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Analysis of Regional Innovation Efficiency and Resource Allocation Driven by Digital Economy

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Abstract

In the context of the rapid development of the digital economy, regional innovation efficiency (RIE) has become an important indicator for measuring regional economic competitiveness. This study establishes an evaluation system for RIE driven by the digital economy, employing a two-stage inverse data envelopment analysis (DEA) model to measure RIE in China. It also conducts an empirical analysis of the allocation of technological resources in Jiangsu Province, providing valuable insights for RIE research within the framework of the digital economy. The research results indicate that from 2014 to 2019, the overall RIE in China gradually improved, with significant increases in innovation efficiency in the eastern and western regions, while the northeastern region experienced a slight decline. Focusing on resource allocation in Jiangsu, we find that as the input proportion gradually increases, it is necessary to reduce output in the technology development stage and enhance output in the achievement transformation stage to maintain the current efficiency level. However, to improve the RIE score, it is essential to simultaneously increase the output levels of both stages.

Keywords

Digital economy; Regional innovation efficiency; Two-stage DEA; Inverse DEA

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1. Introduction

The Fifth Plenary Session of the 19th Central Committee of the Communist Party of China has explicitly stated the need to uphold innovation as the central role in China's modernization efforts, fully implement the innovation-driven development strategy, strengthen the national innovation system, and promote the optimization and upgrading of the economic system. As the cornerstone of national scientific and technological innovation, the national innovation system significantly impacts the country's global competitiveness. Regional innovation, as a crucial component of the national innovation system, plays a vital role in advancing the country's scientific and technological progress (Chen *et al*., 2018; Wang and Ceng, 2024).

With the deep digital transformation of the global economy, the digital economy has become one of the key engines driving social and economic development. It has not only profoundly changed the production methods, business models, and management practices of traditional industries but has also given rise to many emerging industries and new economic growth points (Wang and Li, 2024). In this context, enhancing regional innovation capability has become particularly important, as it directly affects a region's position and development potential in global competition (Lou *et al*., 2024). Particularly in China, the significant differences in economic development levels and degrees of digitalization among regions make the evaluation and optimization of regional innovation efficiency (RIE) an urgent issue to address (Wang and Ceng, 2024).

The development of the digital economy has brought unprecedented opportunities for regional innovation. Firstly, the widespread application of digital technologies has significantly enhanced the speed and breadth of information dissemination, facilitating the rapid accumulation and spread of knowledge and providing richer resources and platforms for regional innovation. Secondly, numerous emerging industries spawned by the digital economy, such as e-commerce, artificial intelligence, and big data, have become new growth points for regional economies, further driving the development of regional innovation. Additionally, the popularization and application of digital technologies have transformed traditional research and development models, enabling cross-regional and cross-disciplinary innovation collaboration and improving the efficiency of regional innovation (Li, 2021; Guo *et al*., 2023; Wen *et al*., 2023). However, the development of the digital economy also presents new challenges for regional innovation. Firstly, the rapid pace of digital economic development means that regions that fail to adapt to and utilize these new technologies in a timely manner may find themselves at a disadvantage in innovation competition. Secondly, the rise of new technological and innovation barriers has led to an imbalanced allocation of innovation resources across regions, exacerbating regional economic disparities (Zhang *et al*., 2021; Wu *et al*., 2023; Yu *et al*., 2023). Therefore, in the context of the digital economy, accurately evaluating RIE, identifying shortcomings in regional innovation development, and proposing corresponding policy recommendations have become crucial research topics.

RIE refers to the extent to which a region's innovation input matches its innovation output, specifically how many high-quality innovation outcomes can be generated with a given amount of innovation resources (Fritsch and Slavtchev, 2011; Bai, 2013). However, with the rapid development of the digital economy, traditional DEA methods may not fully capture the complex changes in innovation patterns and networks. Therefore, there is a need to further analyze the optimization of regional technological resource allocation to enhance innovation capabilities, promote economic and social development, reduce regional disparities, and achieve national strategic goals (Chen, 2022). The introduction of inverse DEA methods provides a more precise computational tool, allowing for the analysis of optimal outputs (or inputs) under given input (or output) conditions while maintaining the efficiency of decision-making units (DMUs) (Wei *et al*., 2000).

