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The impact of digital infrastructure on regional green innovation efficiency through industrial agglomeration and diversification

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This study reveals the spatial impact of digital infrastructure (DI) on regional GIE, introducing two novel perspectives of industrial agglomeration - its concentration (IC) and diversification (ID). The results reveal that local DI significantly improves local GIE but has a "siphon effect" on neighboring areas, leading to an inhibitory effect. Local DI promotes local IC and ID, which enhances local GIE. However, local DI's spillover effects decrease neighboring areas' IC and ID, which reduces neighbors' GIE. The spatial impact of DI on GIE exhibits heterogeneity among different city sizes, regional technological levels, and traditional infrastructure development. As regions' DI develops, the siphon effect of DI on neighboring GIE gradually diminishes and thus DI promotes long-term GIE. Introducing LE and PE, this study provides rich empirical evidence for understanding the relationship between DI and GIE.

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Introduction

In response to the significant challenges presented by resource depletion, climate change, and ecological degradation across the globe, the concept of sustainable development has garnered considerable worldwide attention from governments and academia. The concept of green innovation (GI) presents a new aspect of technological innovation that combines economic growth and environmental protection (García Vaquero et al. 2021; Fang et al. 2022). GI has become an important means of addressing environmental issues and promoting the coordinated development of the economy and ecology. GI focuses on the application and development of new technologies and emphasizes efficiency improvement in innovation activities while prioritizing environmental protection or green innovation efficiency (GIE). Compared with the pursuit of innovation's quantity, improving GIE or promoting the transformation of innovation in the direction of paying equal attention to its quantity and quality is key to promoting sustainable growth (Miao et al. 2017). Therefore, an in-depth study of the influencing factors of GIE has important theoretical and practical significance for guiding policymaking, optimizing resource allocation, and improving environmental quality. Existing research on GIE predominantly focuses on the industrial level (Liu et al. 2020; Zhu et al. 2021) or the enterprise level (Li et al. 2023). However, research on the driving mechanisms of GIE at the city level remains insufficient. As cities are the basic units of national policy implementation, the research on the influencing factors of urban GIE can provide a valuable reference for urban policy planning (Dong et al. 2023).

Driven by the global development of the digital economy, digital infrastructure (DI) has emerged as a new driving force for promoting economic development. As a foundational support and significant driver of the digital economy, DI is reshaping the global economic pattern and social operations. The potential impact of integrated DI development with the real economy on regional GI activities is worthy of investigation (Greenstein, 2020). DI promotes knowledge sharing and dissemination by enhancing information transmission efficiency and reducing transaction costs (Tang et al. 2021), which provides a strong support for GI and advances environmental conservation and economic growth objectives. DI also has a key influence on improving environmental governance capacity and stimulating innovation vitality. DI improvement can enhance the efficiency and accuracy of responses to environmental challenges, promote resource utilization efficiency, and reduce resource waste (Oliver, 2019), thus reducing the threshold of GI activities in which enterprises and individuals can participate. DI improvements can also improve overall GI efficiency, which is essential for promoting economic structure transformation in a more environmentally friendly and efficient direction. In addition, DI has accelerated the formation of highly integrated and intelligent networks in cities, optimized environmental management capabilities (Shi et al. 2018), improved policy formulation and implementation effectiveness, and ensured that policies and measures related to GI can be accurately implemented to maximize policy effects.

DI is often accompanied by a multitude of subsidies from central and local government policies, which can attract many talents and high-tech enterprises to gather, thereby promoting GIE (Dong et al. 2022). This paper argues that industrial agglomeration exhibits a dual effect in this process. On the one hand, the concentration of related enterprises brought about by agglomeration forms economies of scale, allowing companies to share innovation resources, R&D facilities, and technology platforms. It significantly reducing the cost of unit innovation and enhancing GIE. On the other hand, the industrial diversification resulting from the agglomeration of different types of enterprises has promoted collaborative innovation through knowledge spillovers and technological complementarity. Through knowledge spillovers and technological complementarity, it accelerates the cross-fertilization of green technologies. However, the local DI crates a "siphon effect[1]" on neighboring areas that cause them to suffer from resource scarcity and talent loss. This leads to lack of relevant input factors in the development process of enterprise, making it difficult for industries to form a scale that is not conducive to the promotional effect of industrial agglomeration (IA) on neighboring areas. At the same time the IA in central cities raises the threshold for green technology innovation, making it difficult for surrounding cities to keep up with the rapid pace of innovation, ultimately leading to a slowdown in their green technology innovation activates.

This study focuses on the rapidly developing emerging economy of China to explore the impact of DI on regional GIE. As the world's largest developing country, China has rapid DI development a wide range and increasingly active GI activities (Tang et al. 2022). The Chinese government has actively promoted the Broadband China strategy and green development policies, providing a unique foundation and rich data support for investigating the relationship between DI and GIE. The rapid progress in DI and the active exploration of GI in China makes it an ideal location for examining this topic. Exploring the impact of DI on GIE in China can provide valuable experience for other developing countries to promote global green economy development.

To better reveal the impact of DI on GIE and its underlying correlation, this paper integrates qualitative and quantitative methods (Sánchez-Bayón, 2022). Based on panel data covering 281 prefecture-level cities in China from 2013 to 2020, this study uses the spatial Durbin model (SDM) to investigate the direct and indirect effects of DI on GIE. From the concentration and diversification of IA, this study examines the mediating role of these two forms. It also analyzes the heterogeneity of urban scales, urban scientific and technological progress, and traditional infrastructure to further explore the long-term impact of DI on GIE in local and neighboring regions.

The contributions of this study are threefold. First, the use of detailed indicators to characterize DI provides a more accurate analytical tool for this research than existing ones. This study uses seven indicators to construct a DI index from three dimensions of informatization, internet, and digital transaction development. Referencing the Bartik method, this study decomposes provincial level indicators to the city level. Second, the findings reveal that the spillover effect of DI on GIE in adjacent regions may be negative in the short term, but positive in the long term. The impact direction of DI on GIE in adjacent regions depends on the relative size of the scale and competition effects from IA. This finding can considerably help understand the dynamic relationship of GI among regions. Third, in contrast to previous studies that use the same index to measure industrial structure, this study divides IA into two perspectives to investigate and compare the effect and mechanisms and test whether the mediating channel of IA comes from the scale effect of centralized enterprise agglomeration or the competitive effect of diversified enterprise agglomeration. The findings supplement the relevant research on the impact mechanism of DI on GIE.

The remainder of this paper is organized as follows. Section "Literature review" presents a literature review. Section "Theoretical analysis" details the impact mechanisms. Section "Method and data sources" describes the empirical strategies and variables. Section "Results and discussion" provides the empirical results and discusses the impact mechanisms. Section "Robustness tests" validates the robustness of the research design. Section

"Additional analyses" introduces additional analyses. The final section draws conclusions and policy implications.

Literature review

Influencing factors of GIE. As a key indicator of sustainable development, GIE receives increasing attention in the literature. GI considers the dual benefits of economic growth and environmental protection, with dual externalities of green and innovation, which are among the most prominent indicators for measuring regions' sustainable development capabilities (Zhang et al. 2021). GIE is an evaluation of GI efficacy that reflects the input-output ratio of innovation activities, including the consideration of environmental constraints or the comprehensive benefits of GI results. Existing literature discusses the factors that affect GIE from multiple perspectives. Environmental regulation is considered to be a key factor affecting GIE. Fan et al. (2021) reveal a positive U-shaped relationship between environmental regulation and urban GIE, indicating that appropriate environmental regulation policies can effectively stimulate GI activities. In addition, the role of internet development and digital technology in promoting GIE is also confirmed by Wang et al. (2022), who find that the internet indirectly improves cities' GI performance by promoting service industry agglomeration and financial development and reducing resource dependence. The impact of foreign direct investment (FDI) on GIE is more complex. Song and Han (2022) note that FDI has positive and negative effects on GIE, but its positive effect is dominant overall. Financial development also has a positive impact on GIE. Dong et al. (2023) confirms that social and cultural factors such as the number of books in public libraries have a significant impact on urban GIE. Although previous research examines the influencing factors of GIE at many levels, investigations concerning how DI affects GIE, particularly at regional levels, remain insufficient. For instance, DI may affect GI by promoting IA centralization and diversification. This is an important consideration worth investigating to explore the mechanisms, effects, and differences in various regions and cities.

