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Digital Economy Dynamics and Green Technology Innovation: A Spatial Analysis of Low-Carbon Development Drivers

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Abstract: Environmental pressures from rapid industrialization emphasize the importance of Green Technology Innovation (GTI) in sustainable development. This study proposes a sustainable digital economy and a kinetic energy model for low-carbon development. Using multiple regression analysis and spatial lag model tests, the results show that market green demand, market competition pressure, entrepreneurship, and government policy support positively impact the green technology innovation index. The influence coefficient of innovation activity level reached 0.456, indicating that the intensity and efficiency of enterprise innovation activities are key factors in promoting GTI. Additionally, the average digitalization and financialization levels of the industrial chain increased from 0.66 in 2017 to 0.76 in 2022, reflecting a significant breakthrough in regional industrial chain integration. The findings demonstrate that the proposed model effectively captures how different social factors promote regional economic development and reveal the spatial correlation and spillover effects of inter-regional innovation activities. The research contributes by constructing a comprehensive theoretical framework, enhancing understanding of the interaction between GTI and the digital economy, and filling gaps in systematic and regional analysis in existing studies. It offers practical decision-making support for policymakers and businesses to accelerate the transition toward a green, healthy, and sustainable development model.

Keywords: Digital economy, green technology innovation, low-carbon development, sustainable development, industrial chain integration.

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1. Introduction

Against a backdrop of economic growth in China, environmental pressures caused by rapid industrialization have become a key challenge that limits Sustainable Development (SD) (Liu et al., 2023). To address this, Green Technology Innovation (GTI) has emerged as an effective way to implement the SD strategy. GTI can enhance resource utilization efficiency and help promote society's green transformation to achieve SD goals. In the current era of a booming digital economy, GTI has become an important driving force for enterprise development. However, enterprises still face many challenges. Therefore, it is important to conduct in-depth research and exploration into the driving mechanisms of GTIs (Purohit and Dave, 2023). Most studies, however, focus on specific regions or countries and may not fully represent the global or broader regional situation. Additionally, technological innovation and changes in the entrepreneurial environment may outpace research predictions, requiring continuous updates to adapt to rapidly changing environments (Elmoghazy et al., 2023). In response, this study systematically explores the dynamic mechanism that empowers Low-Carbon Development (LCD) toward a sustainable digital economy by constructing the Sustainable Digital Economy-Low Carbon Development Momentum Model (SDED-LCDMM). This model incorporates multiple factors, such as market, enterprise, government, and technology, into the analysis framework, providing a new perspective on understanding GTI. Furthermore, the model's effectiveness is validated using a spatial lag model. The study examines the mutual influence of GTI across regions, revealing the spatial correlation and spillover effects of innovation activities. Lastly, the model's effectiveness and practicality are further validated through simulations of enterprise operations using the Repast simulation platform (Yang and Zhang, 2023). The research aims to develop an SDED-LCDMM to offer valuable decision support for enterprises and accelerate China's transition toward a green and healthy SD model. The remainder of the paper is structured as follows: Section 2 reviews relevant background literature, summarizes existing research, both domestically and internationally, on the effects of GTI and the digital economy on LCD, and identifies limitations and potential areas for improvement in current studies. Section 3 details the construction of SDD-LCDMM, examines the operating principles of the low-carbon technology innovation-driving mechanism, and discusses the development mechanism model for the digital economy's role in enabling the low-carbon industrial chain. Section 4 presents an empirical analysis of how the model's indicators influence GTI and their real-world effects, validating its effectiveness through statistical and simulation techniques. Finally, Section 5 summarizes the research findings, provides policy recommendations, and suggests directions for future research.

2. Related Works

With increasing global attention to environmental issues, more researchers are beginning to discuss the driving force of the digital economy on LCD (Liu and Yao, 2023). Sturgeon (2021) suggested methods to improve business processes through technological innovation, government growth policies, and digital entrepreneurship in response to the Asian digital economy. The new value chain is transforming how Asian countries participate in global manufacturing. The digital economy and social index have also become important references for the development of Asian countries and social economies. Wang (2024) proposed a digital economy innovation method that incorporates incubators to gain support and resources to address entrepreneurial risks and the entrepreneurial environment. Entrepreneurs like Min reduced their entrepreneurial risks and obtained free office space and equipment services through incubator assistance. This approach helps develop entrepreneurial projects and achieve entrepreneurial dreams. Rudy et al. (2024) introduced the new policy tool, Digital Industrial Clusters (DIC), to meet policy demands in the context of the digital economy and Industry 4.0. DIC, as a new policy instrument, combines the advantages of industrial clusters and the digital economy, offering policymakers and cluster organizations guidance on utilization strategies. This enabled researchers to empirically identify early forms of DIC. Guang and Mingli (2024) proposed a method for analyzing the relationship between the digital economy and the ecological environment using the entropy-weight method and a random-effects model. The development of the digital economy positively impacts the ecological environment, with regional differences. The effect is significant in the eastern and central regions but less so in the western regions. Jingyan et al. (2024) proposed a pricing strategy for multi-version information products based on the valuation of future earnings by different entities. Equilibrium pricing depends on differences in product quality and the valuation of future returns by various parties. Implementing behavioral pricing might not always maximize consumer surplus and social welfare. Strategies need to be formulated based on specific circumstances.

Yari et al. (2024) proposed a systematic literature review method to examine the characteristics of climate-adaptive cities. Climate-adaptive cities boost the adaptability and resilience of various urban components to climate change, supporting SD and flexibility within the city. This was accomplished through low-carbon economic strategies, including effective resource management, forward-looking planning, education, and innovative governance. Helena (2024) developed a regression model to analyze the effects of carbon pricing and green bonds on carbon dioxide emissions, addressing the challenges of low-carbon economic transformation. The implementation of national carbon pricing and green bonds led to average reductions of 11% and 14%, respectively. However, the combined effect of both measures showed no significant interactive impact. These results should be interpreted with caution, as other factors may also influence emission reductions. Yang et al. (2024) introduced an empirical testing method using panel data from 276 Chinese cities from 2011 to 2022 to explore the relationship between financial technology and green growth. Financial technology exhibited a U-shaped effect on green growth, with innovation acting as a mediating factor. This effect remained consistent across different urban characteristics. Xiaopeng and Zi (2024) devised a method for quantifying tourism-related carbon dioxide emissions and analyzing the tourism economy. They examined evolutionary characteristics, focusing on the development of low-carbon tourism in the Yellow River Basin. The tourism industry in this region initially displayed features of the environmental Kuznets curve. Tourism and carbon emissions mutually influence each other, and the total factor productivity of low-carbon tourism is improving. Nonetheless, low-carbon tourism is still in its early stages. Cao et al. (2024) proposed a low-carbon economic scheduling approach based on a multi-objective chaotic artificial hummingbird algorithm to optimize the scheduling of regional integrated energy systems. This method reduced system operation costs by 8.8% and carbon emissions by 14.2%, demonstrating its dual benefits for the economy and environmental protection.