This study aims to explore methods and applications for evaluating RIE in the context of the digital economy. By constructing a new RIE evaluation model based on the digital economy, the study will comprehensively analyze the current status and trends of innovation resource input, innovation output, and efficiency levels across various regions. Specifically, the objectives of this research include the following aspects: First, to develop an RIE evaluation system under the digital economy. This involves designing a set of evaluation indicators that cover multiple dimensions, such as innovation input and output, tailored to the characteristics of the digital economy and the practical situation of regional innovation (Guo *et al*., 2023). Second, to analyze the spatial differences and evolution patterns of RIE. Using actual data from regions across the country, the study will apply the constructed model to measure RIE, analyze its spatial distribution characteristics and temporal evolution patterns, and reveal the differences in innovation efficiency between regions and their causes (Lan and Zhao, 2020). Finally, to propose policy recommendations for improving RIE. Based on the results of the empirical analysis, the study will offer targeted policy suggestions for different regions' innovation efficiency statuses, aiming to provide decision-making references for local governments in formulating innovation-driven development strategies.

Compared to existing research, our study is unique in several aspects: First, it refines the selection of regional innovation evaluation indicators and efficiency measurement in the context of the digital economy. Second, it employs inverse DEA methods to analyze and optimize regional technological resource allocation. Finally, it further enriches the application of inverse DEA methods in two-stage production systems. The remainder of this paper is organized as follows: Section 2 reviews relevant literature on the digital economy, inverse DEA methods, and RIE evaluation; Section 3 constructs a measurement path for RIE under the digital economy and designs DEA and inverse DEA models for two-stage production systems; Section 4 measures RIE and conducts a resource allocation analysis for Jiangsu; and finally, the paper concludes with a summary and recommendations for future research.

2. Literature review

2.1. Digital economy

The concept of the digital economy initially described an "information-based" economy, characterized as a new economic system driven by the digital revolution in information and communications technology (ICT) and built on the networking of human intelligence. It primarily focused on industries related to information technology and their market applications, such as communication equipment manufacturing, information technology services, and digital content (Su *et al*., 2023). With the advent of innovations in digital technologies like artificial intelligence and the Internet of Things, along with the convergence of traditional industries, the scope of the digital economy has gradually expanded to encompass the "new economy" emerging from the widespread use of the internet, signifying new economic phenomena supported by digital information technology (Cusumano, 2014). Broadly, the digital economy can be understood as economic activities driven by digital technology innovation, centered around data resources, facilitated by internet platforms, and characterized by new formats and models (Chen *et al*., 2022). Narrowly, it refers to the digital sector based on ICT that produces digital products and provides digital platform services (Bukht and Heeks, 2017).

As the digital economy continues to evolve and deeply integrate with traditional industries, the application of digital technologies has become an essential tool for promoting cross-domain and cross-regional collaboration among various innovation entities, transforming innovation activities across sectors. In product innovation, digital technology's inherent advantage in continuous self-innovation allows management platforms to quickly incorporate vast amounts of product data into the design and development of new products, giving rise to new manufacturing models like personalized and networked collaborative manufacturing (Yoo *et al*., 2010). In production management, digital intelligent management and networked service platforms have effectively enhanced resource utilization efficiency and overall productivity (Liu and Zheng, 2022). In innovation collaboration, the internet and other digital media have broken down spatial and geographical barriers, enabling multi-party innovation across regions through digital platforms (Miao, 2021). The development of the digital economy has reduced the costs of economic activities, improved operational efficiency, and had a profound impact on various aspects of the national economy, including production, consumption, and distribution (Goldfarb and Tucker, 2019).

In summary, the digital economy can be viewed as a sector based on ICT, involved in producing digital products and providing digital platform services. It encompasses economic activities driven by digital technology innovation, with data resources at its core, supported by internet platforms, and characterized by new formats and models.