Impact of DI on economic development. As the key carrier of information dissemination and the core of digital economy support (Hong et al. 2023), the impact of DI on economic development attracts extensive research attention. Early studies assess the direct contribution of DI to economic growth. Most studies affirm the positive role of DI in economic development, and assert that DI can compress the space–time distance between supply and demand sides, improve knowledge transmission speed, reduce information asymmetry, improve the efficiency of resource allocation and produce positive spillover effects (Röller and Waverman, 2001; Oliver, 2019; Dong et al. 2022). Czernich et al. (2011) reveal the positive correlation between broadband infrastructure penetration and economic growth, analyzing member countries of the Organization for Economic Cooperation and Development, finding that the growth rate of per capita GDP increased by 0.9%–1.5% for every 10% increase in broadband penetration. Castaldo et al. (2018) further confirm this finding, emphasizing a positive correlation between broadband diffusion and economic growth in the short, medium, and long term. Sánchez-Bayón (2022) utilizes heterodox review methods, analyses digital transformation promotes the development of high-end labor and creates new job opportunities by heterodox review methods. In contrast, some studies find that the promotional effect of informatization on productivity growth is extremely minimal (Acemoglu et al. 2014), and the impact of information and communications technology (ICT) on developed countries' economic growth has a short-term positive impact, but may transition into a negative impact in the long term (Raheem et al. 2020). With the deepening of research, the impact of DI on environmental sustainability is a popular research topic. Amid the increasing challenges of global climate change, scholars also explore the potential of DI for promoting green development. Tang et al. (2022) employs a quasi-natural experimental method to explore the impact of telecommunications infrastructure on urban ecological efficiency in China, finding that it improves ecological efficiency by promoting GI and technology spillover effects. Hong et al. (2023) examines the impact of the Broadband China policy on urban energy intensity from the perspective of climate change, claiming that the policy significantly reduced cities' energy consumption intensity. This provides a new perspective for coping with climate change. Li et al. (2024), Pan and Yang (2024) further explore the impact of DI on green innovation and green resource allocation. Li et al. (2024) systematically explores the impact and spatiotemporal dynamic effects of DI on urban green innovation, which talent agglomeration, increased R&D investment, and industrial structure upgrading play significant roles in this process. Pan and Yang (2024) emphasize non-linear impact of DI on the efficiency of green resource allocation in the service industry. Overall, DI has complex and diverse impacts on economic development. The current relevant research demonstrates the enormous potential of DI for promoting environmental sustainability and improving ecological efficiency.

Impact of DI on innovation. The broad application of the internet can accelerate information dissemination. The continuous accumulation of social human capital in the process of information dissemination ultimately promotes innovation activities and the adoption of innovative technologies (Czernich et al. 2011; Audretsch et al. 2015). Koutroumpis (2009) estimates the impact of broadband investment on economic growth from the perspective of macroeconomic production using a structural econometrics model. The results reveal that broadband penetration has a significant positive effect on economic growth after reaching a certain critical quality. This finding provides an important perspective for understanding how the internet can accelerate technological innovation by promoting information flow and knowledge sharing. Paunov and Rollo (2016) focus on the role of the internet in promoting inclusive innovation in developing countries. The authors assert that the use of the internet can strengthen knowledge spillover effects and improve enterprises' average productivity and innovation performance. Zhang and Wang (2019) reveal the core role of ICT in the difference of innovation efficiency between developed and emerging countries through comparative research, emphasizing the importance of rapid ICT development in improving innovation efficiency. Tang et al. (2021) and Wang et al. (2022) examine the role of the internet in green technology innovation. Tang et al. (2021) uses the Broadband China pilot policy as a quasi-natural experiment of telecom infrastructure, applying a difference-in-differences model on data at the enterprise level to evaluate its impact on enterprises' green technology innovation. The research confirms that telecom infrastructure can significantly promote green technology innovation by improving informatization, increasing media attention, and improving corporate governance. Wang et al. (2022) evaluate urban GI efficiency using the super-efficiency epsilon-based measure (EBM) model including unexpected output, and find that internet development can advance urban GI efficiency by promoting productive services agglomeration, driving financial development, and reducing resource dependence.

In summary, DI affects innovation efficiency by promoting information flow and knowledge sharing, strengthening knowledge spillovers, improving informatization and media attention, improving corporate governance, and promoting IA. These empirical studies not only reveal the positive effect of DI on innovation, but also provide a strong scientific basis for policymaking.

Although previous studies thoroughly examine the economic performance of DI, the research on GIE spillover effects and the impact of regional GIE remains in its infancy. Therefore, an in-depth investigation of the impact of DI on regional GIE and its mechanisms from a regional spatial perspective is crucial for understanding the potential of DI in promoting sustainable development.

Theoretical analysis

Direct effect of DI on GIE. The Solow model and endogenous growth theory both assert that technological innovation has a significant role in economic growth (Solow, 1987; Romer, 1990). As an important carrier of information transmission, DI promotes the generation and dissemination of technology by improving information transmission efficiency (Hayek, 1945), which reduces factor transmission costs, expands the flow boundary of factors, and strengthens factors' overflow depth (Raghupathi et al. 2014). By promoting factors' cross-temporal and spatial flow and cross-border integration, DI improves resource allocation efficiency, promotes the production and impact of innovative thinking, produces coordinated innovation, and improves regional GIE (Fang et al. 2022) by strengthening knowledge spillover and competition effects. DI can reduce the cost of production factor flow between enterprises and regions (Bernard et al. 2019), enhance coordination and cooperation and resource sharing to expand the knowledge spillovers, and promote technological innovation. It can also change the forms of cooperation and competition, strengthen competitive relationships, encourage enterprises to conduct technological innovation through the competitive effect (Tang et al. 2021). DI also facilitates the elimination of inefficient enterprises in the market and improves GIE in an entire region (Paunov and Rollo, 2016). In addition, the interconnection characteristics of DI can effectively reduce information asymmetry in the market and reduce the transaction costs for innovation activities (Tian and Lu, 2023). The information technology development generated by DI can effectively improve energy efficiency (Niebel, 2018; Lahouel et al. 2021), reduce energy consumption, and ultimately promote GIE.

H1: DI significantly promotes GIE in the region.

Indirect effect of DI on GIE. Unlike other infrastructure, DI has network externalities that break the restrictions of spatial distance, reduce transaction costs, and realize regional division and cooperation (Bressand, 1996). The externalities also strengthen the diffusion of environmental protection knowledge and technology between regions, with a radiation effect on green technology innovation in adjacent regions (Wang et al. 2022). However, the levels of DI between cities may not be balanced, resulting in a digital divide that can produce a siphon effect, promoting the central city's attraction of talent and capital from neighboring regions, affecting surrounding cities' GIE, and hindering collaborative innovation between regions. Due to the complex competition and cooperation between regions and enterprises, enterprises may not disclose their core technologies, only choosing to spread fewer complex technologies outward, which may lead to low complexity in the technology transmitted to other regions through the radiation effect (Tang et al. 2021). In addition, the development of DI in a region may also increase the complexity and entry threshold of green technology, making it difficult to effectively promote GIE in adjacent regions due to a lack of key technologies. Moreover, DI has the attribute of a public good, which may lead to free riding (Kleer, 2010). Surrounding cities in the urban agglomeration may rely on the digital public goods provided by central cities, reducing capital investment in DI. Therefore, the impact of DI on GIE in adjacent regions may exhibit a restraining effect due to the reallocation of resources and intensified market competition.

H2: DI inhibits GIE in neighboring regions.