Although the above studies have contributed to their respective fields, they have limitations, including a lack of in-depth analysis of long-term impacts, oversimplified model assumptions, and limited data sources. Additionally, there is a lack of integration and comparison across studies, making it difficult to develop a comprehensive, systematic understanding. Therefore, this study thoroughly and systematically examines the driving mechanism of a sustainable digital economy empowering LCD based on SDED-LCDMM. The study enhances the analysis of long-term impacts, simplifies model assumptions, and addresses limitations in data sources. Using the SDD-LCDMM model, various factors like market, enterprise, government, and technology are systematically integrated to explore how a sustainable digital economy can effectively promote LCD. This model not only fills gaps in existing literature but also offers targeted strategic recommendations for policymakers and practitioners, helping to advance the practice and implementation of SD.

3. Construction of SDED-LCDMM

3.1. Operating Principle of Low-Carbon Technology Innovation Driving Mechanism

GTI is the key driving force behind LCD. Exploring its operational mechanism helps identify key factors, optimize resource allocation, and promote sustainable economic development (Kuznetsov and Gasenko, 2024; Li et al, 2024). Therefore, before investigating the driving mechanism that empowers LCD toward a sustainable digital economy, this study first examines GTI's operational model. The operation of the GTI driving mechanism is a complex system involving multiple elements. These elements are interconnected and mutually influence one another, collectively fostering the ongoing progress and development of green technology. Market demand, as a market orientation for GTI, plays a very important role in Fig. 1.

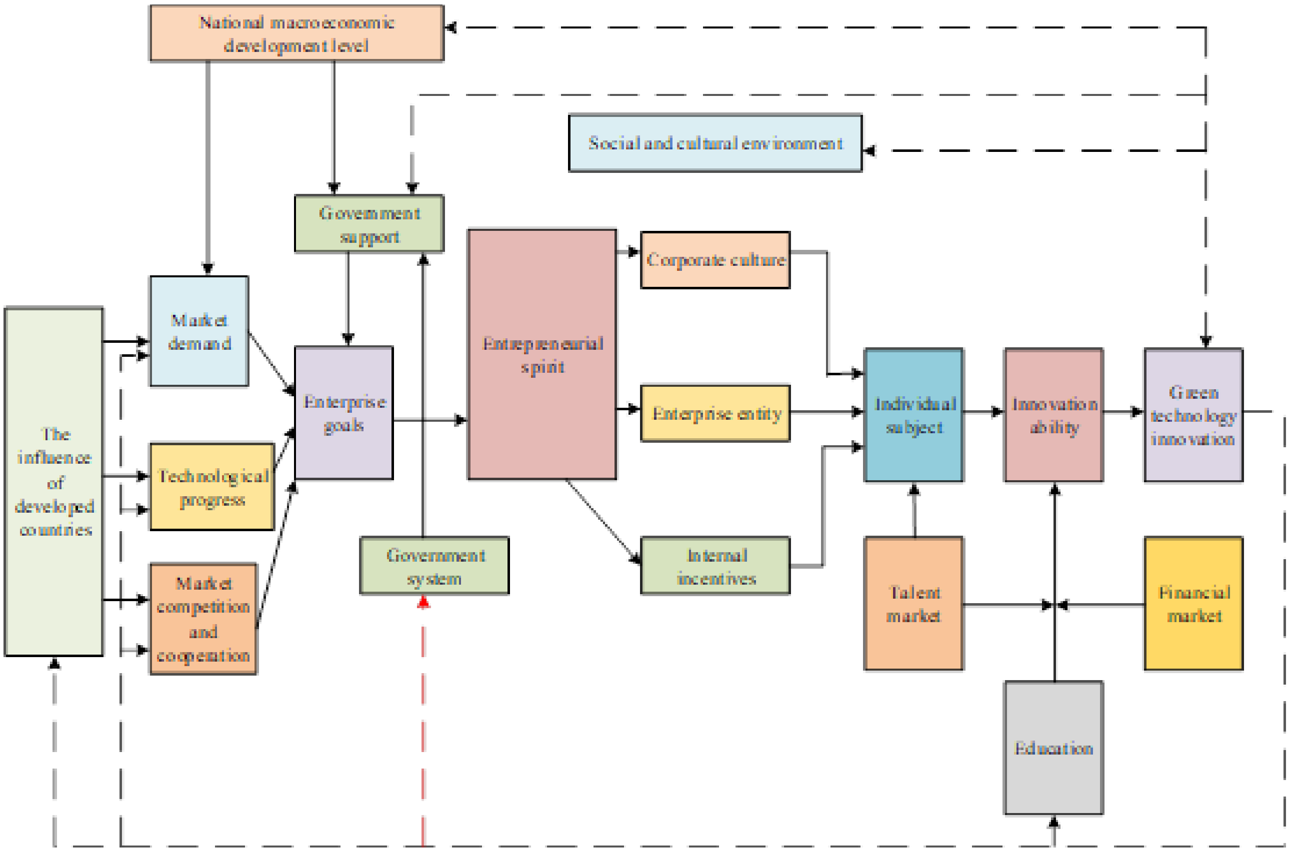


Fig. 1. Operation of GTI motivation mechanism

In the mechanism of GTI, the market's green demand pull, competitive pressure, and cooperative pressure interact with the driving force of science and technology and the supporting force of government policy behavior. They are directly or indirectly transformed into driving forces for corporate goals, thereby promoting GTI in enterprises. The comprehensive index of GTI power is represented by Eq. (1).

$$\mathrm{GTIDFI} = f\left(M_D, S_C, T_P, G_S, E_I, C_E, I_M, P_T, A_C, H_D, S_E, G_T\right) \tag{1}$$

In Eq. (1), GTIDFI refers to the Green Technology Innovation Driving Force Index. M_D refers to the green demand pull of market demand. S_C refers to market competition pressure. T_P refers to the driving force of cooperation. G_S refers to government policy support. E_I refers to entrepreneurial spirit. C_E refers to corporate culture. I_M refers to the internal incentive mechanism. P_T refers to policy tools. A_C refers to technical absorption capacity. H_D refers to human capital. S_E refers to the social environment. G_T refers to the Green Technology Foundation. In this system, entrepreneurial spirit is indispensable. The entrepreneurial spirit has an induction and amplification effect on the driving force for goals, directly motivating the main body of enterprises to engage in innovative practices. Meanwhile, by shaping a positive corporate culture and establishing effective internal incentive mechanisms, entrepreneurs indirectly drive individual entities to engage in technological innovation. The induction and amplification effects of entrepreneurial spirit on the driving force for corporate goals are represented by Eq. (2).

$$E_{\text{drive}} = \alpha \times E_I + \beta \times \left(C_E + I_M\right) \times P_T \tag{2}$$

In Eq. (2), E_{drive} refers to the driving force of entrepreneurial spirit on corporate goals. α and β These are coefficients that reflect the strength of the impact of entrepreneurial spirit and other factors on the goal-driving force. Fig. 2 shows the impact of entrepreneurial spirit on a company's innovation capability.

