, y_{jmax} and y_{jmin} mean the corresponding extreme values for negative indicators. x_{jmax} and x_{jmin} display the highest and lowest values of the jth positive indicator across all years. Since all indicators in the evaluation system have positive attributes, a unified positive standardization method is adopted. Based on this, the relative weight of each indicator for each year needs to be calculated. Equation 2 expressed the specific calculation formula for weight p_{ij}.

$$p_{ij} = \frac{x_{ij}^*}{\sum_{i=1}^{n} x_{ij}^*} \tag{2}$$

In Equation 2, $\sum_{i=1}^{n} x_{ij}^*$ displays the sum of the values of indicator j for all years. The calculation process for the entropy values of each indicator is shown in Equation 3.

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{3}$$

In Equation 3, when e_j approaches 1, the data dispersion is low, the indicator information content is small, and the weight should be reduced. When e_j approaches 0, the data dispersion is high, the indicator information content is large, and the weight should be increased. If $p_{ij} = 0$, $p_{ij}\ ln(p_{ij}) = 0$ needs to be set, or zero values need to be avoided through translation. Following that, each indicator's coefficient of variation is determined, as indicated by Equation 4.

$$d_j = -e_j + 1 \tag{4}$$

In Equation 4, the larger the value of d_j, the higher its importance. The calculation process for the weights of each indicator is shown in Equation 5.

$$w_j = \frac{d_j}{\sum_j^m d_j} \tag{5}$$

Finally, the level of comprehensive development of each indicator is calculated. The specific calculation process is shown in Equation 6.

$$u_j^d = \sum_j^m w_j^d p_{ij}^d \tag{6}$$

In Equation 6, w_j^d represents the indicator weight. To evaluate the degree of GED at the provincial level, the study employed the SBM super-efficiency model, which included unexpected output variables in the efficiency measurement [26, 27]. The input indicators cover three types of factors: labor, capital, and energy [28]. Capital input is shown in Equation 7.

$$F_t = (1-\eta_t)F_{t-1} + I_t / O_t \tag{7}$$

In Equation 7, η_t represents the depreciation rate. The study uses 2000 as the base period and estimates the depreciation rate at 9.96%. Investment volume I_t is represented by fixed asset investment. The consumer price index O_t is used for price deflation. EC is directly taken from the total provincial EC. The expected output indicator is regional gross domestic product. Non-expected outputs focus on typical pollutants, covering three indicators: carbon dioxide emissions, sulfur dioxide in exhaust gases, and chemical oxygen demand in wastewater. The super-efficiency SBM model (SESBM) is an important extension of the traditional DEA framework by Tone, with its core lying in the introduction of slack variables and the reconstruction of the reference set [29, 30]. Excluding the evaluated decision units from the reference set establishes a new production frontier. This allows efficiency values to exceed 1, enabling a more precise distinction between efficient decision units. Mathematically, the model determines efficiency values by minimizing the total of weighted input redundancy and output deficiency. Equation 8 illustrates the particular evaluation model.

$$\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \alpha_i^- / N_{i0}}{1 + \frac{1}{\alpha_1 + \alpha_2}\left(\sum_{r=1}^{\alpha_1} \alpha_r^g / \beta_{r0}^g + \sum_{r=1}^{\alpha_2} \alpha_r^b / \beta_{ro}^b\right)} \tag{8}$$

Equation 8 represents the core mechanism of the SESBM, which uses a strictly decreasing function ρ^* (0-1) as the efficiency benchmark and constructs a multidimensional optimization space through three sets of key relaxation variables. Specifically, it includes the three vectors of input redundancy α_i^-, expected output deficiency α_r^g, and unexpected output excess α_r^b, which correspond to the actual deviations of the original input N_{i0}, positive output β_{r0}^g, and negative output β_{ro}^b, respectively. However, traditional DEA-SBM is constrained by linear convex frontiers and static windows, making it difficult to map the nonlinear network effects and dynamic evolution of DT. Additionally, high-dimensional indicators induce dimensionality disaster, causing stability to plummet, and the distinction between super-efficiency becomes blurred in big data scenarios. GA relaxes the frontier shape into a non-convex free surface through chromosome encoding and embeds entropy value weights in the fitness function. The calculation process of dynamic weights is shown in Equation 9.

$$F(C)=\frac{1}{1+\sum w_j(\theta_i-\theta_i)^2+\lambda\cdot \text{Slack}} \tag{9}$$

In Equation 9, θ represents the efficiency value. λ represents the penalty coefficient, which ranges from 0.05 to 0.2. *Slack* represents the total slack of input/output variables. The fitness function is automatically corrected according to the skewness of the DT index, as shown in Equation 10.

$$F'(C) = F(C)\cdot(1+\tanh(\text{Skewness}/3)) \tag{10}$$

In Equation 10, a statistical measure of the asymmetry of data distribution, skewness is represented by the *Skewness*. In DT measurement, its definition is given in Equation 11.

$$\text{Skewness}=\frac{E[(X-\mu)^3]}{\sigma^3} \tag{11}$$

In Equation 11, E represents the expectation operator. σ is the standard deviation (SD), and μ represents the mean. In dynamic weight adjustment, the adjusted Fisher-Pearson coefficient is used for calculation, as displayed in Equation 12.

$$g_1=\frac{\sqrt{n(n-1)}}{n-2}\cdot\frac{m_3}{m_2^{3/2}} \tag{12}$$

In Equation 12, m_2, m_3 represents the second-order and third-order central moments. The crossover and mutation operators continuously reconstruct the frontier in a probabilistic manner during global search, thereby breaking free from linear assumptions. The fitness function directly targets inter-period efficiency increments, enabling each generation of the population to automatically extend the time dimension during iteration, achieving dynamic tracking. Multi-objective chromosome compression reduces redundant metrics, maintaining a balanced ratio between dimensions and decision units while suppressing fluctuations. Parallel evaluation and elite retention strategies quickly converge on large-scale data. Fitness differences are used to distinguish ultra-efficient units, which addresses the shortcomings of traditional models.

2.3. Construction of a Spatial Overflow Measurement Model

The cross-regional spillover characteristics of DT mean that its impact on the GE is not limited to its place of origin. It also has a spatial transmission effect on surrounding regions through channels such as technology spillover, policy learning, and industrial chain linkages [31]. According to new economic geography and Tobler's first law of geography, economic interactions between geographically adjacent regions are more intimate. Geographically, the green transformation brought about by DT can expand, encouraging the region's GE to evolve in unison. However, this spatial impact is dual in nature. The local ecosystem may be strained by problems like the movement of pollutants across borders and the transfer of companies with high energy consumption. Under conditions of imbalance between regional resource endowments and policy supply, the contradiction between these positive and negative effects is even more pronounced. Therefore, analyzing the driving role of AI in the green efficiency of DT from a spatial perspective can more clearly reveal the geographical attributes and regional differentiation characteristics of its impact mechanism. Figure 5 shows the SSE structure of DT [32].