Mechanism of IA. DI enhances the spatial carrying capacity of the city by improving the management level and operation efficiency of the city (Dong et al. 2022) that create conditions for IA. The development of the internet can break the barriers of factor flow in the market and promote production factor agglomeration in regions with more sophisticated network facilities (Arenius et al. 2005). Therefore, DI can attract the landing and agglomeration of high-tech industries. IA increases horizontal and vertical coupling between industries. The increased exchange and cooperation between enterprises expand the knowledge spillover effect and influence the economies of scale (Li et al. 2021), which improves innovation efficiency and the spread of green technology in the region. The scale agglomeration effect formed by IA can optimize the social division of labor in the region, improve the efficiency of resource allocation, reduce energy consumption, improve enterprises' production efficiency, reduce the factor input required by unit innovation output, and ultimately reduce the cost of innovation (Wang et al. 2022). In addition, the IA brought by well-developed DI can usually make innovation resources such as talent, capital, technology, and other relevant needs converge rapidly. This factor agglomeration effect provides factor support that improves the positive externalities of regional green technology innovation. The flow and agglomeration of talent between different enterprises improve GIE in the entire city by intensifying competition and promoting innovation and technology diffusion across the industrial chain (Wang and Zhang, 2016). Capital agglomeration improves capital allocation efficiency and the scale of financial supply and demand, providing additional support and guarantee for enterprises' green technology innovation. The agglomeration of technological elements and their wide spread across different enterprises drive continuous change of the industrial production mode and promote the new technological generation (Dong et al. 2022). However, DI development has intensified the siphon effect, attracting high-end elements to regions with better DI. This leads to unbalanced IA between regions. Due to the loss of talent, capital, and technology in adjacent areas, the driving effect of IA may not be brought into play in the short term, resulting in insufficient R&D for new technologies, poor knowledge flow and inadequate innovation resources (Chen and Wang, 2022), thus reducing GIE in neighboring regions. This study argues that DI predominantly affects regional GIE through industrial concentration and diversification.

Industrial concentration (IC). IC can continuously expand the number and scale of enterprises in related industries in a region, forming a scale effect, and accelerating the diffusion of knowledge and the formation of specialized markets (Yu et al. 2020). DI provides enterprises with efficient information exchange platforms and data processing capabilities. This enables enterprises to collaborate and share resources more effectively, which accelerates R&D and green technology applications (Huang et al. 2020). A large number of enterprises, research institutions, and professionals in the agglomeration area interact and develop a rapid knowledge flow and learning

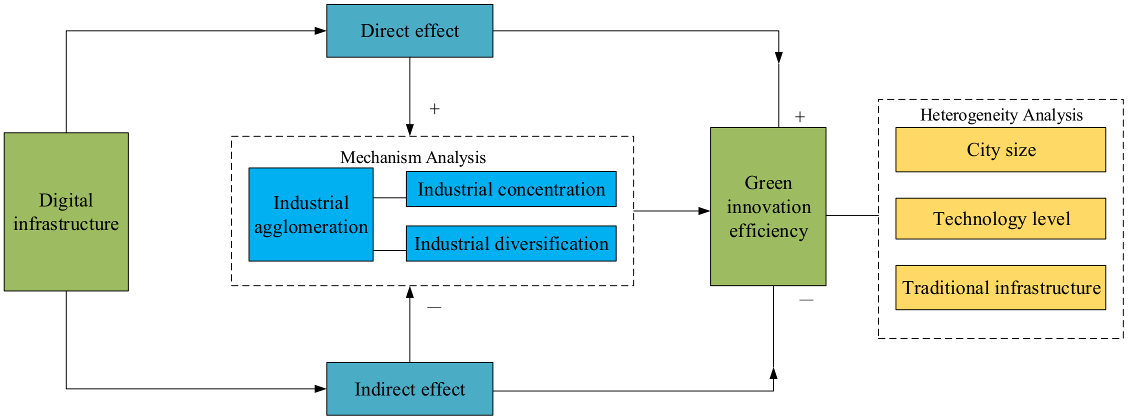

Fig. 1 Flow chart of the study's framework and mechanisms.

network, promoting the rapid spread of green technology (Tang et al. 2021). At the same time, IC advances the division of labor, reduces the crowding out effect of transaction costs on GI, and improves the efficiency of resource allocation (Dong et al. 2022), allowing enterprises to obtain the required resources for accelerating innovation. For neighboring regions, the scale effect of IC can promote knowledge and technology dissemination and drive surrounding regions' innovation and development by strengthening regional cooperation (Arthur, 2007). Conversely, the scale effect may lead to the loss of resources and talent in adjacent areas, and the strong attraction of concentrated areas may result in the flow of various resources from adjacent areas to the region, weakening adjacent areas' GIE.

Industrial diversification (ID). ID can increase the number and types of enterprises in different industries in a region, establish a diversified competitive environment, which stimulates competition effects and promotes the integration and innovation of cross domain knowledge and technology (Wang et al. 2022). DI constructs platforms for mutual understanding and cooperation between enterprises in different industries. The interaction of diversified enterprises inspires novel innovative thinking and business models and increases enterprises' innovation power and competitive consciousness. To maintain advantages amid fierce market competition, enterprises will continue to seek innovation breakthroughs (Paunov and Rollo, 2016). The interaction between enterprises in different fields also promotes the transfer of cross domain knowledge and technology. The competitive pressure and knowledge intersections generated by ID promote GIE in the region, and can promote GIE in adjacent areas, with demonstration and catch-up effects between regions (Smith and Telang, 2009). On the one hand, it enables adjacent areas to imitate and learn advanced GI technology and management experience, so as to improve their GI ability. On the other hand, adjacent areas may be blocked by higher GI technology thresholds due to DI (Dong et al. 2022). Facing market congestion effect and innovation rent seeking caused by the agglomeration area, GIE could be weakened.

H3.1: DI improves regional GIE by enhancing the regional IC and ID of IA.

H3.2: DI reduces regional GIE by inhibiting IC and ID of IA in adjacent areas Fig. 1.

Method and data sources

Model design

Spatial econometric model. DI and regional GIE have strong spatial correlation (Hu et al. 2023; Song et al. 2018; Li and Du, 2021). Should this study neglect this inherent spatial spillover effect, it would produce biased empirical result. Hence, the model employs a spatial panel model. Spatial econometric models are valuable tools for analyzing spatial spillovers, and primarily include the spatial autoregressive model (SAR), the spatial autocorrelation model (SAC), the spatial error model (SEM), and the SDM (LeSage and Pace, 2009; Anselin, 2013). Spatial correlations may arise from the dependent variable, the explanatory variable, or the error term. The SDM effectively captures the spatial correlation from various sources (Elhorst, 2014). LeSage and Pace (2009) conduct a comparison of the four models above, assuming that the original data adhered to the data generation process of SAR, SEM, SDM, and SAC, respectively. The authors examine the estimation results that may have been caused by potential model errors, determining that the SDM model is the only model that can obtain unbiased estimations. According to the purpose of this study and the hypotheses in Section "Theoretical analysis", this study constructs the following SDM panel approach:

$$GIE_{it} = \alpha + \varphi \sum_{j=1}^{n} w_{ij} GIE_{jt} + \beta DI_{it} + \rho \sum_{j=1}^{n} w_{ij} DI_{jt} + \gamma X_{it} + \theta \sum_{j=1}^{n} w_{ij} X_{jt} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

$$\varepsilon_{it} = \varphi \sum_{j=1}^{n} w_{ij} \varepsilon_{it} + \mu_{it}, \mu \sim N(0, \sigma_{it}^2) \tag{2}$$

where GIE denotes the regional GIE, DI represents the regional DI index, X represents control variables, α is a constant term, ε is a random error, i represents the prefecture-level region, t pertains to the year, μ_i and λ_t refer to regional and time fixed effects, w_{ij} denotes a spatial weight matrix, φ is the spatial regression coefficient. β, ρ, γ and θ are the coefficient to be estimated.

Selection of spatial distance matrix. A spatial weight matrix is used to quantify the spatial adjacency of locations to reveal spatial interaction effects. Constructing a suitable spatial weight matrix can describe the degree of correlation between spatial units. Due to the large number of prefecture-level cities in China, simply determining whether the cities are adjacent may result in a loss of valuable information. There may be deviations in measuring the spatial correlations between regions by any distance standard (geographical distance, economic distance). Therefore, referencing Parent and LeSage (2008), this study adopts the nested matrix of geographical and economic distance (WW), which considers the spatial impact of geographical distance and simultaneously reflects the regional spillover and radiation effects of economic factors. This spatial weight matrix reflects the spatial correlation degree between regions more comprehensively and objectively, and its specific form is as follow:

$$Ww = \varphi Wd + (1-\varphi)We \tag{3}$$

$$Wd = \frac{1}{d_{ij}^2}, We = \frac{1}{|g_j - g_i|} \tag{4}$$

where Wd is the reciprocal square of the distance between the longitude and latitude of regions i and j, and We represents the reciprocal of the absolute value of the difference in per capita GDP between regions i and j. This φ value is set at 0.5.