Enterprise innovation capability is a key factor in ensuring the smooth progress of GTI activities. This ability enables enterprises to effectively transform innovative ideas into practical technological achievements. The enterprise's innovation capability and the conversion rate of technological achievements are expressed by Eq. (3).

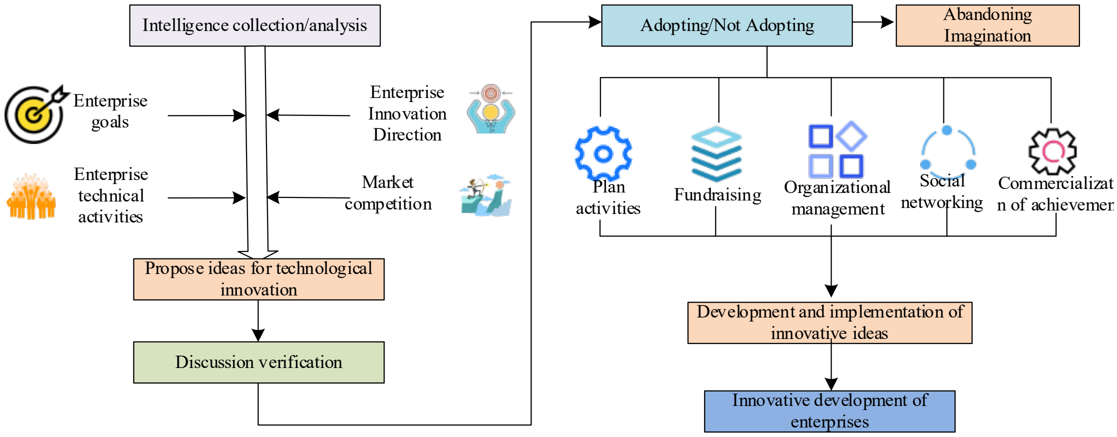


Fig. 2. Influence of entrepreneurship on enterprise innovation ability

$$T_{\text{conversion}} = \frac{A_C \times G_S \times P_T}{1 + \gamma \times \left(H_D + S_E\right)} \tag{3}$$

In Eq. (3), γ is a coefficient that reflects the impact of macroeconomic and socio-cultural environment on innovation capability. Successful GTI activities will have a negative impact on technology, markets, governments, and the environment, stimulating new innovation demands. This reaction not only drives enterprises to achieve self-breakthroughs at higher levels but also creates a virtuous cycle across the entire innovation process. The dynamic model of the virtuous cycle of innovation activity is represented by Eq. (4).

$$I_{t+1} = I_t + \delta \times \left(I_t \times \left(M_D - I_t\right)\right) \tag{4}$$

In Eq. (4), I_t represents the level of innovation activity at the time t. I_{t+1} refers to the level of innovation activity at the next time point. δ is a coefficient that reflects the rate of growth in innovation activities. The new round of innovation will drive further technological breakthroughs and market demand, thereby promoting the continued development of GTI activities. In addition, external factors such as macroeconomic development, social and cultural environment, government support, the influence of newly developed countries, technological progress, and the improvement of government systems also provide broad space and strong guarantees for GTI. Internal incentive mechanisms, talent markets, financial markets, market competition, and cooperative education have also injected new impetus into GTI.

3.2. Development Mechanism Model of Digital Economy Empowering Low-Carbon Industry Chain

In the comprehensive role model of the development market for digital technology, various links are closely connected, forming a circular, innovation-promoting ecosystem (Kamal et al., 2024). Basic research is the starting point of innovation, providing theoretical support for technological inventions. With market feedback, companies may discover new demands that further stimulate the generation of innovative ideas. The innovative concept is developed through research and development, forming a prototype, which is then manufactured and sold, and finally re-launched into the market. Fig. 3 shows a comprehensive model of the interaction between digital technology and the market.

In the mechanism model of empowering low-carbon industrial chain development through the digital economy, the continuous progress of digital technology not only promotes the industrial chain's development towards greater efficiency and lower carbon emissions (Alvaro et al., 2024). Changes in market demand also promote innovation in digital technology, fostering a two-way interaction between technology and the market and jointly driving a virtuous cycle of industry chain resilience and SD. To further explore the mechanism of this virtuous cycle, a model of the development motivation mechanism in the digital economy empowering the low-carbon industry chain is constructed. Firstly, the digital economy provides strong technical support for the low-carbon manufacturing industry chain through data integration, knowledge integration, and intelligent integration. The data integration and knowledge dissemination model is represented by Eq. (5).

$$V_k = \frac{I_d \cdot I_k}{\Delta t} \cdot f(D) \tag{5}$$

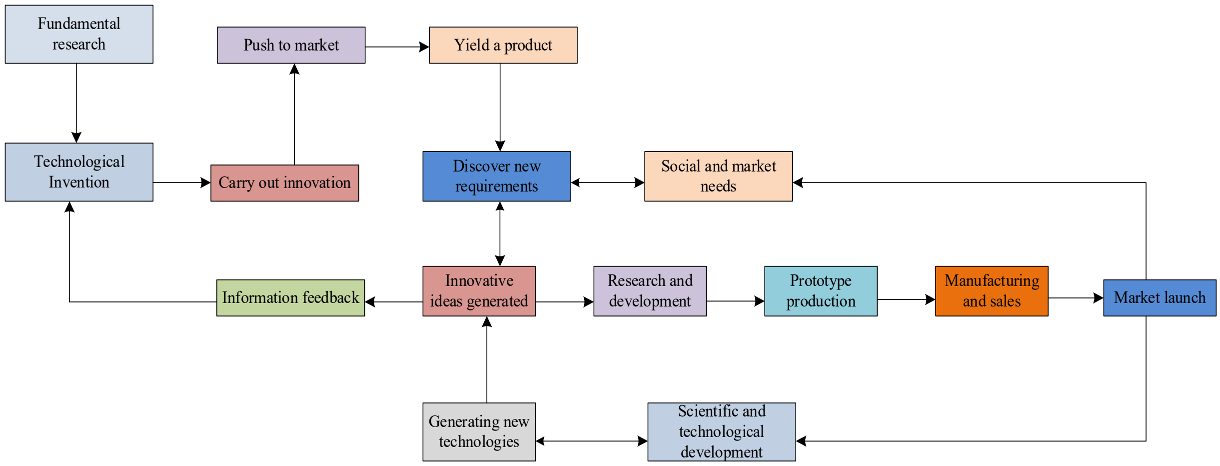


Fig. 3. Combined action model of digital technology and market

In Eq. (5), V_k refers to the speed of knowledge dissemination between enterprises. I_d refers to the ability of enterprise data integration. I_k refers to the ability to integrate knowledge. Δt refers to information transmission delay. $f(D)$ is a function related to data quality D. In an environment with complex and ever-changing market demands and short product update cycles, these integrated orientations enable enterprises to quickly respond to market changes. The coordination efficiency within the industrial chain is improved through high-frequency collaborative scenarios. The efficiency model of industrial chain coordination is represented by Eq. (6).