2.2. Research on RIE

An accurate measurement of RIE is crucial for enhancing the management and investment in regional economic science and technology. This topic has gained increasing scholarly attention in recent years. Zabala-Iturriagagoitia *et al*. (2007) utilized the DEA methodology to evaluate regional innovation system performance using data from the European Innovation Scoreboard for 2002 and 2003. Fritsch and Slavtchev (2010) assessed regional efficiency in Germany by developing a model that connected regional R&D investment with output. Given the complexity of the regional innovation process, some studies have expanded the measurement of regional efficiency by focusing on the innovation process itself, distinguishing between upstream knowledge creation and downstream knowledge application sub-processes (Guan and Chen, 2012). Chen *et al*. (2018) argued that overall efficiency should be assessed dynamically by considering the connections between consecutive periods in a multi-period system, since certain activities, like R&D capital stock, impact both the current and future periods. Wang and Zhang (2022) employed dynamic network DEA to estimate the overall, period-specific, and sub-stage innovation efficiency in China, further elucidating the complex regional innovation process. Additionally, regression-based parameterization methods, such as the Cobb-Douglas production function (Fritsch and Slavtchev, 2011) and stochastic frontier analysis (Barra and Ruggiero, 2022), are also used to develop RIE scoring models. However, due to their complexity, DEA methods are more commonly employed in evaluating RIE.

Regardless of the methods used to measure RIE, significant regional differences in innovation efficiency scores are apparent. Even regions with abundant scientific and technological resources often face the challenge of low efficiency (Faria *et al*., 2020). Recent research has also examined the factors influencing regional efficiency. From a policy perspective, government and public sector financial support significantly enhances RIE by improving R&D efficiency (Cao *et al*., 2023). Resource-wise, the number of innovative entities and the regional distribution of innovation resources play a crucial role, as more developed regions tend to attract a greater influx of innovative talent (Yu *et al*., 2023). From an environmental standpoint, a favorable innovation environment facilitates cross-disciplinary, cross-regional collaboration and foreign investment (Fan *et al*., 2020; Li *et al*., 2018). On the industrial side, producer services and high-tech industries significantly impact RIE, particularly in the context of the digital economy. The application of artificial intelligence, digitalization, and other technologies in high-tech industries has accelerated resource flow and improved resource allocation efficiency (Wu *et al*., 2023; Yang *et al*., 2022).

Currently, the impact of the digital economy on RIE has not been sufficiently explored, and the existing efficiency evaluation systems are incomplete. Most studies focus on the efficiency analysis of traditional innovation resources, with few incorporating digital economy-related indicators into the evaluation of RIE. There is a lack of a comprehensive assessment of RIE in the context of the digital economy and regional integrated development.

2.3. DEA and inverse DEA

DEA, as a non-parametric method, does not require the prior construction of a production function. It can independently provide efficiency scores and assess the efficient frontier through both multiplier and envelopment models. Consequently, it has become a widely used tool for evaluating relative efficiency (Charnes *et al*., 1978). However, traditional DEA models treat the system as a "black box," ignoring its internal structure and calculating only overall efficiency. This approach makes it difficult to determine the efficiency of individual sub-processes, potentially introducing biases in efficiency assessments. To address this limitation, network DEA models were developed and have gained rapid popularity (Ratner *et al*., 2023). In practice, efficiency evaluations often involve more complex scenarios, where calculations are divided into two or more sub-processes, including serial, parallel, hybrid, hierarchical, and dynamic structures (Kao, 2014).

Research by Zhang and Cui (1999) on project evaluation systems has paved the way for new directions in DEA studies. Their work focuses on determining the additional input required to maintain a machine's current efficiency while increasing its output by a specified amount. Building on this, Wei *et al*. (2000) developed the inverse DEA model to estimate the necessary input and output levels. The inverse DEA method has gained significant popularity in recent years, with extensive development in both theoretical and applied research. Theoretically, Yan *et al*. (2002) expanded the inverse DEA framework by incorporating preference cones for input and output estimation in resource allocation. Lim (2016) further advanced the model by introducing changes in the production frontier. Ghiyasi and Zhu (2020) developed an inverse DEA model using semi-directional radial measures to handle negative data and also addressed pollution caused by technologies that fail to produce expected outputs. Ghomia *et al*. (2021) proposed an inverse DEA model that accommodates random data, while Modhej *et al*. (2017) enhanced the method by integrating inverse DEA with neural networks to maintain relative efficiency values. Zhang and Cui (2020) introduced a general non-radial inverse DEA model where slacks play a crucial role. Jahanshahloo *et al*. (2015) proposed cross-temporal inverse DEA dependency using multi-objective programming. As the theory and methods of inverse DEA have developed, its applications have become increasingly widespread across various fields, including commerce, supply chain management, education, sustainable production, energy, and the environment (Emrouznejad *et al*., 2023).

Despite the broad applications of inverse DEA, there is still limited research on its use in evaluating RIE. Therefore, our study extends the application of inverse DEA to RIE, as well as to two-stage production systems.