Mediating effect model. To investigate the transmission mechanisms of potential mediating variables on the impact of DI on regional GIE, referencing Dell (2010), this study employs the following two-step method to establish a mediating effect model:

$$\begin{aligned} lMech_{it} = {} & \alpha_1 + \varphi_1 \sum_{j=1}^{n} w_{ij} Mech_{jt} + \beta_1 DI_{it} + \rho_1 \sum_{j=1}^{n} w_{ij} DI_{jt} \\ & + \gamma_1 X_{it} + \theta_1 \sum_{j=1}^{n} w_{ij} X_{jt} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{5}$$

where $Mech_{i,t}$ represents a series of intermediate variables, and other symbols are consistent with Eq. (1).

Variable interpretation

Dependent variable. Regional GIE is the explanatory variable of this study. According to the assumption of constant return to scale, referencing Wang et al. (2022), this study uses the undesirable super-efficiency EBM model to assess regional GIE. The undesirable super-efficiency EBM model is constructed as follows:

$$\rho = \min \frac{\phi - \varepsilon^- \sum_{m=1}^{M} w_m^- s_m^- / x_{k,m}}{\theta + \varepsilon^+ (\sum_{j=1}^{J} w_j^+ s_j^+ / y_{k,j} + \sum_{p=1}^{P} w_p^{u-} s_p^{u-} / u_{k,p})} \tag{6}$$

$$s.t. \begin{cases} \sum\limits_{n=1, n\neq k}^{N} x_{n,m}^t \lambda_n^t + s_m^- \leq \phi x_{k,m} \\ \sum\limits_{n=1, n\neq k}^{N} y_{n,j}^t \lambda_n^t + s_j^- \leq \theta y_{k,j} \\ \sum\limits_{n=1, n\neq k}^{N} u_{n,p}^t \lambda_n^t + s_p^- \leq \theta u_{k,p} \\ \lambda \geq 0, s_m^- \geq 0, s_p^+ \geq 0 \end{cases} \tag{7}$$

where ρ refers to the GIE of the area being assessed; x_m, y_j, and u_p denote the input, desirable output and undesirable output, respectively; w_m^-, w_j^+, and w_p^{u-} denote the weights of the input, desirable output, and undesirable output, respectively; s_m^-, s_j^+, and s_p^{u-} denote the slacks of the input, expected output, and unexpected output, respectively. Parameters ϕ and θ denote the radial components. Additionally, ε is a key parameter reflecting the combination of radial and nonradial relaxation, and its value is between 0 and 1. When ε's value is 0, the model is equivalent to the radial model, and when its value is 1, the model will degenerate into a nonradial SBM model. Considering data availability, the input and output variables for calculating regional GIE are defined as follows:

The input variable includes labor, capital, and energy, which are measured by the total number of regional R&D personnel (people), internal regional R&D expenditure (10,000 yuan), and regional power consumption (10,000 kwh), respectively. Expected output includes economic, green technology innovation, and ecological income outputs, which are measured by actual urban GDP (10,000 yuan), the number of regional GI patent applications (pieces), and the green space coverage rate of urban built-up areas (%), respectively. Actual urban GDP is measured by the constant price in 2013. For unexpected output, this study uses the entropy weight method to calculate the comprehensive pollutant emissions index, which is respectively expressed by the emissions of urban industrial wastewater (tons), urban industrial waste gas (tons), and urban solid waste (tons). To ensure that the conclusions are robust and credible, the robustness test uses the ratio of total number of green invention patent applications and urban government scientific research expenditure to construct replacement indicators.

Core explanatory variables. DI is the core explanatory variable of this study. Some controversies concerning the measurement of DI still remain in existing studies, and the Broadband China policy pilot is predominantly used as an indicator to measure DI (Ma and Lin, 2023). However, DI is a comprehensive, multi-dimensional concept. In view of this, referencing Tang and Yang (2023), this study constructs a comprehensive DI index, using three dimensions of information development (measured by optical cable and mobile phone base station density), internet development indicators (measured by traditional internet penetration, mobile internet penetration, the number of internet broadband access ports, and number of IPv4 addresses), and digital transaction development indicators (measured by the number of websites per 100 enterprises). These measures are then integrated into the comprehensive DI index using an entropy weight method. Due to data limitations in the China Urban Statistical Yearbook, the majority of previous research uses indicators such as the number of internet users per capita and the volume of post and telecommunications services as proxy variables to measure DI at the urban level. Although these are directly related to cities' supply of DI, they are more affected by consumers' communication demand. In contrast, this study uses the above indicators to build a comprehensive DI index to quantify DI at the city level to identify the impact of exogenous changes in the supply of urban DI on the efficiency of regional GIE more accurately. Because the supply side DI data are only reported at the provincial level, this study references Bartik (1991), calculating the weight index of the number of urban internet users as an exogenous weight, and decomposing the level of DI at the provincial level to the urban level as follows:

$$DI_{it} = weight_{ij} infras_{pt} \tag{8}$$

where *weight* is the proportion of the number of internet users in each city in the province, and $infras_{pt}$ is the DI index in each province.

Control variables. To accurately capture the net impact of DI on regional GIE, this study introduces the following series of control variables into the regression model based on relevant research.

Human resources (HR): Education provides the HR required for advancing national innovation, and regions with high HR are able to attract high-tech enterprises (Zhang et al. 2020). This variable is measured by the number of students in colleges and universities per million people.

Openness degree (OPEN): The advanced production equipment, technology, and management experience of foreign enterprises have spillover effects, which may improve local GI efficiency; however, the pollution paradise hypothesis contends that excessive OPEN will inhibit GIE (Hao et al. 2023). This variable is measured by the ratio of total imports and exports to GDP.

Table 1 Descriptive statistics.

VARIABLES	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max	(6) P25	(7) P50	(8) P75
GIE	2,248	0.606	0.202	0.091	1.196	0.462	0.577	0.721
DI	2,248	0.072	0.106	0.008	0.822	0.028	0.038	0.055
HR	2,248	32.83	29.66	1.292	265.9	14.59	24.41	39.16
OPEN	2,248	0.254	0.787	0	17.18	0.029	0.090	0.220
FF	2,248	0.453	0.218	0.070	1.541	0.279	0.418	0.603
IS	2,248	0.448	0.104	0.107	0.794	0.386	0.456	0.515
PD	2,248	5.75	0.954	1.371	7.966	5.228	5.902	6.478
GDP	2,248	10.81	0.54	9.219	13.06	10.41	10.78	11.16
GS	2,248	13.33	0.814	10.36	16.57	12.82	13.31	13.77

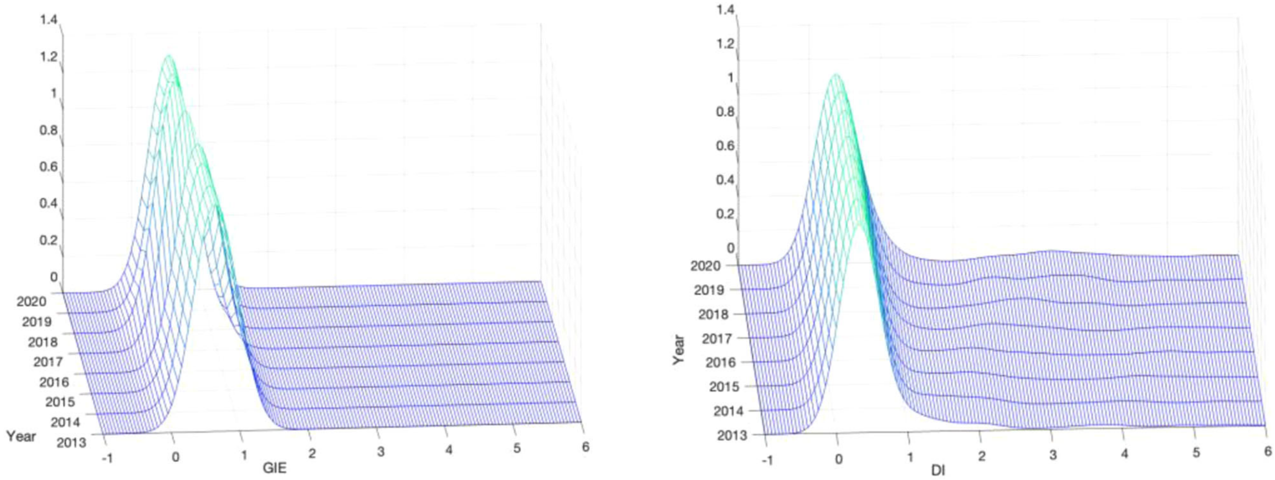

Fig. 2 Dynamic evolution of DI and GIE (2013–2020).