$$E_c = C_d^{\gamma} \cdot T_i^{-\delta} \cdot e^{-\grave{o} T_r} \tag{6}$$

In Eq. (6), E_c represents the internal coordination efficiency of the industrial chain. C_d^{γ} is the digital connectivity between enterprises. $T_i^{-\delta}$ stands for information transparency. T_r is the collaborative response time. γ, δ, and $\grave{o}$ are weight coefficients. The digital characteristics are reflected in the rise of data element platform enterprises. Enterprises achieve broader knowledge application through the digital integration of diverse forms of knowledge. Business intelligence decision-making is achieved through digital construction. Fig. 4 presents a model of the development motivation mechanism in the digital economy that empowers the low-carbon industry chain.

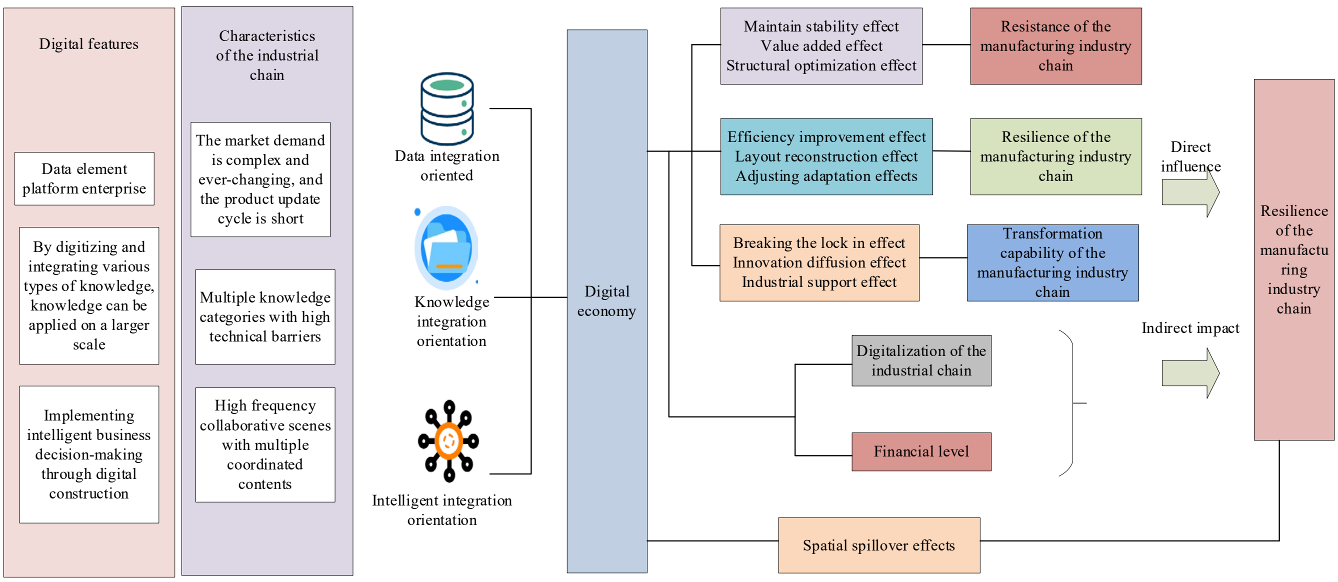


Fig. 4. Dynamic mechanism model of the development of low-carbon industrial chain

Secondly, the digital economy has had stabilizing, value-added, and structural-optimization effects on the manufacturing industry chain. These effects directly affect the manufacturing industry's supply chain. This enables the industrial chain to remain stable amid external shocks. The model of maintaining stability and resistance through value creation and structural optimization is represented by Eq. (7).

$$R_e = \beta_1 \cdot S_s + \beta_2 \cdot V_a + \beta_3 \cdot O_s + \varepsilon \tag{7}$$

In Eq. (7), S_s refers to maintaining a stable effect. V_a refers to the value appreciation effect. O_s is the structural optimization effect. $\beta_1, \beta_2, \beta_3$ are the effect coefficients, representing the specific contribution of each effect to resistance. ε is a random perturbation term. The enhancement of resistance plays a direct and important role in enhancing the resilience of the low-carbon manufacturing industry chain. In addition, the digital economy affects the resilience of the manufacturing industry chain through efficiency improvements, layout restructuring, and adaptation. Through innovation diffusion and industrial support, this resilience enhancement also plays a key role in strengthening the resilience of the low-carbon manufacturing industry chain, as expressed by Eq. (8).

$$R_c = \gamma_1 \cdot E_u^{\eta_1} + \gamma_2 \cdot L_r^{\eta_2} + \gamma_3 \cdot A_a^{\eta_3} + \xi \tag{8}$$

In Eq. (8), $E_u^{\eta_1}$ refers to the efficiency improvement effect. $L_r^{\eta_2}$ refers to the layout reconstruction effect. $A_a^{\eta_3}$ refers to the impact of adjusting adaptation effects. $\gamma_1, \gamma_2, \gamma_3$ are coefficients. η_1, η_2, η_3 are nonlinear indexes that reflect the marginal change in effect intensity with increasing variables. ξ is an error term. Finally, the spatial spillover effects of the digital economy and the improvement of digitalization and financialization of the industrial chain indirectly affect the resilience of the low-carbon manufacturing industry chain. These impacts indirectly strengthen the industrial chain's resilience by advancing its overall development.

3.3. SDED-LCDMM and Variable Composition

SDED-LCDMM includes multiple interconnected elements that work together to promote the development of a low-carbon economy. Market demand drives technological invention and innovation activities, while being influenced by technological progress and the social and cultural environment. The entrepreneurial spirit shapes individual innovation ability through corporate culture and internal incentive mechanisms. Technological progress enhances data and knowledge integration capabilities, supporting intelligent integration efforts. Government policy actions provide support and guidance for technological innovation. The digitization and financialization of the industrial chain improve its resilience by boosting coordination efficiency and capital flow. The stability, value appreciation, and structural optimization effects collectively strengthen the industrial chain's resistance and resilience. The spatial spillover effect encourages technological exchange and coordinated economic development across regions. Based on these insights, the SDED-LCDMM is constructed. Fig. 5 illustrates a schematic diagram of its structure.