2.4. Literature summary

Existing research still has several shortcomings. First, as mentioned in our introduction, the digital economy has transformed traditional innovation models and accelerated resource flow. The relationship between the digital economy and RIE is complex and multifaceted, requiring consideration from multiple dimensions. Most current studies explore the impact of the digital economy on RIE using economic models but often fail to incorporate digital indicators into the DEA model. Second, existing research on RIE evaluation primarily focuses on the efficiency analysis of traditional innovation resource input and output, lacking a reasonable assessment of RIE in the new context of digital economy and regional integration development. Lastly, the application of the inverse DEA model to RIE is still relatively rare. Given the uneven distribution of technological resources among regions, it is crucial to utilize the inverse DEA model to optimize regional resource allocation. This study has the following two main contributions compared to existing research: First, building on traditional RIE assessments, we delve into the evaluation transition against the backdrop of the digital economy, providing a new perspective for RIE evaluations. By constructing an RIE assessment index system specifically designed for digital economic conditions, we selected input and output indicators closely related to the digital economy, such as digital capital, digital industrialization and industrial digitization. This innovation not only enhances the relevance of RIE assessments but also enriches the existing assessment indicators, allowing the results to more accurately reflect the impact of the digital economy on regional innovation. Second, the study applies an inverse DEA model to optimize resource allocation in a two-stage production system, further expanding the application of inverse DEA methods in the field of RIE evaluation. Through detailed analysis of resource allocation, we can identify bottlenecks and deficiencies in the innovation processes of various regions, thereby proposing targeted policy recommendations. The application of this method not only improves the accuracy and reliability of the assessments but also provides data support and theoretical foundations for practical decision-making.

3. Conceptual Framework and Methodology

3.1. Regional innovation process driven by the digital economy

Building on existing research, this article adopts an innovation value chain perspective (Hansen and Birkinshaw, 2007), categorizing regional innovation activities into two crucial stages: technological development and achievement transformation. In the context of the evolving digital economy, the innovation chain is further enriched and expanded through the lenses of supply, value sharing, and application, as illustrated in Fig. 1.

During the technological development stage, the key players are enterprises, universities, and research institutions (Xiong *et al*., 2020). At this stage, each innovation entity engages in R&D activities tailored to market and societal demands. Inputs include R&D funds and personnel, while outputs primarily take the form of patents and scientific papers. Moving to the achievement transformation stage, enterprises play the central role. Guided by market orientation, enterprises strategically invest in patents and engage in small-scale and pilot processes to meet customer demands. The ultimate goal is to develop new products that drive economic gains through both domestic sales and foreign exports.

In the digital economy, digital capital investment becomes a critical factor during the technology development stage. The rise of digital collaborative innovation, enabled by internet platforms, breaks down the internal barriers of regional innovation activities. Technology development increasingly