Fiscal freedom (FF): A higher degree of government FF indicates higher talent accumulation and capital investment, which can increase GIE (Lin and Ma, 2022). This variable is measured by the ratio of regional general public budget revenue to regional general public expenditure.

Industrial structure (IS): Industrial structure differences can objectively reflect variations in resource endowment, input factors, and other conditions at the city level. This difference may generate different degrees of difficulty and choices for entrepreneurship in different cities, which will affect cities' GIE (Zhang et al. 2023). This variable is measured by the proportion of the city's added value by the secondary industry.

Population density (PD): Overly high PD may produce increased environmental pollution, which reduces regional GIE. This variable is measured using the logarithm of urban per capita land use area.

Degree of economic development (GDP): Economic growth may stimulate the improvement of GIE (Zeng et al. 2021; Dian et al. 2024). This variable is measured by the logarithm of per capita GDP.

Government support (GS): GS for enterprise R&D funds and market economy intervention can mitigate the externalities of technological innovation activities and reduce the R&D risks associated with GI (Zhu et al. 2021). This variable is measured by the logarithm of government expenditure on science and education.

Data description. Given data availability and accessibility, this study uses balanced panel data of 281 prefecture-level cities in China from 2013 to 2020. This study obtains the patent grant data of GIE from the State Intellectual Property Office of China. The regional GDP index is from the China Statistical Yearbook (2013–2020). The DI indicators' data are from the China Provincial Statistical Yearbook (2013–2020). Other indicators come from the city wide data in the statistical yearbook of Chinese cities (2013–2020). In addition, missing data for individual samples are obtained from the statistical yearbook of each prefecture-level city, statistical bulletins, official websites, the WIND database, or supplemented using interpolation. The descriptive statistics of all variables are presented in Table 1. As noted in the descriptions above, certain variables are transformed into natural logarithms to reduce heterogeneous randomness.

Using the nonparametric kernel density estimation equation and MATLAB software, this study determines the kernel density curve of China's urban DI level and GI efficiency from 2013 to 2020 (Fig. 2). The nuclear density analysis can describe the dynamic evolution of China's regional DI and GIE. Four notable findings emerge from this analysis. (1) From the position of the main peak, in terms of DI, the focus has been moving to the right from 2013 to 2020, indicating that regional DI in China increased during the study period. In terms of GIE, the focus shifted slightly to the right from 2013 to 2020, indicating regional GIE improvement. (2) Examining the shape of the main peak, the prominent peak of the curve exhibits a rising trend, revealing that the absolute differences in DI and GIE between regions are narrowing. This indicates that the height of the main peak continues to rise, and the width is gradually shrinking, showing that DI and GIE have improved to some extent. (3) From the perspective of distribution extensibility, a right tailing phenomenon is revealed in the construction of DI and GIE, revealing a gap within the region based on large regional development differences, including regions with high DI and regions with high GIE. Furthermore, the two distribution curve reveal a broadening convergence trend, indicating that although differences in regional DI and GIE are evident, the absolute difference has a narrowing trend. (4) From the perspective of polarization, no obvious polarization phenomenon in DI and GIE is apparent, with no gradient effect between them. DI construction is the core support for advancing regional digital and green development.

Results and discussion

SDM results. The Moran's index (Moran's I) scatter diagram and spatial correlation test (Appendix Tables A.1 and A.2 and Fig. A.1) confirm the presence of significant spatial correlation in China's regional GIE. Estimation results obtained from the ordinary least squares (OLS) model may deviate from this empirical evidence. Thus, it is appropriate to incorporate the spatial econometric model into this study. In addition, because no continuous and dynamic process occurs in regional GIE, this study uses the static spatial econometric model to explore the impact of DI on regional GIE. In view of this, the study determines the suitable regression model for this study using a series of tests, employing Lagrange multiplier (LM), likelihood ratio (LR), Hausman, and Wald tests in Eq. (1) to determine the specific estimation form of the spatial econometric model. First, the study obtains the LM test and its robust statistic (R-LM) using OLS estimation without spatial effects, then tests the choice between SAR or SEM. Second, if the LM test indicates that the panel econometric model incorporates spatial effects, as suggested by Elhorst (2014), the SDM model with greater overall significance can be directly employed for spatial econometric estimation. Third, the study employs the LR test method to examine the SDM fixed effect to ascertain whether it incorporates spatial (SFE) or time (TFE) fixed effects. Fourth, the study employs the Hausman test to assess the SDM's fixed and random effects. Fifth, the study applies Wald or LR tests to the SDM to determine whether it should be transformed into SAR or SEM models. The test results in Table 2 indicate that the SDM model with double fixed effects is the most suitable approach for spatial econometric estimation in this study. Therefore, based on the test results, the study applies the static SDM model as the benchmark regression model to estimate the impact of DI on regional GIE. The estimated results are presented in Table 2. To compare the regression outcomes, we employed the double fixed effect panel model and the static SDM model, respectively.

Table 2 reveals that the estimated coefficient of DI in the GIE equation is 0.367, which is significantly positive at the 1% level. This indicates that DI has significantly promoted local GIE, verifying H1. Furthermore, the spatial correlation coefficient of WDI is −2.881, which is significantly negative at the 1% level, indicating that DI has a significant spatial spillover effect that inhibits GIE in adjacent regions. This verifies H2. A possible rationale for this negative effect is that DI promotes resource integration and knowledge sharing among various institutions and enterprises, enhances R&D for environmentally friendly technologies, and reduces transaction costs through data sharing and collaboration platforms, thereby effectively promoting regional GIE (Sun et al. 2023; Lu and Wang, 2023). This exerts a siphon effect in the construction and development of DI, absorbing adjacent cities' human capital and high-end elements of resource. Therefore, DI exhibits a significant negative spatial spillover effect on GIE in adjacent cities. In contrast, the first law of geography indicates a tendency toward spatial correlation between neighboring regions (Anselin, 2013). The contemporarily thriving digital economy drives improvements in the quality, efficiency, and dynamic evolution of regional economic development. However, it is also exacerbating disparities in regional resource allocation, which intensifies the siphon effect and reduces GIE in adjacent areas.

Table 2 Benchmark regression.

Variables	GIE	
	OLS model	Static SDM model
DI	0.246***	0.367***
	(2.58)	(4.48)
WDI		−2.881**
		(−2.52)
HR	0.000	0.001
	(0.50)	(0.81)
OPEN	−0.006	0.001
	(−0.98)	(0.26)
FF	0.158***	−0.069
	(3.34)	(−1.53)
IS	0.225***	−0.171**
	(3.74)	(−2.39)
PD	0.006	−0.042***
	(0.33)	(−2.59)
GDP	−0.073***	0.121***
	(−4.12)	(5.68)
GS	−0.081***	0.044**
	(−3.96)	(2.20)
Constant	2.246***	
	(9.74)	
ρ		0.565***
		(5.76)
Wald		56.850**
		[0.000]
Hausman	172.010***	89.040***
	[0.000]	[0.000]
LM-Lag		10.179***
		[0.001]
Robust LM-Lag		103.780***
		[0.000]
LM-Error		52.061***
		[0.000]
Robust LM-Error		145.662***
		[0.000]
LR-SDM-SAR		71.890***
		[0.000]
LR-SDM-SEM		60.690***
		[0.001]
LR-both-time		2804.05***
		[0.000]
LR-both-ind		26.440**
		[0.001]
City fixed effects	YES	YES
Year fixed effects	YES	YES
N	2248	2248
R^2	0.114	0.157

*** and ** indicate significance at 1% and 5% levels, respectively. Figures in parentheses are z-values. Figures in brackets are the p-values.