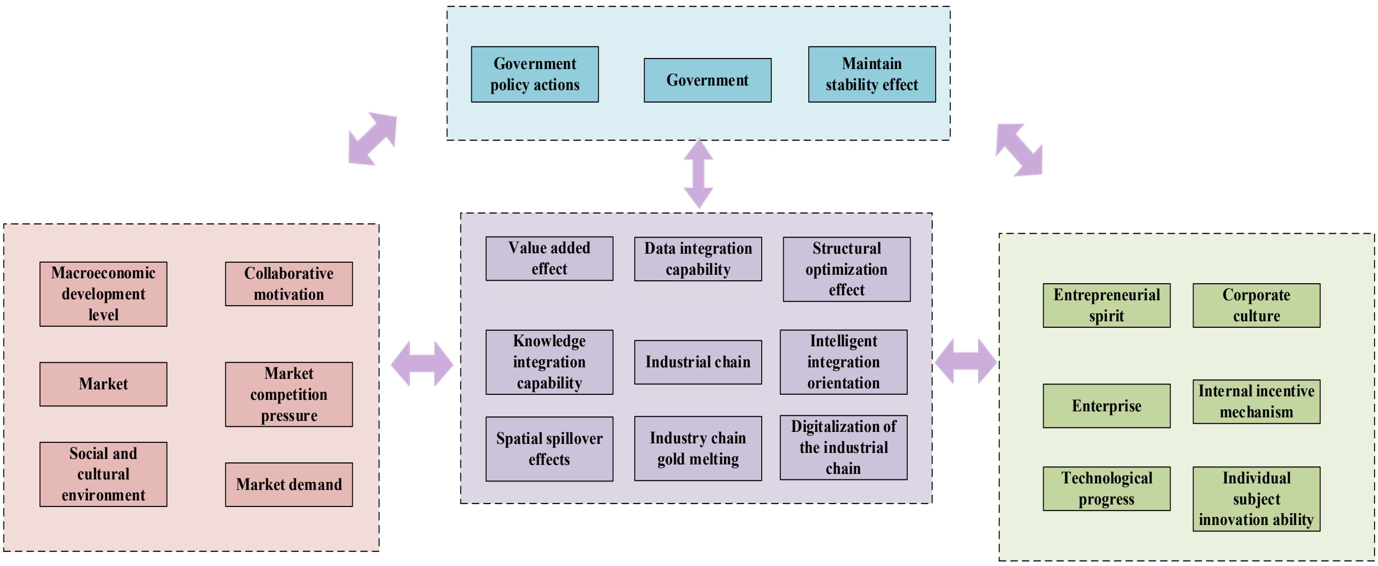


Fig. 5. Schematic representation of SDED-LCDMM structure

Fig. 5 presents a schematic diagram of SDED-LCDMM, which mainly includes four aspects: market, industry chain, enterprise, and government, each with different elements. The market is primarily composed of five elements: macroeconomic development level, cooperation momentum, market competition pressure, market demand, and social and cultural environment. The industrial chain mainly consists of eight elements: value-added effect, data integration ability, knowledge integration ability, structural optimization effect, spatial spillover effect, industrial chain gold melting, industrial chain digitization, and intelligent integration orientation. The enterprise primarily comprises five elements: entrepreneurial spirit, corporate culture, internal incentive mechanisms, individual innovation ability, and technological progress. A spatial lag model is used in this study to verify its effectiveness, primarily by considering the spatial lag correlation of the dependent variable, as represented by Eq. (9).

$$Y = \rho WY + \beta X + \varepsilon \tag{9}$$

In Eq. (9), Y represents a dependent variable. ρ is a spatial autoregressive coefficient. W is a spatial weight matrix. β is a regression coefficient. X represents an explanatory variable. ε is a random error term. The study uses the following notations: Y represents the GTI index, which measures the level and performance of a region or organization in green technology innovation. X1 represents Green demand pull, referring to the market demand for green products and services. X2 represents Market competition pressure, indicating competition among enterprises in the same industry for market share. X3 represents Entrepreneurial spirit, fostering attitudes and cultures that promote risk-taking, innovative thinking, and proactive pursuit of new opportunities within enterprises or organizations. X4 represents Government policy support, referring to policies and measures enacted by the government to promote green technology innovation and SD, such as financial subsidies, tax reductions, R&D funding, and relevant laws and regulations. CC represents Corporate culture and incentive mechanisms, which refer to the values, beliefs, and behavioral norms within an organization that influence employees' work attitudes and willingness to innovate. TA represents Technological advancement, indicating the development and application of new technologies in production and service processes. SCE represents Socio-cultural environment, encompassing social values, customs, education levels, and public awareness that influence corporate operations and innovation behaviors. DF represents the digitalization and financialization of the industry chain, reflecting the development level of the industry chain in information technology and digital finance. IAL represents the level of innovation activity, referring to the frequency and intensity of activities conducted by enterprises in areas such as technology R&D, product development, and market engagement innovation. Fig. 6 shows the constructed SDED-LCDMM indicators.