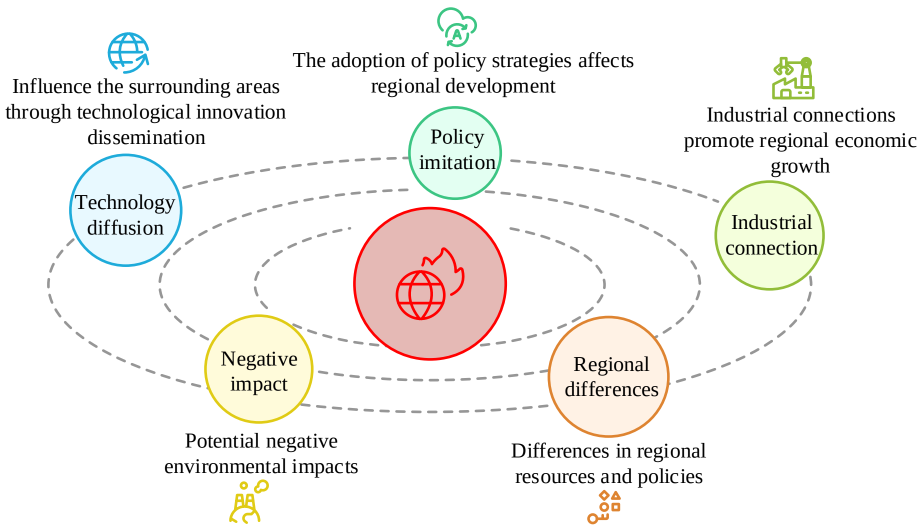


Figure 5. Spatial spillover effects of DT

To systematically analyze the impact pathways and SSEs of AI_DT on GED, this study constructs a multidimensional empirical model system combining SE models and nonlinear threshold models. SDM can simultaneously identify the SSEs of both the explained variable and the explanatory variables (EVs), making it suitable for analyzing interregional linkage characteristics [33], as shown in Equation 13.

$$Green_{it} = \rho WGreen_{it} + \beta_1 AI\_DT_{it} + \theta_1 WAI\_DT_{it} + \gamma X_{it} + \lambda WX_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{13}$$

In Equation 13, $Green_{it}$ is the level of GED. AI_DT_{it} denotes the AI_DT index. X_{it} means the set of control variables (CVs). W means the spatial weight matrix (SWM), with robustness comparisons conducted using both the geographic adjacency matrix and the economic distance matrix (EDM). ρ is the spatial lag coefficient of GED. β_1 is the direct effect coefficient of the EVs, θ_1 is the SSE of the EVs, and λ denotes the spatial spillover coefficient of the CVs. μ_i and δ_t are provincial and time fixed-effects (FEs). ε_{it} denotes the disturbance term. Equation 13 effectively captures the direct and indirect impacts of DT on local and surrounding regions' GED under AI-enabled conditions. To further identify the nonlinear characteristics of AI_DT's influence on GED, the study introduces a panel threshold model, as shown in Equation 14.

$$Green_{it} = \begin{cases} \alpha_1 AI\_DT_{it} + \zeta_1 X_{it} + \varepsilon_{it},\ AI\_DT_{it} \le \tau \\ \alpha_2 AI\_DT_{it} + \zeta_2 X_{it} + \varepsilon_{it},\ AI\_DT_{it} > \tau \end{cases} \tag{14}$$

In Equation 14, τ represents the threshold value (TV), estimated using the Hansen (1999) method by minimizing the sum of squared residuals across the sample data to determine the optimal TV. To make sure the TE is robust, significance testing is done using the Bootstrap approach [34]. α_1 and α_2 are the coefficients of AI_DT's impact on the GE before and after the threshold, respectively. ζ_1 and ζ_2 represent the coefficients of the CVs before and after the threshold, respectively. Equation 14 is used to detect whether AI_DT exhibits a "diminishing marginal returns" or "non-linear U-shaped" effect, providing theoretical support for identifying the double-edged sword mechanism. Table 1 illustrates the definitions and descriptions of the primary variables.

Table 1. Definition and description of primary variables

Variable type	Variable name	Indicator description
The explained variable	The level of GED (Green)	Green total factor productivity
Explanatory variable	Artificial intelligence-enabled DT (AI_DT)	Interaction items of indicators related to DT and artificial intelligence
Control variable	ED level (GDP)	Per capita regional GDP
	Industrial structure (Indstr)	The proportion of the tertiary industry in GDP
	Intensity of environmental regulation (Erule)	Environmental protection expenditure per unit of GDP
	Fiscal support (Fiscal)	The proportion of government spending on environmental protection or technology
	Population density (PopDens)	Regional population density
	Education level (Edu)	The proportion of college students in the total population

In Table 1, the level of GED is measured primarily by GTFP, while AI_DT is reflected through the interaction between DT indicators and AI-related data. Control variables are comprehensively considered from the dimensions of ED, Indstr, environmental regulation, fiscal support, PopDens, and education level to ensure that the model can fully identify the effect of various factors on the GE. The study conducts a number of tests and robustness studies both before and after the empirical analysis. These primarily includes spatial dependency tests, model specification tests, multicollinearity detection, and robust regression analysis. First, to verify whether GED exhibits significant spatial correlation, the study employs Moran's I (MI) for spatial autocorrelation (SA) testing, as shown in Equation 15.

$$I = \frac{n}{S_0} \cdot \frac{\sum_i \sum_j \omega_{ij} \left(-\bar{x} + x_i\right)\left(-\bar{x} + x_j\right)}{\sum_i \left(-\bar{x} + x_i\right)^2} \tag{15}$$