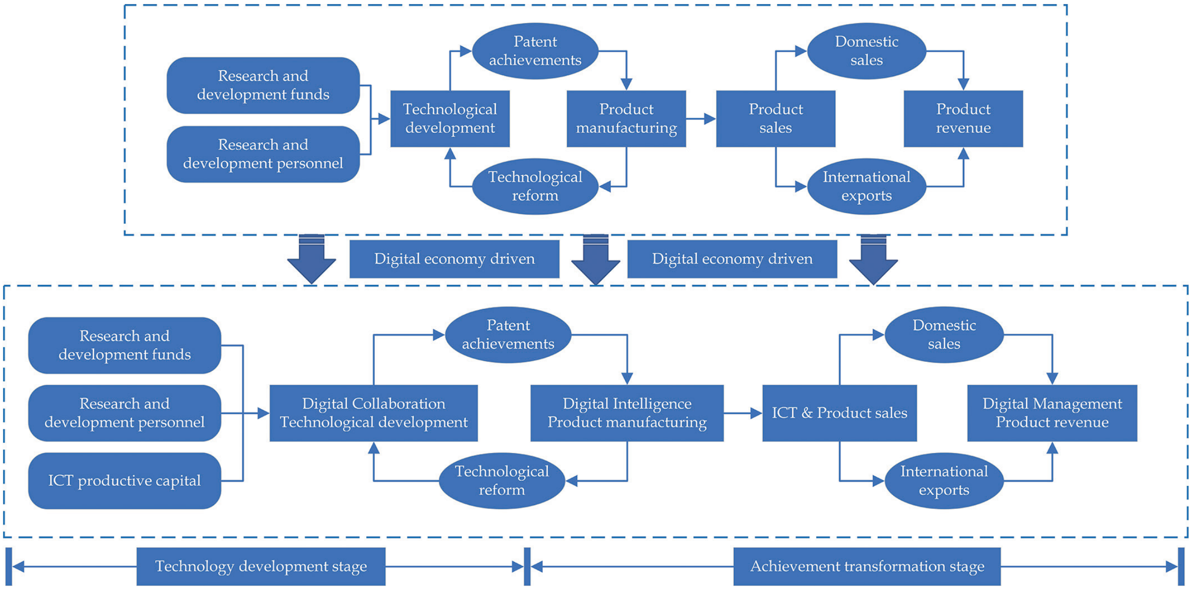

Fig. 1. Regional innovation process driven by the digital economy.

integrates with big data feedback from the demand side, while digitization and intelligent manufacturing drive cost savings and efficiency improvements in production processes. In the achievement transformation stage, digital technology provides essential tools for regional sales of digital products, facilitating the exploration of domestic market potential and expansion into international markets. The digital management model is key to reducing operating costs and increasing profits. Total revenue from telecommunications and software businesses serves as an indicator of the extent of digital application (Guo *et al.*, 2023).

3.2. The model of two-stage production systems and inverse DEA

For a two-stage production process with n DMUs, as shown in Fig.2, the number of inputs in stage 1 is m, the number of outputs in stage 1 is s_1, the number of intermediate outputs that links stage 1 and stage 2 is q, and the number of outputs in stage 2 is s_2.

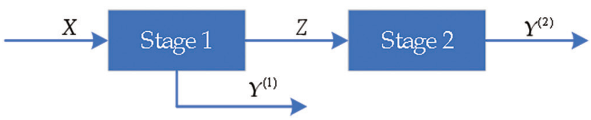

Fig. 2. Two-stage production process.

For DMU$_j$, let X=(x_{1j}, x_{2j}, ..., x_{mj}) denote the observed inputs in stage 1, Y$^{(1)}$=($y^{(1)}{}_{1j}$, $y^{(1)}{}_{2j}$, ..., $y^{(1)}{}_{s1j}$) denote the observed outputs in stage 1, z=(z_{1j}, z_{2j}, ..., z_{qj}) denote the observed intermediate indicators that links stage 1 and stage 2, Y$^{(2)}$=($y^{(2)}{}_{1j}$, $y^{(2)}{}_{2j}$, ..., $y^{(2)}{}_{s2j}$) denote the observed outputs in stage 2. Assume that all input, intermediate and output indicators are positive. The output-oriented constant returns to scale (CRS) ratio-form is model (1).

$$\min \frac{\sum_{i=1}^{m}\nu_i x_{i0}+\sum_{d=1}^{q}\eta_d z_{d0}}{\sum_{r_1=1}^{s_1}\mu_{r_1}y_{r_1 0}+\sum_{r_2=1}^{s_2}\mu_{r_2}y_{r_2 0}+\sum_{d=1}^{q}\eta_d z_{d0}}$$
$$s.t.\begin{cases}\dfrac{\sum_{i=1}^{m}\nu_i x_{ij}}{\sum_{r_1=1}^{s_1}\mu_{r_1}y_{r_1 j}+\sum_{d=1}^{q}\eta_d z_{dj}}\geq 1\\ \dfrac{\sum_{d=1}^{q}\eta_d z_{dj}}{\sum_{r_2=1}^{s_2}\mu_{r_2}y_{r_2 j}}\geq 1\\ \nu_i,\eta_d,\mu_{r_1},\mu_{r_2}\geq 0\\ j=1,2,\ldots,n\end{cases} \tag{1}$$

By solving model (1), we can obtain the overall efficiency, which is equal to 1 if and only if both the first stage and the second stage are efficient. By performing the Charnes-Cooper transformation, which is to set $1/t=\sum_{r_1=1}^{s_1}\mu_{r_1}y_{r_1 0}+\sum_{r_2=1}^{s_2}\mu_{r_2}y_{r_2 0}+\sum_{d=1}^{q}\eta_d z_{d0}$, $t_{vi}=\tau_i$, $t_{\eta d}=\pi_d$, $t\mu_{r1}=\delta_{r1}$, and $t\mu_{r2}=\delta_{r2}$, we can obtain the linear programming model. To better analyze the impact of altering a condition in linear programming on the objective function, we examine the dual form of model (1), referred to as model (2).