At the same time, GI may have externalities such as the free riding behavior of GI. When the income from GI R&D of enterprises in adjacent areas is lower than that from R&D for other technological innovation, enterprises prefer to allocate investment in other technological innovation R&D, resulting in the decline of GIE.

In the control variables, the coefficients of IS and PD are significantly negative, indicating that a high proportion of the secondary industry and high population density are correlated with the reduced GIE. The coefficients of GDP and GS are significantly positive, indicating that GDP and GS promote regional GIE. In addition, the coefficients of HR, OPEN, and FF are not significant, revealing that these control variables represent long-term processes, and may not have significant short-term impacts on regional GIE. In the future, it will be necessary to normalize and improve the relevant influencing factors to provide corresponding support for green technology innovation.

SDM decomposition. To further explore the internal impact mechanism of DI on regional GIE, based on the SDM estimations, this study references LeSage and Pace (2009), using variable variation partial differential to decompose impact into short- and long-term direct and indirect impacts. The direct impact refers to the impact of DI on regional GIE, while the indirect impact indicates spatial spillover effects, which reflects the impact of DI in the region on GIE in adjacent regions. Table 3 presents the decomposition results, revealing that DI has significantly promoted GIE, demonstrating that regional DI can improve the local GIE through knowledge spillover and economies of scale effects (Czernich et al. 2011). The spatial spillover effect of DI is significantly negative, indicating that regions' DI hinders the GIE of adjacent regions. The rationale for this may be that the DI exacerbates the depression effect. DI expands the broadband network coverage, improves information network service quality, and further attracts high-tech enterprises and R&D talents, which promotes the regions' GIE but crowds out information and innovation resources in other regions with similar economic development. In the short term, the construction of digital technology facilities has a strong influence on promoting local GIE. In the long run, DI has a strong negative effect on adjacent areas' GIE, which is consistent with the benchmark regression results.

Table 3 Decomposition effects.

Variables	GIE			
	Short term		Long term	
	Direct	Indirect	Direct	Indirect
	(1)	(2)	(3)	(4)
DI	0.367*** (4.48)	−2.881** (−2.52)	0.344*** (3.94)	−6.454* (−1.84)
Control Variables	YES	YES	YES	YES
ρ	0.565*** (5.76)			
City fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
N	2248	2248	2248	2248
R^2	0.157	0.157	0.157	0.157

***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. Figures in parentheses are z-values.

Transmission mechanism. With the continuous improvement of DI, the barriers of time and space that hinder the flow of market resources will continue to be dismantled, facilitating the efficient circulation of GI factors. IA is a major theoretical basis of new economic geography, which contends that due to increasing returns to scale, even if two regions are extremely similar in terms of natural conditions, some accidental factors may lead to superior IA in only one region. IA promotes GIE through sharing, matching, and learning. From the perspective of IA, the impact of IA on regional innovation can be divided into two aspects. On one hand, the IC of a single industry within a region can facilitate technology spillover and the sharing of capital and labor. Thereby it enhances regional innovation efficiency (Marshall, 1920; Romer, 1990). On the other hand, the agglomeration of different industries within a region fosters knowledge spillover and technological externalities, which contribute to the complementarity of knowledge and cross-integration of technologies between industries. Ultimately, it increases regional innovation efficiency (Glaeser et al. 1992; Li, 2015). Therefore, IC and ID contribute to enhance GIE. As described previously, referencing Acemoglu et al. (2010), this study divides IA into IC and ID to examine the mechanism of IA on the impact of DI on regional GIE. IC is expressed by the local economy, meaning that enterprises can benefit from the economic activities of local enterprises in a given region in the same industry, promoting the agglomeration of the same industry and growth of the industry in this region. ID is expressed using Porter externality. Enterprises can benefit from diversification, and spillovers primarily come from enterprises in different industries, rather than enterprises in the same industry. Furthermore, the complementarity of different industrial clusters contributes to the integration and spillover of knowledge innovation (Qin et al. 2023). Their functional relationships are obtained as follows:

Table 4 Mediating effect models.

Variables	Mediating effect	
	IC	ID
DI	1.366*** (2.75)	0.700*** (4.07)
WDI	−5.695** (−2.21)	−2.269** (−2.36)
Control Variables	YES	YES
ρ	0.549*** (4.72)	0.647*** (7.21)
N	2248	2248
R^2	0.010	0.177

*** and ** indicate significance at 1% and 5% levels, respectively. Figures in parentheses are z-values.

$$IC = \frac{g_i/Y_i}{\sum_i g_i/\sum_i Y_i} \tag{9}$$

$$ID = \frac{N_i/g_i}{\sum_i N_i/\sum_i g_i} \tag{10}$$

where g_i represents the industrial added value of city i, N_i represents the number of enterprises in city i, and Y_i represents the GDP of city i. A higher IC value indicates a greater concentration of regional industries, which is more conducive to knowledge spillover. This phenomenon indicates a higher degree of industry clustering in regions with a higher IC value. A higher ID value indicates a greater level of regional industrial diversification, which promotes technological innovation.

This study's theoretical analysis illustrates that DI's technology spillover and economies of scale effects improve regional IA and GIE. DI's siphon effect inhibits adjacent areas' IA and GIE. To test this mechanism, this study examines the IC and ID of IA, constructing a two-step spatial mediating model for regression, presenting the results in Table 4. The findings reveal that DI

Table 5 Robustness tests.

Variables	GIE				
	Geographical distance matrix	Adjacency weight matrix	Replacement of dependent variables	Replacing independent variables	Excluding municipalities directly under the central government
	(1)	(2)	(3)	(4)	(5)
DI	0.364***	0.410***	0.187***	0.339**	0.212**
	(4.37)	(5.02)	(4.09)	(1.99)	(2.40)
WDI	−2.841**	−0.391**	−0.594**	−7.175***	−2.619**
	(−2.55)	(−2.23)	(−2.34)	(−3.02)	(−2.13)
Control Variables	YES	YES	YES	YES	YES
ρ	0.587***	0.223***	0.659***	0.501***	0.573***
	(5.81)	(8.22)	(7.26)	(4.80)	(5.82)
N	2248	2248	2248	2248	2248
R^2	0.035	0.001	0.297	0.027	0.165

*** and ** indicate significance at 1% and 5% levels, respectively. Figures in parentheses are z-values.

significantly promotes regions' IC and ID and significantly reduces IC and ID in adjacent regions, verifying H3.1 and H3.2. These results explain that DI establishes the material foundation, technical support and talent agglomeration for the transmission and transfer of information and data elements (Li et al. 2024). It creates accommodating conditions for the transformation and agglomeration of industries in the region that increase local IC and ID. IA promotes interindustry technical assistance, facilitates information sharing, and supports the establishment of branches. Through technology and knowledge spillovers, it strengthens enterprises' specialization, improves labor productivity, and reduces production and operation costs (Lu and Wang, 2023), which contributes to stimulating urban GI vitality and urban GIE.

Enterprises within the agglomerated cluster area have a spatial spillover effect on surrounding areas, promoting industrial development in adjacent areas and contributing to GIE improvement in surrounding areas. As financial resources accumulate in a specific geographic area, market congestion is likely to occur, increasing the cost of labor, capital, and other production factors within the agglomeration area, subsequently raising enterprises' overall production costs in the region (Alfaro et al. 2019). In response to such cost pressures, enterprises will gradually relocate production plants to surrounding areas with relatively lower prices, which enhances GI in these areas. The region where the factory was initially located absorbs advanced technology and high-quality production factors from other areas, and actively engages in technological reinnovation to improve local GIE (Hu et al. 2023b). However, DI will exacerbate the market effect within the region and intensify the competition effect between regions caused by IA. The DI in a particular region may lead to the acquisition of production factors from surrounding regions at lower cost, creating a seizing effect that diminishes adjacent regions' IA and reduces GIE. The weakening of IA in adjacent regions may lead to "innovation rent-seeking" behavior, triggering regional innovation inertia. Due to the scarcity of production factors causing the cost of self-research and development for enterprises to be higher than the cost of introduction. Enterprises will directly import innovative achievements from other areas with IA, thereby reducing the overall GIE in adjacent regions.