In Equation 15, n means the sample size. x_i displays the GED level of the i region. $\bar{x}$ displays the sample mean. ω_{ij} displays the SWM element, $S_0 = \sum_i \sum_j \omega_{ij}$. When MI I > 0 and significant, the variable has positive spatial clustering characteristics. Before applying SDM, spatial heterogeneity testing is necessary. Spatial heterogeneity typically manifests as the non-constancy of model parameters across different spatial units. This study employs two methods to address and test this phenomenon. In terms of model specifications, SDM can capture nonlinear relationships and interaction effects caused by spatial heterogeneity to some extent by including spatial lag terms for both the explained and EVs. This offers greater flexibility than traditional spatial lag or spatial error models. To more directly test the existence of spatial heterogeneity, this study conducts grouped regression tests and Wald tests before formal regression. Initially, the stability of the parameters is assessed by grouping the full sample according to geographical location or ED level and comparing the significant differences in the coefficients of key variables. After SDM estimation, the Wald test is further used to determine whether SDM would degenerate into a spatial lag or spatial error model. If the null hypothesis is rejected, it indicates that the SDM specification is necessary. Its introduction of spatial lag terms for EVs is precisely to capture the differential spillover effects caused by spatial heterogeneity. Second, the study judges the applicability of FEs and random-effects models through the Hausman test [35]. The results indicate that the FEs model better fits the data characteristics. Therefore, to account for unobservable heterogeneity issues, the SDM settings incorporate regional and time FEs. Furthermore, to test for severe multicollinearity among variables, the variance inflation factor (VIF) of each EV is calculated, as shown in Equation 16.

$$VIF_j = \frac{1}{1-R_j^2} \tag{16}$$

In Equation 16, regressing the jth EV on the other EVs yielded the coefficient of determination, or R_j^2. If VIF>10, strong multicollinearity is considered to exist. The VIF values of all variables in the study are well below this threshold, indicating that there are no significant collinearity issues. Finally, the study conducts robustness tests in the following ways. First, it modifies the way the explained variable is measured, replacing GTFP with the percentage of green patents and green employment. Second, it changes the form of the SWM and compares the consistency of the regression results under the geographic adjacency matrix and the EDM. Third, it lags the EVs and removes extreme observations to control for potential endogeneity interference. All robustness tests shows that the sign and significance of the coefficient of the core EV AI_DT do not change substantially ($p<0.05$). It is indicated that the benchmark regression results have good stability and are significant under different model settings and data processing methods. To further capture the nonlinear characteristics of spatial dependence, namely the spatial heterogeneity of the influence coefficient of AI_DT on GED in different geographic units, this study introduces the Geographically Weighted Regression (GWR) model for analysis. The GWR model allows the core parameters to vary with geographic location, and can more accurately reveal the spatial variation law of the relationship between variables. Its basic form is shown in Equation 17.

$$\text{GED}_{it} = \beta_0(x_i, y_i) + \beta_1(x_i, y_i)AI\_DT_{it} + \sum_{\text{k}=2}^{7}\beta_{\text{k}}(x_i, y_i)X_{kit} + \varepsilon_{\text{it}} \tag{17}$$

In Equation 17, GED_{it} represents the green ED level of the i-th province in year t. (x_i, y_i) represents the geographical coordinates of the i-th province. β_0 represents the local constant term of the i-th province, which varies with geographical location. β_1 represents the local regression coefficient of the AI_DT variable of the i-th province, which has spatial heterogeneity. β_k represents the local regression coefficients of each CV of the i-th province, which all vary with geographical location. X_{kit} represents the set of CVs. ε_{it} represents the random error term, which follows an independent and identically distributed $N(0, \sigma^2)$. Meanwhile, an adaptive kernel function is used to determine the bandwidth in order to balance local fit goodness and estimation stability.

3. Results

3.1. Statistical Characteristics of Key Variables

The experiment selects provincial panel data from China as the sample, with data primarily sourced from authoritative publications such as the China Statistical Yearbook and the China Environmental Statistics Yearbook, as well as publicly available platforms of provincial and municipal governments. To ensure data integrity and consistency, a systematic data processing workflow is adopted. For a small number of missing data points, multiple imputation is used based on their missing patterns and mechanisms. A chain equation-based multiple imputation method is used for randomly missing time-related data, utilizing other complete variables for predictive imputation. This generates five complete datasets, which are then aggregated as the final result. For variables that are not randomly missing or have been missing for several consecutive years, mean imputation or trend extrapolation is used for imputation. All price variables are deflated using the corresponding price index with 2000 as the base year to eliminate the impact of price changes. Finally, to eliminate dimensional differences and enhance data stability, some continuous variables are log-transformed or standardized. Meanwhile, multivariate cross-validation is performed to compare data from different sources, identify and correct outliers, and ensure data reliability [36]. Prior to formal regression analysis, the study conducts descriptive statistical analysis on all major variables to understand their distribution characteristics and regional differences, with the sample size uniformly set at 420. Table 2 depict the details.

Table 2. Descriptive statistics of the main variables

Variable type	Variable name	Mean	Standard deviation	Minimum value	Maximum value
The explained variable	Green	0.452	0.196	0.064	1.016
Explanatory variable	AI_DT	0.287	0.324	0.015	1.608
Control variable	GDP	10.344	0.448	9.201	11.205
	Indstr	48.92	5.69	32.14	63.29
	Erule	0.301	0.126	0.061	0.704
	Fiscal	3.22	1.06	1.17	6.02
	PopDens	6.498	0.938	4.105	8.681
	Edu	22.07	4.59	11.63	35.13

Table 2 shows the significant differences among regions. The mean (MV) of GED within the sample is 0.452, and the SD is 0.196, with a minimum of only 0.064 and a maximum of 1.016. This indicates a significant gradient gap in the level of green ED among Chinese provinces. Some provinces have reached the efficiency frontier, while others remain at a lower stage of development. This is consistent with China's reality of unbalanced regional development. The mean of AI_DT is 0.287, indicating an imbalance in the integration of digitalization and intelligentization across regions. The mean Indstr in CVs is 48.92, with a SD of 5.69. This indicates that, while the tertiary industry is relatively concentrated, it is still differentiated across provinces. The mean of environmental regulatory intensity is 0.301, and the SD is 0.126, reflecting the overall weakness of current provincial environmental regulations and regional differences. All variables have no extreme outliers, meeting the basic prerequisites for subsequent spatial regression analysis. To understand the linear relationships among the variables, the study conducts Pearson correlation coefficient analysis between the explained variable, EVs, and CVs. Table 3 displays the findings.

Table 3. The correlation coefficient matrix of the main variables

Variable	Green	AI_DT	GDP	Indstr	Erule	Fiscal	PopDens	Edu
Green	1	0.432**	0.388**	0.361**	0.317**	0.219**	0.291**	0.329**
AI_DT	-	1	0.472**	0.386**	0.285*	0.198	0.248*	0.403**
GDP	-	-	1	0.444**	0.291*	0.173	0.411**	0.366**
Indstr	-	-	-	1	0.224	0.109	0.187	0.275*
Erule	-	-	-	-	1	0.314*	0.248	0.212
Fiscal	-	-	-	-	-	1	0.127	0.175
PopDens	-	-	-	-	-	-	1	0.292**
Edu	-	-	-	-	-	-	-	1

Note: * and ** indicates significance at the 10% and 5% significance level.