$$\max\ \theta_0$$
$$s.t.\begin{cases}\sum_{j=1}^{n}\lambda_j x_{ij}\leq x_{i0}\\ \sum_{j=1}^{n}\lambda_j y_{r_1 j}\geq\theta_0 y_{r_1 0}\\ \sum_{j=1}^{n}\gamma_j y_{r_2 j}\geq\theta_0 y_{r_2 0}\\ \sum_{j=1}^{n}\lambda_j z_{dj}-\sum_{j=1}^{n}\gamma_j z_{dj}\geq(\theta_0-1)z_{d0}\\ \lambda_j\geq 0,\ \gamma_j\geq 0,\ \theta_0\ \textit{unrestricted}\end{cases} \tag{2}$$

The optimal solution of model (2) is θ_0^*, and $\theta_0^*\geq 1$. When $\theta_0^*\neq 1$, DMU$_0$ is deemed inefficient. For $z_{d0}>0$, we can obtain $\sum_{j=1}^{n}\lambda_j z_{dj}\geq\sum_{j=1}^{n}\gamma_j z_{dj}$ from the fourth constraint of model (2), which implies intermediate inputs consumed at stage 2 may not exceed intermediate outputs produced at stage 1. Suppose stage 1 inputs of inefficient DMU$_0$ increase from x_{i0} to $x_{i0}+\Delta x_{i0}$ where $\Delta x_{i0}\geq 0$ with at least one element of $\Delta x_{i0}\neq 0$. Let $\beta_{r_10}^{(1)}=\{\beta_{10}, \beta_{20}, \ldots, \beta_{r_10}\}$ and $\beta_{r_20}^{(2)}=\{\beta_{10}, \beta_{20}, \ldots, \beta_{r_20}\}$ denote a set of output targets and $\tilde{z}_{d0}=\{\tilde{z}_{10}, \tilde{z}_{20}, \ldots, \tilde{z}_{q0}\}$ denote a set of intermediate targets of DMU$_0$. A DEA-type model (3) that estimates , $\beta_{r_10}^{(1)}$, $\beta_{r_20}^{(2)}$ and $\tilde{z}_{d0}$ to maintain a pre-specified relative efficiency level ($1/\theta'_0$).

$$\max\ \left\{\beta_{r_1 0}^{(1)},\beta_{r_2 0}^{(2)}\right\}$$
$$s.t.\begin{cases}\sum_{j=1}^{n}\lambda_j x_{ij}\leq(x_{i0}+\Delta x_{i0})\\ \sum_{j=1}^{n}\lambda_j y_{r_1 j}\geq\theta_0^*\beta_{r_1 0}^{(1)}\\ \sum_{j=1}^{n}\gamma_j y_{r_2 j}\geq\theta_0^*\beta_{r_2 0}^{(2)}\\ \sum_{j=1}^{n}\lambda_j z_{dj}-\sum_{j=1}^{n}\gamma_j z_{dj}\geq(\theta_0^*-1)\tilde{z}_{d0}\\ \sum_{j=1}^{n}\lambda_j z_{dj}\geq\tilde{z}_{d0}\\ \sum_{j=1}^{n}\gamma_j z_{dj}\leq\tilde{z}_{d0}\\ \beta_{r_1 0}^{(1)}\geq y_{r_1 0},\beta_{r_2 0}^{(2)}\geq y_{r_2 0}\\ \lambda_j\geq 0,\ \gamma_j\geq 0,\ \beta_{r_1 0}^{(1)},\beta_{r_2 0}^{(2)},\tilde{z}_{d0}\ \textit{unrestricted}\end{cases} \tag{3}$$

Suppose $\beta_{r_1 0}^{(1)}$, $\beta_{r_2 0}^{(2)}$ and $\tilde{z}_{d0}$ is obtained in a Pareto optimal solution of model (3). When a new DMU with inputs $x_{i0}+\Delta x_{i0}$, outputs $\beta_{r_1 0}^{(1)}$, $\beta_{r_2 0}^{(2)}$ and intermediate measures $\tilde{z}_{d0}$ is added to the observed DMU set, relative efficiency of the new DMU is $1/\theta_0'$. Simultaneously, the frontier of best performance established by the observed DMU set does not change (Kazemi and Galagedera, 2023, Galagedera, 2024).