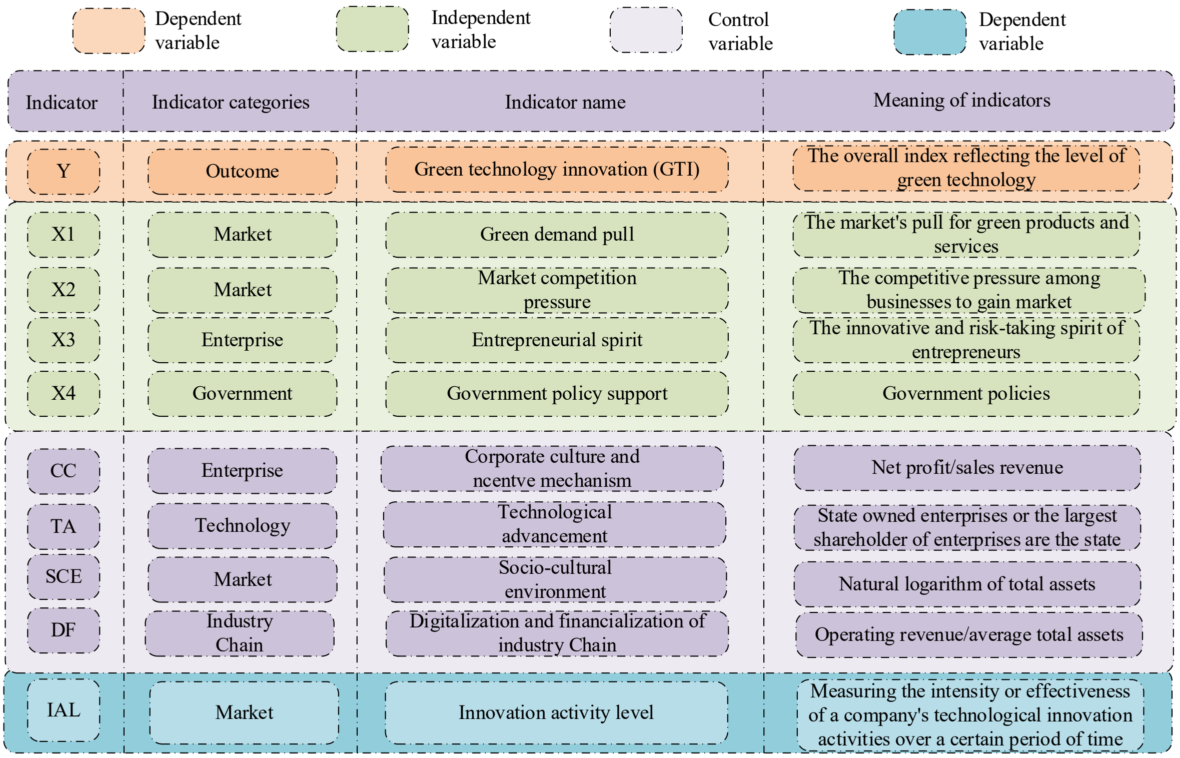


Fig. 6. SDED-LCDMM indicator composition

4. Exploring Motivation Mechanism of Digital Economy Empowering LCD

4.1. Theoretical Analysis of Influence of SDED-LCDMM Indicators

The study developed SDED-LCDMM to investigate the driving mechanism model of a sustainable digital economy that empowers LCD. To analyze the relationships among these indicators statistically, a sample of observations was collected. Statistical software was used in this experiment to determine the mean, standard deviation, minimum, and maximum values. Table 1 presents the descriptive statistical results indicators. From the descriptive statistics, the average values of each indicator mostly ranged between 60 and 80, showing that the various elements involved in SDED-LCDMM were generally high. The average values of government policy support (indicator X4) and Technological Advancement (indicator TA) were relatively high, indicating that these two factors significantly influenced GTI (indicator Y). Meanwhile, the standard deviation reflected the variability within each indicator, with some indicators like SCE and IAL exhibiting larger standard deviations. This suggested notable differences in the social and cultural environment and innovation activities among different samples. It implied that, when developing relevant policies, a comprehensive approach should consider various factors to promote sustainable innovation and the growth of green technologies. The study used SPSS13 software to conduct multiple regression analysis on the model. Table 2 presents the regression analysis results using the Variance Inflation Factor (VIF).

Table 1. Descriptive statistics of indicators

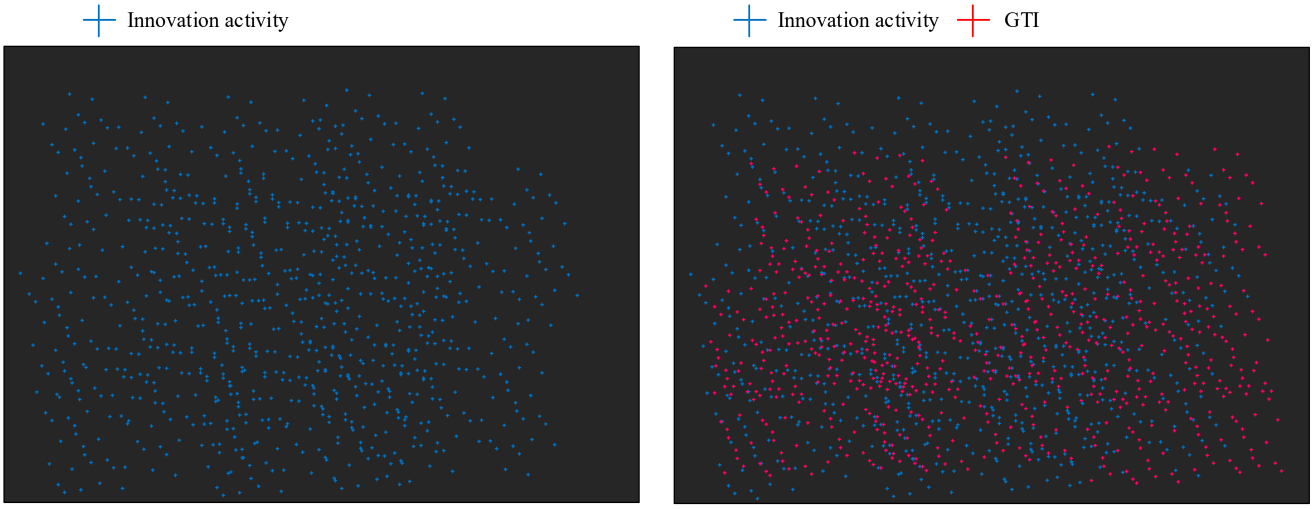
Indicator	Average value	Standard deviation	Minimum value	Maximum value
X1	65.789	10.235	40.031	90.012
X2	58.456	12.345	30.040	80.031
X3	72.154	15.678	45.051	103.004
X4	78.765	9.876	61.033	95.034
Y	70.123	14.321	52.031	95.022
CC	74.321	8.765	61.032	90.043
TA	81.234	6.543	70.031	95.001
SCE	65.432	19.876	30.441	110.032
DF	68.765	13.210	45.413	85.213
IAL	55.678	18.765	23.123	90.413

Table 2. Regression analysis results obtained through VIF

Indicators	Coefficient (β)	Standard error	T-value	*p*-value
Y	0.378	0.124	3.048	0.003
X1	0.219	0.032	6.884	< 0.001
X2	0.156	0.041	3.785	0.000
X3	0.105	0.029	3.586	0.001
X4	0.234	0.035	6.667	< 0.001
CC	0.183	0.037	4.954	< 0.001
TA	0.297	0.030	9.852	< 0.001
SCE	0.171	0.034	5.021	< 0.001
DF	0.312	0.038	8.202	< 0.001
IAL	0.456	0.040	11.412	< 0.001

In the results of multiple regression analysis shown in Table 2, T-value and p-value are key indicators used to assess the significance of regression coefficients. The T-value is a standardized statistic that compares the ratio of the regression coefficient to its standard error. It helps determine whether the impact of two indicators is statistically significant. The p-value represents the level of significance for testing hypotheses, indicating the probability of observing the current data if the null hypothesis is true. It is generally used to decide whether the regression coefficient significantly differs from zero. Based on the multiple regression analysis in Table 2, indicators X1, X2, X3, X4, as well as CC, TA, SCE, DF, IAL, and others, all had a positive impact on GTI. The impact of IAL was the most notable, with a coefficient of 0.456. This suggested that the intensity and efficiency of enterprise technological innovation activities were crucial factors in boosting GTI. TA and DF also demonstrated significant influence, highlighting the vital role of new technology application and industrial chain upgrading in green innovation. Overall, this regression analysis showed that various factors, such as the market, enterprises, government, and technology, worked together to promote GTI, indicating that digital technology played an important role in advancing a low-carbon economy. To verify this conclusion, the study simulated enterprise operations within a regional environment using Java on the Repast simulation platform. The model included entities such as enterprises, governments, markets, and industrial chains (Huang et al 2024). Fig. 7 shows the simulation results.