Table 3 demonstrates a definite positive association between the degree of AI_DT development and the level of GED ($p<0.05$). The fact that the former promotes the latter is confirmed by this preliminary. Furthermore, the degree of AI_DT is favorably connected with both the ED and the Indstr status, suggesting that it could impact the GE by encouraging economic growth and industrial upgrading and optimization. Additionally, there is a favorable relationship between PopDens, education level, and GED. This reflects the fact that human capital and urban agglomeration effects provide support for GD to a certain extent.

3.2. Performance Analysis of DT Measurement Based on DEA-SBM

The study does an experimental comparison between the conventional DEA-SBM model and the DEA-SBM-GA model after adding the GA in order to confirm the effectiveness of the DT measurement. Table 4 shows the experimental environment and parameter settings.

Table 4. Experimental environment and parameter setting

Component	Configuration specifications	Parameter category	GA	DEA-SBM
CPU	Intel Xeon Gold 6248R (3.0GHz, 24 cores)	The efficiency value range is θ	[0,2]	[0, 1]
GPU	NVIDIA Tesla V100 (32GB HBM2)	Convergence threshold	1e-8	1e-6
Memory	DDR4 256GB (2933MHz)	Maximum number of iterations	300	500
Storage	NVMe SSD 3.2TB (7GB/s)	Parallel granularity	16	Single thread

Table 5 demonstrates the application of DEA-SBM to the field of DE research, which features complex network characteristics, strong spatial correlation, and dynamic evolution. It compares the evaluation results of various indicators between the traditional DEA-SBM model and the DEA-SBM-GA model.

Table 5. Comparison results of index evaluation effects of DEA-SBM model before and after optimization

Indicator	DEA-SBM	DEA-SBM-GA	Extent of increase
Single iteration time (s)	48.7	6.2	-87.3%
Peak memory usage (GB)	18.4	9.2	-50.0%
The algebra required for convergence	412	187	-54.6%
Eastern efficiency mean	0.812	0.847	+4.3%
Coefficient of variation of Western efficiency	0.321	0.285	-11.2%
Inter-provincial technological gap	0.458	0.392	-14.4%
Calculation time consumption (min)	390	82	-79.0%
Frontier compactness	0.872	0.923	+5.1%
Spatial effect R^2	0.31	0.49	+58.0%

In Table 5, in the field of DE research, the DEA-SBM-GA model, which combines the DEA-SBM model with the GA, demonstrates significant advantages across multiple dimensions. The DEA-SBM-GA model demonstrates superior computational efficiency, reducing the single iteration time by 87.3% compared to conventional models. It also decreases total computational time by 79%, halves peak memory usage, and reduces the algebra required for convergence by 54.6%. DT involves massive amounts of nonlinear data such as cross-border data flows and platform transaction records. Traditional models are unsuitable for processing large-scale provincial panel data due to their low efficiency and high memory consumption. DEA-SBM-GA significantly improves efficiency through parallel evaluation and elite retention strategies using GAs. These improvements significantly enhance the model's ability to process complex network data, making it more suitable for analyzing large-scale data in the DE. In terms of evaluation effectiveness, the mean of Eastern efficiency increased by 4.3%. The coefficient of variation of Western efficiency decreases by 11.2%. The inter-provincial technological gap narrows by 14.4%. This indicates that, through dynamic weight calibration, the model can better identify the advantages of eastern provinces in digital infrastructure and TI. The model avoids the systematic underestimation of underdeveloped regions that traditional models tend to produce. It also more objectively reflects the actual progress of digital transformation in western provinces. These results indicate that the model can more accurately capture regional development differences and reduce the bias of traditional models. Meanwhile, the boundary compactness improved by 5.1%, meaning that the fit of the production frontier is closer to actual economic activity, reducing measurement bias caused by slack variables. The spatial R^2 value increased by 58%, indicating that the model successfully captured the spatial correlation characteristics of DT. This is challenging to achieve with traditional DEA-SBM models because of the linear frontier assumption. It effectively overcomes the limitations of traditional DEA-SBM in handling nonlinear network effects, providing a more reliable measurement tool for DE research.

3.3. Space Spillover Effects and Benchmark Regression Analysis

Before conducting SE analysis, the level of GED is first tested for significant SA. MI index is used to test the SA of the level of GED in each province from 2010 to 2023. The results are shown in Figure 6.