Robustness tests

Revised spatial weight matrix. To assess the robustness of the spatial econometric estimation results presented above, this study constructs a corresponding geographical distance spatial weight matrix (Wdr) and an adjacency weight matrix (W01) based on the longitude and latitude distance of cities' location, proposing a new spatial matrix to replace that used in the initial model. The robustness of the influence of each variable are tested again. We construct the spatial weight matrix as follows:

This study establishes the geographical distance matrix using the reciprocal of the geographical distance matrix (Wdr) in the following specific form:

$$Wdr = \frac{1}{d_{ij}} i \neq j \tag{11}$$

Where d_{ij} is the urban distance that is calculated using longitude and latitude data. The geographical distance matrix measures the proximity of the geographical location of a spatial unit, where the closer the city is, the more pronounced is its spatial impact.

To determine the adjacency weight matrix, this study considers whether cities are adjacent. The weight of adjacent cities is 1, and the weight of nonadjacent cities is 0, as is given by:

$$W01 \begin{cases} 1 \\ 0 \end{cases} i \neq j \tag{12}$$

where region i is adjacent to region j, the value of the element W_{ij} in W_{01} is 1, otherwise it is 0. The adjacency weight matrix assumes that spatial interactions will occur when spatial units have a common geographical boundary.

Columns (1) and (2) in Table 5 present the results, revealing that under the setting of Wdr and W01, DI significantly promotes local regions' GIE and inhibits GIE in adjacent regions, which aligns with the previous findings.

Replacing dependent variables. This study assesses the regional GIE by calculating the ratio of GI output to the regional GI input for that year. This study uses data from the World Intellectual Property Organization, which launched a tool designed to facilitate the retrieval of patent information related to environment friendly technologies called the green list of International Patent Classification (IPC) in 2010 that enables the accurate identification of GI at the city level. Referencing Feng et al. (2022), this study obtains the number of green patent applications in each city based on the IPC green inventory classification number as a fundamental indicator to quantify GI. Green patent data are widely considered to represent GI output (Yan et al. 2020). Therefore, this study uses the number of green invention patent applications per 10,000 people and the number of green utility model invention patent applications per 10,000 people as the fundamental indicators of GI output. Prefecture-level cities' scientific research expenditure is the basic indicator of GI investment. GIE takes a logarithm of the ratio of the GI input to the GI output. Notably, since the regional GIE calculation in this study employs a cross-sectional comparison in the same year, there is no need to adjust the statistical caliber and to reduce the price of this index. Column (3) of Table 5 presents the results. DI significantly promotes local regions' GIE and inhibits adjacent regions' GIE. The results are consistent with the benchmark regression.

Replacing core independent variables. This study uses the proportion of employed people in telecommunications and other information transmission services in various cities in the province to replace the exogenous weight of DI at the city level, decomposing DI at the provincial level and reconstructing the DI index for robustness testing. Column (4) of Table 5 presents the results, revealing that DI significantly promotes local regions' GIE and inhibits GIE in adjacent regions, which is consistent with the benchmark regression.

Excluding municipalities under the direct jurisdiction of the central government. Compared to other prefecture-level cities, China's four municipalities directly under the central government (Beijing, Shanghai, Tianjin, and Chongqing) surpass other prefecture-level cities in terms of digital economy development, technology, human capital, and other relevant characteristics due to unique economic development trajectories. Therefore, heterogeneity may be evident for various prefecture-level cities, which may cause deviations in the estimation results. Thus, this study excludes the sample data of municipalities directly under the central government and re-evaluates the impact of DI on GIE. Column (5) of Table 5 (5) presents the results. The DI significantly promotes GIE in the local region and inhibits GIE in adjacent regions, which remains consistent with the benchmark regression.

Instrumental variable. We now consider the potential for a reverse causal relationship between DI and regional GIE and many unknown factors that could potentially affect the regional GIE. Although some factors are controlled, the concern of missing variables remains, which may produce biased results. For this reason, referencing Tang et al. (2023), this study uses the multiplicative term of the historical data for post and telecommunications at the end of 1984 and the virtual year as the instrumental variables (IVs) for DI. The rationale for these choices is as follows. (1) in terms of exogeneity, the historical data of post and telecommunications in 1984 are exogenous to regional governments' decision making behavior. Furthermore, the historical data of post and telecommunications in 1984 are a predetermined variable, which satisfies the exogeneity requirements. (2) As an extension of the traditional telecommunications infrastructure, DI is more favorable in areas with a well-developed local historical infrastructure, indicating a correlation with IVs. This study employs the two-stage least squares (2SLS) method.

Table 6 presents the regression results with the IVs. Column (1) reveals the regression findings from the first stage, demonstrating that the IVs exhibit a significantly positive correlation in the context of DI at a 1% significance level, indicating a strong association with the IVs. Column (2) reports the regression results of the second stage with the IVs. The findings reveal that DI has a significantly positive impact on regional GIE, which is congruent with the benchmark regression results. In addition, the Durbin–Wu–Hausman test statistics in columns (1) and (2) confirm no endogenous problem, and Shea's partial R-squared statistics, F statistics, and minimum eigenvalue statistics indicate that the IVs are not weak instruments.

Table 6 Instrumental variable estimation.

Variables	First-stage regression	Second stage regression
	DI	GIE
	(1)	(2)
IV	0.014***	
	(8.81)	
DI		0.764***
		(6.84)
Control Variables	YES	YES
Constant	−0.373**	1.853***
	(−2.71)	(4.36)
Durbin score chi2		10.455**
		[0.012]
Wu-Hausman F		7.743***
		[0.005]
First-stage F test	80.433***	
	[0.000]	
Minimum eigenvalue	329.416	
5% Wald test	16.38	
N	1792	1792
R^2	0.952	0.775

*** and ** indicate significance at 1% and 5% levels, respectively. Figures in parentheses are z-values. Figures in brackets are p-values.

Table 7 City size heterogeneity.

Variables	GIE		
	Large cities	Medium-sized cities	Small cities
DI	0.866***	0.134	−0.995
	(9.12)	(0.97)	(−1.52)
WDI	−7.859***	1.476	60.598
	(−3.74)	(0.65)	(0.76)
Control Variables	YES	YES	YES
ρ	0.918***	0.797***	−8.452**
	(2.97)	(4.93)	(−2.46)
N	712	1,440	96
R^2	0.051	0.008	0.171

*** and ** indicate significance at 1% and 5% levels, respectively. Figures in parentheses are the z-value.

Additional analyses

City size heterogeneity. The diversity in city sizes produces industrial structure variations and different concentration level of resources and scientific and technological development between larger cities and smaller cities, causing heterogeneous impacts of DI on the improvements in urban GIE. In this study, the city scale is categorized into large, medium-sized, and small cities based on urban population size, where large cities have permanent populations above 5 million, medium-sized cities have permanent populations between 1 and 5 million, and small cities have permanent populations below 1 million.

The regression results presented in Table 7 reveal that the DI in large cities significantly promoted local GIE, but significantly inhibited that in adjacent areas. However, in medium-sized cities, DI promoted GIE in the region and adjacent areas, but the impacts were not statistically significant. In contrast, DI inhibited small cities' local GIE and promoted GIE in adjacent areas, but

Table 8 Scientific and technological heterogeneity.

Variables	GIE	
	Low-tech areas	High-tech areas
DI	0.051	0.472***
	(0.17)	(5.63)
WDI	0.540	−7.258***
	(0.10)	(−4.30)
Control Variables	YES	YES
ρ	0.542*	0.804***
	(1.78)	(4.40)
N	1128	1120
R^2	0.087	0.296

*** and * indicate significance at 1% and 10% levels, respectively. Figures in parentheses are z-values.

Table 9 Traditional infrastructure heterogeneity.

Variables	GIE	
	Low level traditional infrastructure	High-level traditional infrastructure
DI	0.116	0.566***
	(0.92)	(5.56)
WDI	3.093	−2.483
	(1.41)	(−1.29)
Control Variables	YES	YES
ρ	0.860***	0.484
	(5.25)	(1.63)
N	1120	1128
R^2	0.116	0.115

*** indicate significance at 1% level, respectively; Figures in parentheses are z-values.

the impacts were not statistically significant. The reason is that large cities have a strong foundation for internet development, and DI can improve large cities' resource allocation efficiency, scientific and technological capabilities, and industrial structure optimization. This will ultimately lead to urban GIE improvements. As large cities' economic development is superior to smaller cities, this will siphon off labor and capital from adjacent areas, thus diminishing GIE in adjacent areas.