In Fig. 7, Fig. 7(a) shows the operational simulation results of the enterprise under the influence of innovation activities; Fig. 7(b) displays the results under the continuous diffusion of innovation activities. The Blue Cross graph represents innovation activity, and the Red Cross graph indicates GTI. The blue cross corresponds to proactive innovation activities initiated by enterprises (such as product iteration, process optimization and management transformation). These activities serve as the initial drivers of innovation diffusion within the system. Through technological exploration, resource integration, and risk-taking, they provide a foundation for enterprises to adapt to environmental changes. The Red Cross highlights the structural innovation enabled by green technologies (such as clean energy applications, circular processes, and carbon-reduction technologies), pushing enterprises from "passive compliance" to "active leadership." Through continuous diffusion of innovative activities, GTI also spreads throughout the system, and after a period of adaptation and development, the system gradually reaches saturation. This suggests that enterprises within the system have successfully adapted to the current environment through ongoing innovation activities, resulting in prosperity and growth, and generating a new positive effect on the entire system. This virtuous cycle underscores the vital role of innovation in promoting enterprise development and the overall system's progress. It also demonstrates that enterprises capable of adapting to and effectively utilizing the external environment will ultimately gain greater competitive advantages and market share positions.



(a) The operation simulation results of enterprises under innovation activities

(b) The operational results of enterprises under the continuous diffusion of innovation activities

Fig. 7. Enterprise operation simulation results

4.2. Analysis of the Actual Impact of Digital Economy

The study fully confirmed that indicators such as X1, X2, X3, and X4 positively affected GTI, which in turn potentially promoted regional economic development. The investigation examined changes in DF, IAL, SCE, and regional economic totals across four regions of Shandong to verify the potential impact of these digital economic indicators on economic growth. Fig. 8 displays the survey results.

From Fig. 8, the average DF index value increased from 0.66 in 2017 to 0.76 in 2022. This indicated that these four regions achieved significant breakthroughs in integrating digitization and financialization into the industrial chain, effectively enhancing their coordination efficiency and resilience. Meanwhile, the average IAL index also rose from 0.64 in 2017 to 0.84 in 2022, reflecting sustained improvement and efficient performance in these regions' technological innovation activities. In addition, although SCE growth was relatively slow, it increased from 0.46 to 0.55. This also showed that society's understanding of environmental protection and SD gradually deepened, which had an important impact on guiding enterprise innovation. Finally, the average GDP of these four regions grew from $30 billion in 2017 to $50 billion in 2022. This not only directly reflected economic development but also resulted from the combined effect of improving the aforementioned innovative indicators. Additionally, the study examined the CC index and the economic development level index across various regions of China in 2020 (Fig. 9).

In Fig. 9 in 2020, the total development index of the digital economy in each region was positively correlated with its corresponding CC index. This discovery was completely consistent with the conclusions drawn from previous in-depth research, further validating the proposed hypothesis. The study used a spatial lag model to validate the above results in Table 3.

According to the spatial lag model validation, the coefficients for all independent indicators were positive, indicating that they positively affected GTI. X1, X2, X3, and X4 all affected the GTI. In addition, CC, TA, SCE, DF, and IAL all affected GTI. A positive Lambda value indicated the presence of a spatial lag effect. The GTI of adjacent regions positively affected the local region's GTI.

5. Conclusion

This study explored the driving mechanism for empowering LCD to support a sustainable digital economy by developing SDED-LCDMM. After conducting multiple regression analyses, factors such as market green demand, market competition pressure, entrepreneurial spirit, and government policy support were found to influence GTI. The innovation activity coefficient reached 0.456, highlighting that innovation activity is a key driver of GTI. The validation of the spatial lag model further confirmed a positive spatial lag effect across regions, with GTI in neighboring areas mutually promoting one another. The growth of the social and cultural environment was relatively slow, increasing from 0.46 to 0.55. However, this also indicated that society's understanding of environmental protection and SD was gradually deepening, which influenced enterprise innovation directions. Lastly, the average GDP of these four regions rose from $30 billion in 2017 to $50 billion in 2022. This increase not only reflected economic growth but also resulted from improvements in the innovative indicators. The study showed that the market, enterprises, government, and technology collectively drove GTI, with innovation activities playing a particularly vital role. Regional innovation efforts displayed significant spatial correlation and spillover effects. After reading this article, managers should adjust their decision-making processes by incorporating the spatial spillover effects of green technology innovation across regions into their collaboration strategies. Additionally, they should enhance resource allocation toward digitalizing the industrial chain and strengthen internal innovation incentives to more effectively drive low-carbon transformation. When extending research findings to different regions and countries, the following approaches can be adopted: First, calibrate model parameters based on local economic, institutional, and cultural characteristics (e.g., lower government policy support coefficients in developed regions and higher coefficients in developing regions). Second, enhance the digitalization of industrial chains (DF) indicators for resource-dependent areas, while focusing on market competition pressure (X2) and green demand (X1) for export-oriented regions. Simultaneously, we employ spatial lag models to identify cross-border or cross-regional spillovers of low-carbon technologies (e.g., EU-ASEAN collaborations). Finally, use the Repast simulation platform to model corporate behavior under various policy scenarios (e.g., carbon pricing and green subsidies). Although the research is comprehensive, it is limited to theoretical models. Future work should incorporate more practical cases and long-term data to better assess the model's effectiveness and limitations in real-world applications.