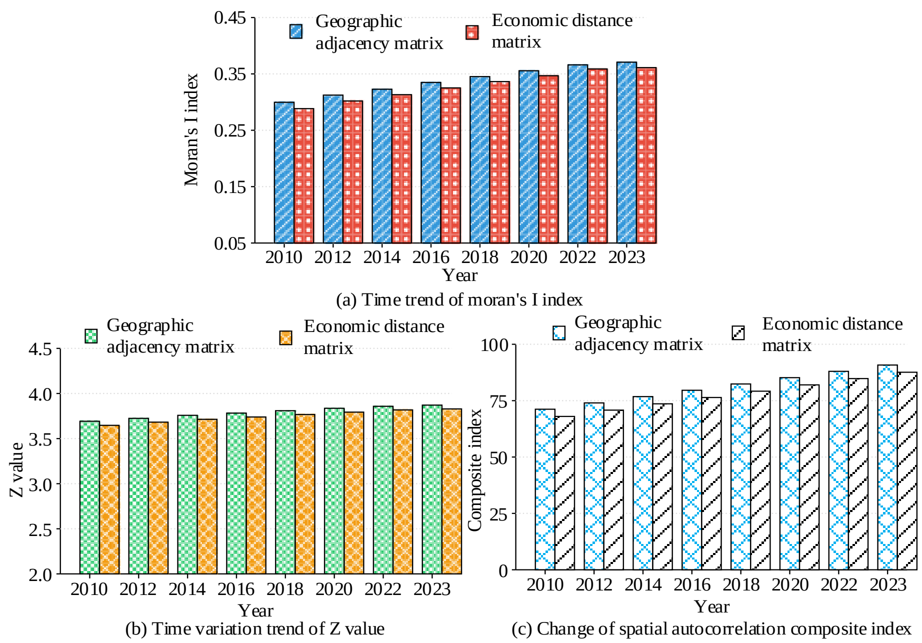


Figure 6. Results of spatial autocorrelation test on the level of GED

In Figure 6(a), during the period from 2010 to 2023, the MI index exhibits a steady upward trend, regardless of whether it is based on the geographic adjacency matrix or the EDM. The MI index of the geographic adjacency matrix increases from 0.234 in 2010 to 0.304 in 2023, indicating a gradual increase in SA. In Figure 6(b), the trend in Z-values aligns with that of the MI index, with all Z-values far exceeding the critical value of 1.96 (p<0.05). This indicates that SA is statistically highly significant, confirming that the level of GED exhibits significant spatial clustering characteristics. In Figure 6(c), the comprehensive SA index shows a continuous upward trend. The comprehensive index of the geographic adjacency matrix increases from 71.2 in 2010 to 90.8 in 2023. The comprehensive index of the EDM increases from 68.0 in 2010 to 87.6 in 2023. This trend indicates that, over time, the spatial correlation of GED levels continues to strengthen, with increasingly obvious synergistic and spillover effects between neighboring regions. The effect of AI_DT on GED is investigated using SDM analysis based on the findings of the SA test. The outcomes of the benchmark regression are presented in Table 6.

Table 6. Benchmark regression results on the impact of AI_DT on green economy

Variable	OLS	OLS standard error	SAR	SAR standard error	SEM	SEM standard error	SDM	SDM standard error
AI_DT	0.142***	(0.028)	0.135***	(0.026)	0.138***	(0.027)	0.129**	(0.025)
GDP	0.089**	(0.035)	0.082**	(0.033)	0.085*	(0.034)	0.078**	(0.032)
Indstr	0.003*	(0.002)	0.003*	(0.002)	0.003*	(0.002)	0.003*	(0.002)
Erule	0.156**	(0.062)	0.148*	(0.059)	0.152**	(0.061)	0.143*	(0.058)
Fiscal	0.021**	(0.011)	0.019**	(0.010)	0.02*	(0.011)	0.018*	(0.010)
PopDens	-0.015*	(0.018)	-0.013	(0.017)	-0.014*	(0.018)	-0.012	(0.016)
Edu	0.004**	(0.002)	0.004	(0.002)	0.004**	(0.002)	0.004*	(0.002)
ρ/λ	-	-	0.245	(0.067)	0.198	(0.058)	0.231	(0.063)
Constant term	-0.756	(0.285)	-0.689	(0.267)	-0.721	(0.276)	-0.654	(0.259)
Observed value	420		420		420		420	
R²	0.687		0.712		0.698		0.724	
Log-likelihood	-		156.78		148.92		162.45	
AIC	-		-295.56		-279.84		-304.9	
Provincial FE	Yes		Yes		Yes		Yes	
Time FE	Yes		Yes		Yes		Yes	

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 6 confirms hypothesis H1 by showing that AI_DT significantly improves GED across all model settings. In the SDM, the coefficient of AI_DT is 0.129 (p<0.05). This means that the level of GED in the area rises by 0.129 units for every unit increase in AI_DT. This implies that the growth of DT has a beneficial knock-on effect on nearby regions in addition to fostering local GE. As predicted by theory, GED is significantly positively impacted by the CVs' ED level, degree of environmental regulation, budgetary assistance, and educational attainment. The effects of SDM are broken down using the partial differential approach in order to further quantify the direct, indirect, and overall effects of AI_DT on GED. Table 7 displays the findings.

Table 7. Decomposition of spatial effects of AI_DT on green economy development

Variable	Direct effect coefficient	Direct effect standard error	Indirect effect coefficient	Indirect effect standard error	Total effect coefficient	Total effect standard error
AI_DT	0.134***	(0.026)	0.112**	(0.045)	0.246***	(0.058)
GDP	0.081**	(0.033)	0.058	(0.052)	0.139**	(0.067)
Indstr	0.003*	(0.002)	0.003	(0.003)	0.006*	(0.003)
Erule	0.149**	(0.059)	0.116*	(0.061)	0.265***	(0.089)
Fiscal	0.019*	(0.010)	0.02	(0.016)	0.039*	(0.021)
PopDens	-0.012	(0.017)	-0.011	(0.024)	-0.023	(0.031)
Edu	0.004**	(0.002)	0.004	(0.003)	0.008**	(0.004)

The spatial effect decomposition results in Table 7 further confirm the multiple impact mechanisms of AI_DT on GED. The direct effect coefficient is 0.134 (p<0.01). It is indicated that AI_DT primarily promotes local GED through channels such as TI and optimization of Indstr. This validates hypothesis H3, indicating that DT positively spills over to neighboring regions' green economies through channels such as knowledge spillovers, demonstration effects, and industrial chain linkages (p<0.05). The total effect coefficient is 0.246 (p<0.01), which is significantly greater than the direct effect. This displays that after considering SSEs, the promotional effect of AI_DT on regional GED is significantly amplified. This suggests that the green effects of DT exhibit distinct spatial transmission characteristics, and policy formulation should fully consider regional coordinated development.

3.4. Nonlinear Threshold Effect Analysis

To further verify hypothesis H2, namely that AI_DT has a nonlinear effect on GED, the study uses the Hansen threshold regression model for testing. First, the existence of TEs is statistically tested. Then, the TVs and corresponding impact coefficients are estimated. Table 8 displays the findings of the TE tests for the various threshold variables.

Table 8. Test and estimation results of threshold effect

Threshold variable	Number of thresholds	F-statistic	p	Critical value (1%)	Critical value (5%)	Critical value (10%)	Threshold value estimation	Confidence interval
Level of TI	Single threshold	28.47**	0.043	31.25	24.83	21.67	0.314	[0.298, 0.329]
	Double threshold	35.62***	0.007	29.84	23.56	19.72	0.721	[0.706, 0.738]
	Triple threshold	18.23	0.156	28.91	22.45	18.93	-	-
Optimization of Indstr	Single threshold	31.84***	0.013	33.67	26.42	22.18	0.283	[0.271, 0.295]
	Double threshold	29.56**	0.037	32.15	25.78	21.64	0.679	[0.663, 0.694]
	Triple threshold	16.89	0.203	30.42	24.67	20.83	-	-
Regional development level	Single threshold	42.73***	0.003	35.28	28.94	24.51	0.267	[0.254, 0.281]
	Double threshold	38.91***	0.009	34.62	27.83	23.76	0.658	[0.641, 0.675]
	Triple threshold	21.47	0.087	33.84	26.95	22.89	-	-
Intensity of environmental regulation	Single threshold	26.35**	0.047	30.18	24.67	20.94	0.392	[0.378, 0.407]
	Double threshold	22.84	0.093	29.73	23.85	19.62	-	-

Note: Bootstrap resampling is performed 300 times.