While medium-sized cities' development is weak, DI enhances the learning effect within the region, improves the absorptive capacity for knowledge spillovers, reduces regional enterprises' production costs, improves independent innovation capabilities, and effectively improves GIE (Dian et al. 2024). Due to the economic development pressure faced by small cities and the considerable difficulty and risk associated with GI, enterprises may prioritize technological innovations that offer high yields with low investment requirements and are easily imitable, which reduces GIE (Xue et al. 2022). Due to the public goods attribute of DI, the adjacent areas of medium-sized and small cities are affected by the knowledge and technology spillover effect of DI development in the region, which effectively improves adjacent areas' GIE; however, DI has a long-term impact on regional GIE. In the short term, small and medium-sized cities' low DI development has no significant impact on regional GIE.

Urban science and technology heterogeneity. Disparities in urban science and technology development can reflect variations in financial development, human capital, industrial structure, and other aspects between different cities, which may lead to different impacts of DI on urban GIE. This study divides the sample into high- and low-tech areas based on the median of urban R&D expenditure. The results in Table 8 show that DI in high-tech areas significantly promotes GIE in local cities and significantly inhibits that in adjacent areas. The impact of DI is not obvious in low-tech areas. The rationale for this is that high-tech cities have strong innovation capabilities. DI drives the development of a series of supporting industries for technological innovation and improves regional GIE. The development of DI in this region attracts adjacent areas' resources and talent, subsequently reducing GIE in adjacent areas. However, in low-tech cities, due to weak innovation capabilities, DI will not have an immediate effect on improving urban GIE (Tang and Zhao, 2023).

Traditional infrastructure heterogeneity. New infrastructure, with network technology as a significant symbol, relies on the previous development of traditional infrastructure. Generally, regions with well-developed traditional infrastructure development such as railways, highways, and airports tend to exhibit less topographic relief and a more developed economy than other regions. DI development is more easily facilitated to fully leverage its advantages, promote efficiency and produce scale effects in the region, and makes a different impact of DI on the growth of urban GIE. This study divides the sample into areas with high and low traditional infrastructure according to the median of urban road area. The results in Table 9 reveal that DI has significantly promoted the growth of GIE in the local region in areas with high traditional infrastructure, and the impact on adjacent areas is negative but not statistically significant. However, in areas with low traditional infrastructure, the impact of DI on GIE in the region and adjacent areas is positive but not statistically significant, indicating that there is a notable correlation between DI and traditional infrastructure. Intuitively traditional infrastructure promotes the mutual flow of production factors between regions, triggering knowledge and technology spillover, which improves economic development and total factor productivity (TFP) (Tang and Zhao, 2023). In areas with well-developed traditional infrastructure, strong economic development provides financial support for GI R&D. More efficient TFP promotes rational resource allocation, high-end human capital attraction and development, and technology sharing for regional GI, which improves GIE (Hao et al. 2023). DI is low in areas with low traditional infrastructure, and although a trend of promoting regional GIE is evident, it does exhibit a significant effect.

Long-term effects of DI on adjacent areas' regional GIE. The previous analysis demonstrates that DI indeed effectively improves regional GIE, but it has a siphon effect on adjacent regions' human capital and production factors, which reduces GIE in adjacent regions. This raises the following questions. Does DI only have a negative spatial spillover effect on GIE in adjacent areas? How long will the siphon effect of DI on adjacent areas last? This study uses the SDM, lagging the regional GIE by five periods, and explores the reasons for the reduction of adjacent areas' GIE caused by the DI. The results in Table 10 reveal that when regional GIE lags behind the fifth phase, the DI significantly promotes GIE in adjacent regions. When regional GIE lags behind to the second phase, the impact of DI on adjacent areas' GIE is not significant. This indicates the presence of a time lag in the impact of DI on GIE in adjacent areas, and the DI in that year will have a positive spatial spillover effect on GIE 5 years later. In addition, the siphon effect of DI on adjacent areas lasted only one year, with no significant impact in the second year. A short-term inhibitory effect may arise due to resource reallocation and intensified market competition. In the long term, it may improve

Table 10 GIE's long-term effect in adjacent regions.

VARIABLES	GIE				
	(1) Lag 1 year	(2) Lag 2 years	(3) Lag 3 years	(4) Lag 4 years	(5) Lag 5 years
WDI	−2.710**	−1.903	−1.414	2.505	4.659**
	(−2.09)	(−1.35)	(−0.88)	(1.50)	(2.40)
Control Variables	YES	YES	YES	YES	YES
ρ	0.580***	0.511***	0.418***	0.052	0.056
	(5.62)	(4.23)	(2.93)	(0.23)	(0.22)
N	1967	1686	1405	1124	843
R^2	0.197	0.242	0.063	0.003	0.020

*** and ** indicate significance at 1% and 5% levels, respectively. Figures in parentheses are z-values.

GIE in adjacent areas due to demonstration and synergy effects (Hong et al. 2023).

Conclusions and policy implications

This study used panel data from 281 cities at the prefecture-level or above in China, covering the period from 2013 to 2020 to analyze the dynamic changes in DI and GIE in each city and explore impacts of DI on GIE using a dual fixed effect SDM model. During this period, DI and GIE exhibited a rising trend. Regional differences are the primary source of variations in DI and GIE among cities. DI has a significantly conducive effect on the local GIE, but a significant inhibitory effect on GIE in adjacent regions. Concerning the transmission mechanism, DI promotes local GIE by improving the IA's concentration and regions' industrial diversity, and weakens that in adjacent regions, reducing GIE in adjacent regions. From the estimation results of cities' size, DI significantly improves GIE in large cities and reduces GIE in their adjacent regions. The DI of medium-sized and small cities has no significant impact on GIE in the local region and adjacent areas.

Regarding urban science and technology levels, the DI in high-tech areas significantly improves the GIE of the local region, but reduces the GIE in adjacent areas, whereas DI in low-tech areas has no significant impact on GIE in the local region or adjacent areas. In terms of urban traditional infrastructure, DI in areas with low traditional infrastructure has no significant impact on GIE in local or adjacent regions, whereas DI in regions with high traditional infrastructure significantly improves local GIE but did not affect that of adjacent regions. Additional analyses reveal that the effect of DI has a time lag on GIE of adjacent areas, wherein DI in that year will significantly promote the GIE of adjacent areas in 5 years. In addition, the siphon effect of DI on GIE of adjacent areas lasts only one year.

Several policy implications arise from the findings of this study. Policymakers should enhance the innovation potential of DI and strengthen collaborative innovation between and within regions. Furthermore, leaders should actively release the resource allocation value of DI, promote the emerging cross-industry mechanisms, cross-region and cross-platform collaboration of production factors, and integration and sharing of other production and innovation factors with digital elements. This requires a cross-regional green innovation cooperation platform, improving the allocation and sharing of innovation resources between and within regions, and promoting regional GIE. At the same time, the government should have a guiding role, take measures to enrich neighbors to turn the siphon effect into a radiation effect through high-level collaborative regional innovation and specialized industrial cooperation, and actively drive the surrounding lagging areas.

Local leaders should endeavor to build a comprehensive digital network system, strengthen the complementary advantages of regional industrial structure, and promote the coordinated development of regional industries. Digital, networked, and intelligent approaches can be used to build an innovative and diversified industrial cluster development layout. A network coordination mechanism should be established to break the transmission barriers of GI technology information at the multidimensional boundaries of industries and regions, promote the spatial diffusion and spillover of GI knowledge and technology across regions, fields, and subjects, and improve cross-regional innovation factor allocation efficiency. Furthermore, policymakers should prioritize improving regional DI, narrowing the digital divide between regions, and creating a collaborative digital ecological environment to fully leverage the efficiency of government implementation. The government should also direct more policy preference to low-tech areas with low grade traditional infrastructure so that areas with poor development can enjoy the dividends of DI spillover effects. Regional collaboration, regional cooperation, and regional integration strategies should be developed to promote the radiation and spillover of low-lying areas with high GIE.

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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Note

1 In economics, the siphon effect refers to a phenomenon where uneven regional development leads to a well-developed area absorbs resources from other regions. It similar to the physical siphon effect. This phenomenon is primarily driven by factors such as economic development, geographical location, and market size, resulting in a one-way transfer of production factors from surrounding areas to central regions.

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