The simultaneous maximization of solutions for $\beta_{r_1 0}^{(1)}$ and $\beta_{r_2 0}^{(2)}$ in model (3) may not exist. A commonly employed approach is to assign preference weights to $\beta_{r_1 0}^{(1)}$ and $\beta_{r_2 0}^{(2)}$, *i.e.*, to find the weighted sum of the objective function (Marler and Arora, 2010). In the weighted sum method, a set of non-negative weights is assigned to $\beta_{r_1 0}^{(1)}$ and $\beta_{r_2 0}^{(2)}$, ensuring that the weighted sum of the objective function is maximized. Assuming $\omega^{(1)}=\{\omega_1^{(1)}, \omega_2^{(1)}, \ldots, \omega_{r_1}^{(1)}\}$ and $\omega^{(2)}=\{\omega_1^{(2)}, \omega_2^{(2)}, \ldots, \omega_{r_2}^{(2)}\}$ represent a set of weights, the objective function can be expressed as finding the optimal value of $\omega^{(1)}\beta_{r_1 0}^{(1)}+\omega^{(2)}\beta_{r_2 0}^{(2)}$, transforming it into the form of a linear programming objective function, referred to as model (4).

$$
\begin{aligned}
&\max\ \left\{\omega^{(1)}\beta_{r_1 0}^{(1)}+\omega^{(2)}\beta_{r_2 0}^{(2)}\right\}\\
&s.t.\begin{cases}
\sum_{j=1}^{n}\lambda_j x_{ij}\le\left(x_{i0}+\Delta x_{i0}\right)\\
\sum_{j=1}^{n}\lambda_j y_{r_1 j}\ge\theta_0^{*}\beta_{r_1 0}^{(1)}\\
\sum_{j=1}^{n}\gamma_j y_{r_2 j}\ge\theta_0^{*}\beta_{r_2 0}^{(2)}\\
\sum_{j=1}^{n}\lambda_j z_{dj}-\sum_{j=1}^{n}\gamma_j z_{dj}\ge\left(\theta_0^{*}-1\right)\tilde{z}_{d0}\\
\sum_{j=1}^{n}\lambda_j z_{dj}\ge\tilde{z}_{d0}\\
\sum_{j=1}^{n}\gamma_j z_{dj}\le\tilde{z}_{d0}\\
\beta_{r_1 0}^{(1)}\ge y_{r_1 0},\beta_{r_2 0}^{(2)}\ge y_{r_2 0}\\
\lambda_j\ge 0,\ \gamma_j\ge 0,\ \beta_{r_1 0}^{(1)},\beta_{r_2 0}^{(2)},\tilde{z}_{d0}\ \textit{unrestricted}
\end{cases}
\end{aligned}
\tag{4}
$$

By solving model (4), one can obtain the Pareto optimal solution for linear programming.

4. Empirical results

4.1. Indicators selection and descriptive analysis

As illustrated in Fig. 3, we categorize regional innovation into two distinct phases: the technology development stage and the achievement transformation stage. Traditionally, the internal expenditure of R&D funds (RDE) and the R&D personnel full-time equivalent (RDP) were considered the primary inputs. However, in the evolving digital economy, we now distinguish these inputs into two categories: digital capital and non-digital capital, incorporating ICT productive capital (ICTC) as a form of digital capital investment. The outputs for the technology development phase are twofold: the number of valid patents (NVP) obtained during the year and the number of papers published (NPP). Notably, the count of valid patents serves a dual purpose, acting both as the output for the technology development phase and as an input for the achievement transformation phase. Traditionally, income from the transfer of scientific and technological achievements (ITA) has been considered the ultimate indicator of a system's output. However, given the significant influence of the digital economy, which requires consideration of both digital industrialization and industrial digitization, we have introduced two additional outputs: total telecommunications business volume (TBV) and software business revenue (SBR). Together, these three outputs (ITA, TBV, and SBR) measure the extent of deep integration between digital technology and the tangible economy.