The results of the TE test demonstrate that there are significant double TEs in the level of regional development, the optimization of Indstr, and the level of TI, as indicated in Table 8. These results validate the expected nonlinear characteristics in Hypothesis H2. Specifically, the dual TVs for the level of TI are 0.314 and 0.721, respectively, with an F-statistic of 35.62 (p<0.01). This indicates that the impact of TI on the GE exhibits distinct stage-specific characteristics. The dual TVs for Indstr optimization are 0.283 and 0.679, and those for regional development level are 0.267 and 0.658. The intensity of environmental regulation only exhibits a single TE, with a TV of 0.392. To more intuitively illustrate the trends and confidence interval characteristics of these TEs, the study visualizes the nonlinear influence paths of each threshold variable, as shown in Figure 7.

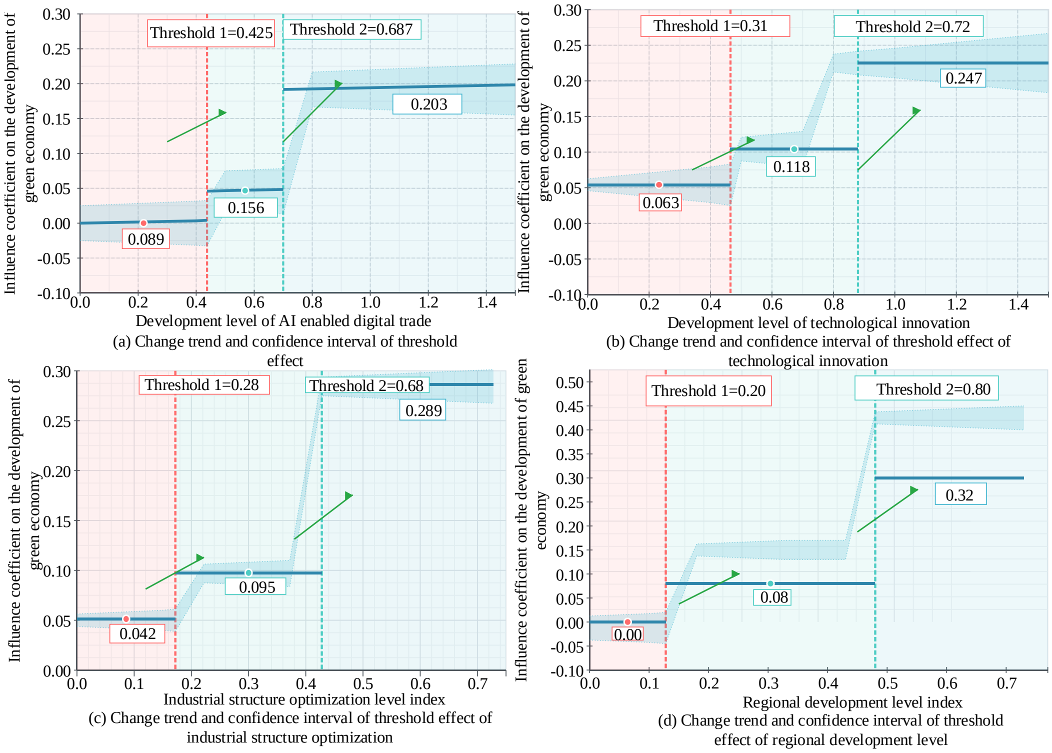


Figure 7. Trend of threshold effect

Figure 7(a) shows that the TE of AI_DT has nonlinear characteristics. It demonstrates converging confidence intervals, strong model robustness, and identification of a statistically significant TV. Figure 7(b) shows that TI has a dual TE on the GE. Below 0.31, the promotional effect is weak. Above 0.72, however, the positive effect is significant at 0.247. Figure 7(c) displays the increasing marginal effect of optimizing Indstr on the GE. Figure 7(d) displays the significant TE of the regional development level: the low level has almost no effect. The coefficient is 0.08 at the medium level and jumps to 0.32 at the high level, establishing it as a key influencing factor.

3.5. Regional Heterogeneity Analysis

To further explore the spatial distribution patterns of GED and verify the regional heterogeneity characteristics in Hypothesis H4, this study adopts SA analysis methods. MI scatter plots are constructed to identify the spatial aggregation patterns of GED levels in each province. Global MI and its significance test are calculated to quantify the degree of SA. The results are shown in Figure 8.

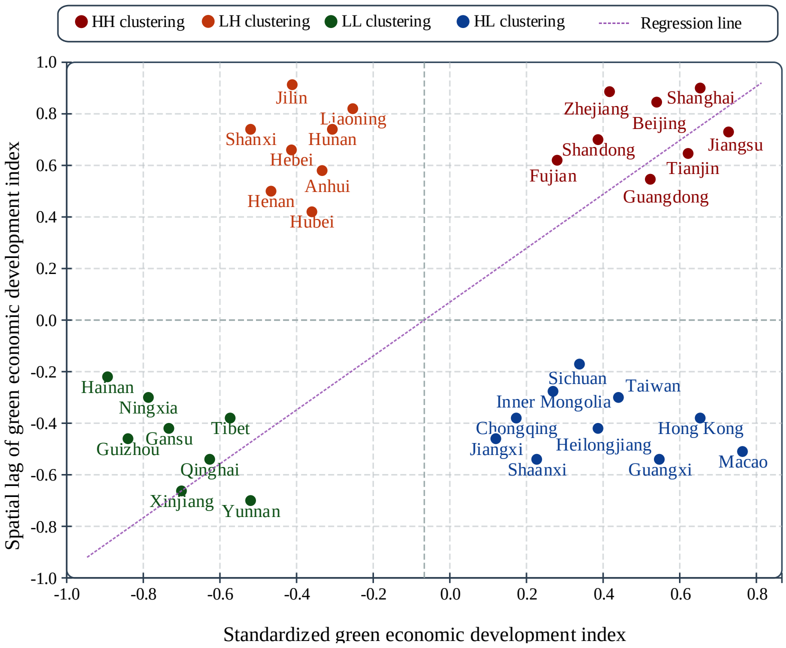
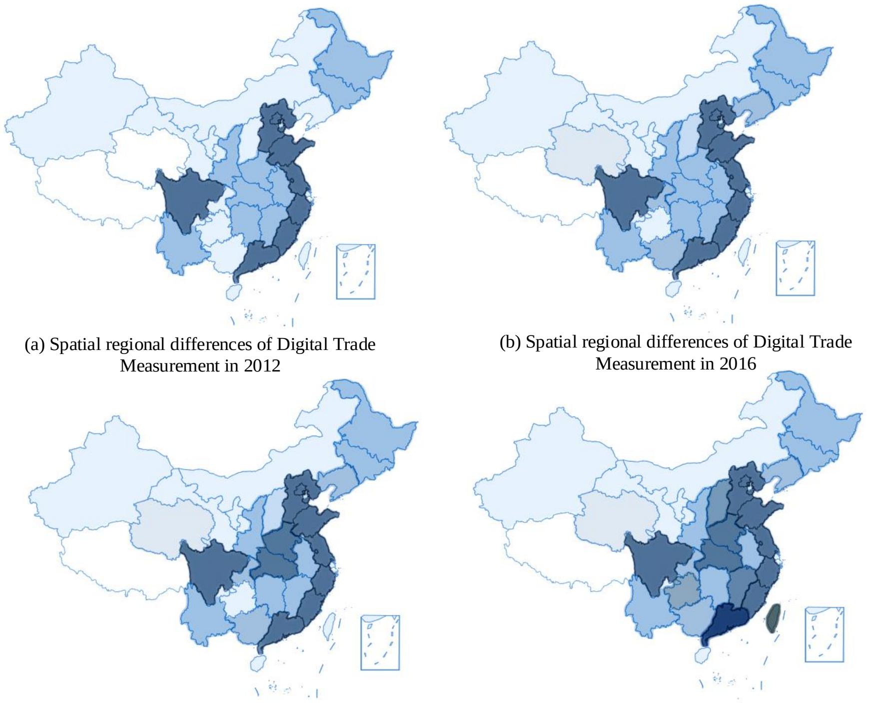