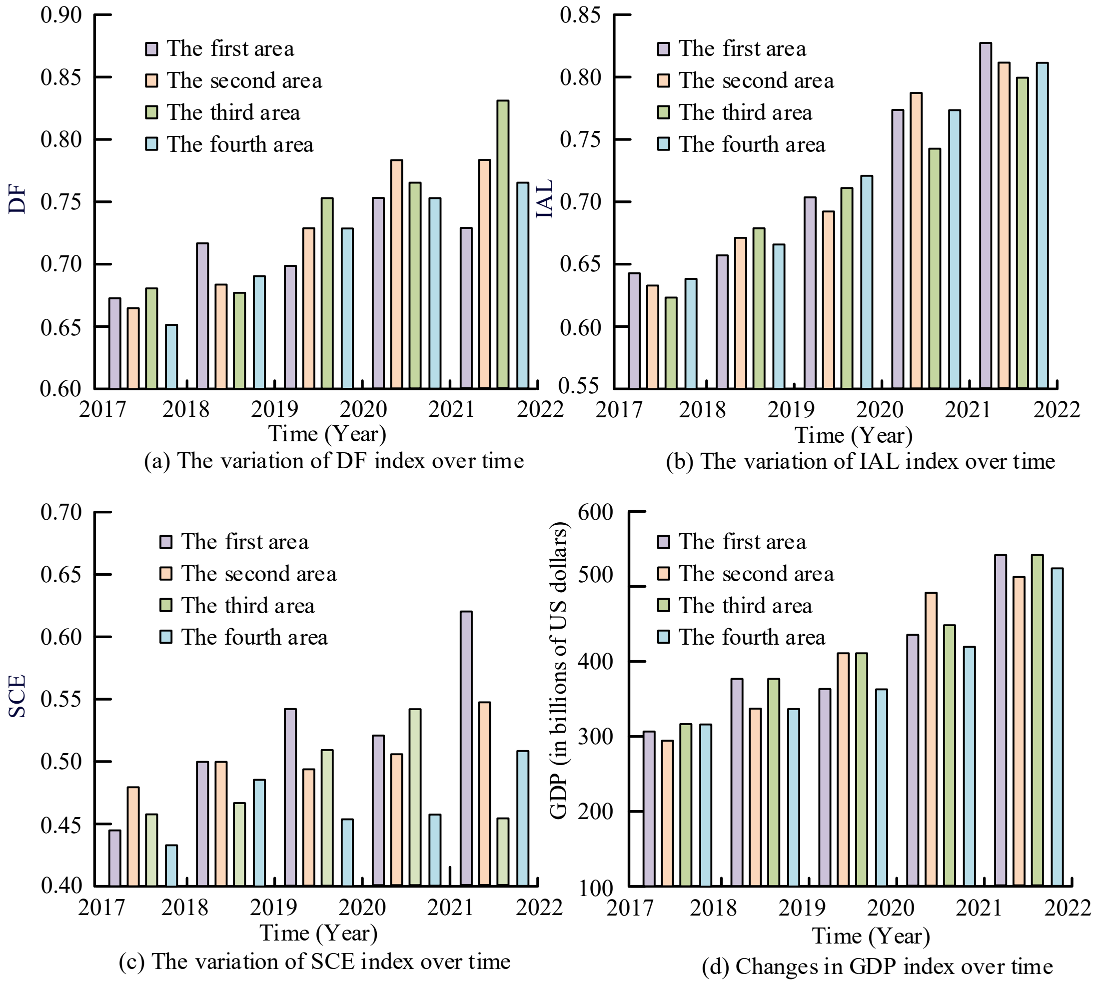


Fig. 8. Digital economy growth and economic aggregate by region (2017–2022)

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Institutional Review Board Statement

Not applicable.

Declaration of Artificial Intelligence (AI) Tools

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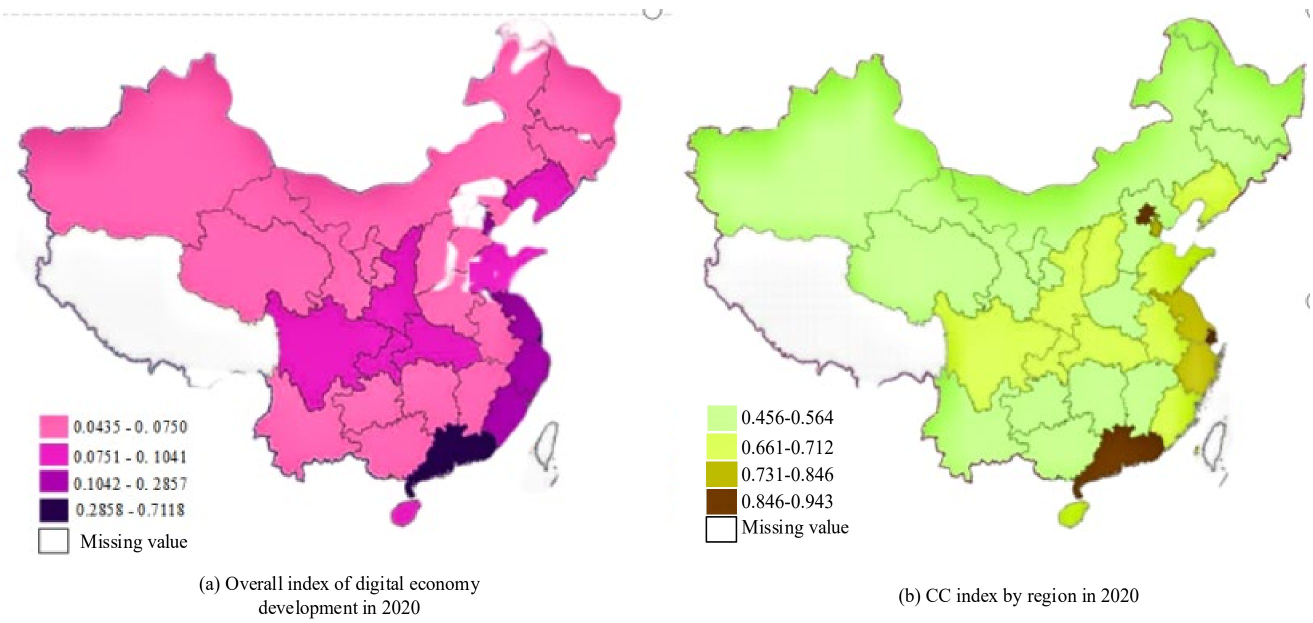

Fig. 9. Comparison of CC index and economic development level index in each region in 2020

Table 3. Results of the spatial lag model indicators

Indicators	Coefficient (β)	Standard error	T-value	P-value
X1	0.123	0.004	30.850	<0.0001
X2	0.034	0.005	6.789	0.0002
X3	0.045	0.006	7.654	<0.0001
X4	0.015	0.002	8.901	<0.0001
CC	0.091	10.007	12.879	<0.0001
TA	0.067	0.003	22.222	<0.0001
SCE	0.018	0.002	9.091	<0.0001
DF	10.028	0.003	9.876	<0.0001
IAL	0.039	10.004	10.123	<0.0001
Lambda	0.056	0.008	7.071	<0.0001
Constant	50.123	1.122	40.678	<0.0001

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