Figure 8. Moran scatterplot of GED level

In Figure 8, the first quadrant (HH agglomeration) mainly includes economically developed regions such as Beijing, Shanghai, Tianjin, Jiangsu, Zhejiang, and Guangdong. These regions not only have a high level of GED themselves, but also form an agglomeration effect with surrounding high-level regions. The second quadrant (LH agglomeration) mainly includes central regions such as Hebei, Shanxi, Anhui, and Henan. Although these regions have a relatively low level of GED themselves, they are influenced by the positive spillover effects of surrounding high-level regions. The third quadrant (LL agglomeration) mainly includes underdeveloped western regions such as Gansu, Qinghai, Ningxia, Xinjiang, and Tibet, which have formed low-level spatial agglomeration. The fourth quadrant (HL agglomeration) mainly includes resource-based regions such as Inner Mongolia, Heilongjiang, and Shaanxi. Despite the relatively high GED levels in these areas, the neighboring areas have comparatively low levels of development. Based on calculations, the MI index for the level of GED across China's provinces is 0.304, with a Z=4.82 and a $p<0.001$. This spatial clustering pattern reflects the geographical and policy diffusion effects of GED. More significantly, it shows that the effect of DT on GED varies significantly by area. This provides strong empirical support for Hypothesis H4. Further analysis is conducted on the spatial distribution of DT measurements from 2012 to 2024. Figure 9 displays the findings.

Figure 9 illustrates the evolution of spatial differences in China's DT measurement from 2012 to 2024. In Figure 9(a), in 2012, high-value areas of DT are concentrated in coastal and some inland key regions, with significant regional differences. In Figure 9(b), by 2016, DT measurement in some inland regions has improved, and the scope of high-value areas has slightly expanded. In Figure 9(c), by 2020, more regions are involved, and the gradient differences have somewhat eased. Figure 9(d) shows that by 2024, high-value zones have expanded further and regional gaps had narrowed. This indicates that DT is penetrating broader regions over time and that development is gradually becoming more balanced. This illustrates how the trade landscape's optimization is fueled by the DE's development.



(a) Spatial regional differences of Digital Trade Measurement in 2012

(b) Spatial regional differences of Digital Trade Measurement in 2016

(c) Spatial regional difference map of Digital Trade Measurement in 2020

(d) Spatial regional difference map of Digital Trade Measurement in 2024

Figure 9. Spatial regional differences of DT measurement from 2012 to 2024

3.6. Nonlinear Spatial Dependence Analysis

To verify the nonlinear spatial dependence of AI_DT on GED, this study estimates the local coefficients of the EVs using the GWR model. Table 9 shows the overall fit of the GWR model.

Table 9. Evaluation of GWR model fitting performance

Indicators	Value
Adjusted R^2	0.786
AIC	-312.47
RSS	0.892
Bandwidth	12.83
Average Local R^2	0.763

In Table 9, the adjusted R^2 of the GWR model is 0.786, which is higher than that of the SDM model (0.724), and the AIC value is lower. This indicates that the GWR model better fits the data and reveals obvious spatial nonstationarity in the relationship between AI_DT and GED. Using a local regression model is necessary and effective.

4. Discussion

The study revealed the dual mechanism of AI_DT on the GE through the DEA-SBM model and SDM. The study embedded the GA into the DEA-SBM model, relaxing the linear frontier into a non-convex surface through chromosome encoding, and dynamically adjusting weights to make the efficiency measure more suitable for the non-linear network effects of DT. Compared to methods based on entropy and grey models, which focused on the objective allocation of indicator weights and emphasized data trend prediction, the proposed method centered on efficiency assessment, directly reflecting the synergistic development level of DT and the GE. Furthermore, while entropy and grey models haddifficulty directly incorporating undesirable outputs, such as carbon emissions, DEA-SBM-GA explicitly integrated these outputs into its model construction. This aligned with the GE's measurement needs. Moreover, entropy methods used fixed weights and grey models rely on data trend inertia. In contrast, DEA-SBM-GA dynamically calibrated weights through crossover and mutation operators in a GA. This captured the nonlinear characteristics of DT network evolution. Unlike Luo et al. [11], who used PCA to reduce the dimensionality of high-dimensional indicators, resulting in information loss, the multi-objective chromosome compression of GA retained key features while reducing the inter-provincial technological gap by 14.4%. This addressed the efficiency bottleneck of traditional DEA-SBM in big data scenarios.

The local GED level increased by 0.129 units for every unit rise in AI_DT ($p<0.01$), and there was a positive SSE, with an indirect effect of 0.112. This result was in line with Ren et al.'s [10] finding that inclusive GG was encouraged by digital economic agglomeration. However, the study further quantified the spatial transmission intensity: the total effect coefficient reached 0.246*, indicating that the cross-regional synergy effect was underestimated in previous studies. The dual TE of TI, with TVs of 0.314/0.721, revealed the critical conditions for the green benefits of DT. When the level of TI crossed the high threshold of 0.721, the impact coefficient of AI_DT jumped from 0.063 to 0.247. This validated the "increasing marginal returns to digital technology" hypothesis proposed by Luo et al. [11].

However, it added a key threshold: DT could only fully unleash its green potential when regional technological accumulation exceeded a critical point. For policymakers, the threshold (0.314/0.721) could provide a quantitative basis for prioritizing investments in TI, resulting in tiered and differentiated investment strategies. For regions with a TI level below 0.314, TI investments should prioritize basic R&D capacity building and digital infrastructure development. Fiscal subsidies should lower the barriers for enterprises to adopt digital technologies while promoting the joint construction of technology training bases by universities and local industries. This will gradually enhance the region's technological foundation. For regions with a TI level between 0.314 and 0.721, investment should shift towards improving technology transfer efficiency. A collaborative innovation fund involving industry, academia, and research could be established to support the integration and application of digital technologies in green industries. This would shorten the technology transfer cycle and drive TI toward higher thresholds. For regions with a TI exceeding 0.721, investment should focus on cutting-edge technology R&D and the construction of cross-regional technology spillover platforms. A special fund for technological radiation should be established to encourage local enterprises to transfer suitable technologies to surrounding areas. This will drive a wider breakthrough of threshold constraints and achieve spatial diffusion of green benefits. Spatial heterogeneity analysis revealed that the Beijing-Tianjin-Hebei region and the Yangtze River Delta formed high-high agglomeration zones (HH), while western provinces were caught in a low-low trap (LL), confirming Wang et al. [17] concerned about the intensification of regional differentiation. However, the study quantified the intensity of agglomeration and its annual strengthening trend using MI.

The significant spatial spillover effect (indirect effect 0.112) and regional heterogeneity revealed by this study provided valuable information for comprehending and improving international trade agreements, such as the RCEP and the DEPA. The cross-regional propagation characteristics of the environmental benefits of DT suggested that broad-based agreements like RCEP could facilitate the green transformation of member countries by enabling technology spillovers and supply chain collaboration through the development of DT in one country. Therefore, agreements should encourage the creation of "DT-GE" zones that reduce trade barriers for digital goods and services, green technologies, and equipment. These zones should also maximize the scope and intensity of positive spatial spillovers. As an agreement specifically regulating the DE, DEPA's modular negotiation structure was well-suited for incorporating green DT clauses. The nonlinear threshold effect suggested that for member countries with weak technological foundations (TI<0.314), DEPA's cooperation module should prioritize supporting their digital infrastructure and basic R&D capabilities to help them overcome the threshold for green transformation. For technologically advanced member countries (TI>0.721), they should be encouraged to open green technology platforms and share digital emission reduction solutions to drive a green leap forward for the entire region. At the same time, it was important to be aware of the potential for negative spatial spillovers, such as the recurrence of the "pollution haven" effect on an international scale. International trade agreements, particularly those involving digital and green sectors, must establish coordinated environmental standards and data certification mechanisms. These mechanisms will prevent high-carbon digital supply chains from clustering in regions with lower standards through investment transfers. This will offset the green spillover benefits globally.

Unlike Xu et al. [9], who argued that the DE directly promoted the greening of foreign trade, the study found that the optimization of Indstr was the core intermediary. Figure 7c showed that optimizing the Indstr had three thresholds (0.283/0.679) and an impact coefficient of 0.289 in the high range. This indicated that DT increased the proportion of the service sector to an average of 48.92%, thereby reducing reliance on high-pollution industries. This explained the controversy surrounding the “green double-edged sword”: In regions where the energy structure was not transformed, the expansion of digital infrastructure would exacerbate carbon emissions through economies of scale. This corroborated the findings of Zhao et al. [19] regarding EC issues in digital rural construction. The study was limited in that it did not quantify the specific contribution of data center EC, and the AI_DT SD reached 0.324, suggesting that imbalances in regional digitalization processes could amplify environmental costs. Differentiated policy measures were needed: HH clusters should strengthen technology spillovers, while LL regions should prioritize the improvement of renewable energy infrastructure. In addition, according to the threshold model, there was a single threshold of 0.392 for the level of environmental control. Therefore, to get past regulatory cost thresholds, it was suggested that progressive subsidies be introduced in the central and western regions.

5. Conclusion

To explore the coordinated development path of DT and the GE and address the shortcomings of existing research in terms of regional coverage, consideration of unintended outcomes, SSEs, and nonlinear impact analysis, this study employed the DEA-SBM model to construct a measurement system for the scale of DT. Furthermore, GA was incorporated into the DEA-SBM model to create the DEA-SBM-GA model, which was then used in conjunction with the entropy approach to gauge each province's degree of DT development. Compared with traditional models, the DEA-SBM-GA model reduced single iteration time by 87.3%, computing time by 79%, peak memory by half, and convergence algebra by 54.6%. The eastern efficiency mean increased by 4.3%, the coefficient of variation of Western efficiency decreased by 11.2%, the inter financial technological gap decreased by 14.4%, the frontier compactness increased by 5.1%, and the spatial effect R^2 increased by 58%, making it more suitable for DT analysis.

The study found that AI_DT significantly promoted the local GE (β=0.129, p<0.01), validating hypothesis H1. TI had a double threshold. After crossing the high threshold, the promotional effect of AI_DT on the GE jumped from 0.063 to 0.247 (p<0.01). The threshold for regional development level was 0.658, and indirect effects increased by 300% (β=0.32) above this value, supporting the U-shaped characteristic of hypothesis H2. MI rose from 0.234 in 2010 to 0.304 in 2023 (Z>4.82), indicating significant spatial agglomeration of the GE and validating hypothesis H4. In addition, there were significant double TEs in terms of the level of TI, optimization of Indstr, and regional development level. This indicated that the impact of DT on the GE had non-linear characteristics. Significant variations in GED levels between locations were found by regional heterogeneity analysis, which also clearly displayed spatial clustering features. DT directly promotes the local GE through TI and optimization of Indstrs. It also drives the development of surrounding areas through SSEs and exhibits significant nonlinear characteristics. However, this study does not quantify the specific impact of data center EC. Furthermore, regional digital imbalances may amplify environmental costs. Further improvements are needed.

6. Declarations

6.1. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.2. Funding

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6.3. Institutional Review Board Statement

Not applicable.

6.4. Informed Consent Statement

Not applicable.

6.5. Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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