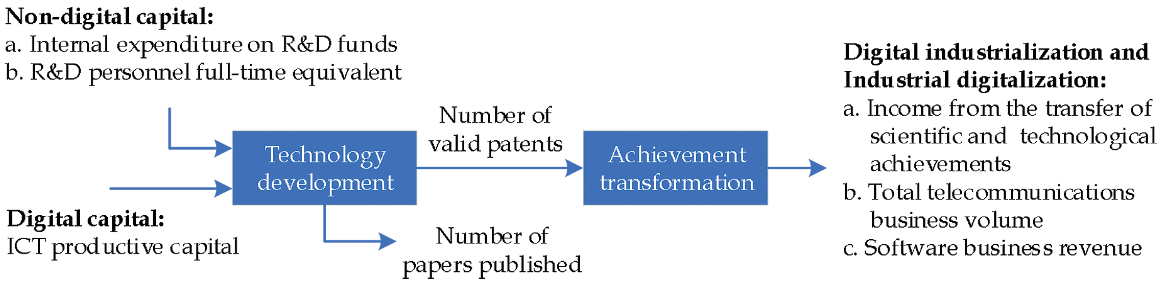

Fig. 3. Regional innovation process driven by the digital economy.

Owing to data accessibility constraints, our study encompasses data from 30 regions in China, specifically excluding Tibet Autonomous Region, Hong Kong and Macao Special Administrative Regions, and Taiwan Province, over the period from 2014 to 2021. Table 1 offers a comprehensive overview of descriptive statistics for input-output indicators.

Table 1
Descriptive statistics.

Variables	Years	Mean	Median	SD	Maximum	Minimum
RDE (Million yuan)	2014 2016 2019	43,376.9 52,248.4 73,797.5	33,406.0 37,807.2 48,901.6	46,966.2 57,786.9 81,174.0	165,282.1 203,514.4 309,848.9	1,432.4 1,399.8 2,056.8
RDP (person)	2014 2016 2019	122,643.9 129,231.1 159,867.4	98,362.0 91,297.0 102,736.5	130,287.9 139,860.1 189,810.3	506,862.0 543,438.0 803,208.0	4,731.0 4,166.0 5,476.0
ICTC (Million yuan)	2014 2016 2019	410,538.1 493,501.2 550,716.3	199,723.3 247,196.6 282,789.9	730,811.3 878,616.1 945,206.2	2,970,193.7 3,674,450.5 4,712,837.6	4,086.1 8,280.3 8,497.4
NPP (piece)	2015 2017 2020	16,887.0 20,154.8 29,202.7	12,369.5 14,165.0 20,750.0	19,119.6 21,831.7 29,381.5	93,502.0 102,763.0 133,339.0	309.0 551.0 1,255.0
NVP (piece)	2015 2017 2020	155,760.4 206,684.4 369,364.8	88,665.0 120,748.0 197,740.5	207,810.8 272,564.5 504,777.1	802,493.0 1,165,677.0 2,296,261.0	2,975.0 3,107.0 12,420.0
ITA (million yuan)	2016 2018 2021	36,436.2 57,124.0 119,854.6	12,111.4 23,216.8 67,732.2	72,994.2 93,125.4 151,720.7	394,097.5 495,782.5 700,565.2	344.3 392.2 1,410.4
TBV (million yuan)	2016 2018 2021	5,194.7 21,790.9 56,642.2	4,772.7 19,006.0 47,788.0	3,874.2 15,340.0 39,881.4	19,913.1 77,984.3 193,237.0	672.1 4,228.1 8,614.0
SBR (million yuan)	2016 2018 2021	160,774.1 206,362.4 318,340.0	34,618.3 47,431.4 78,412.5	238,031.0 303,904.7 502,228.6	822,339.2 1,068,743.2 2,038,210.0	115.4 141.1 249.0

Table 1 shows that the mean values of input indicators, output indicators, and intermediate measures all increased over the years. Specifically, RDE rose from 43,376.9 million yuan in 2014 to 73,797.5 million yuan in 2019, reflecting a 70.1% increase. RDP and ICTC also grew by 30.4% and 34.1%, respectively, during the same period. The annual average growth rates for RDE, RDP, and ICTC were 11.2%, 5.4%, and

6.1%, respectively, indicating a stable trend in these indicators, which justifies their consideration as input indicators. For intermediate measures, NVP increased alongside the input indicators, showing a growth of 137.1% from 2014 to 2019, with an annual average growth rate of 18.9%, slightly outpacing the input indicators' growth. In terms of output indicators, NPP during the technology development phase nearly doubled between 2014 and 2019. During the achievement transformation phase, there was significant growth in the indicators: SBR increased by 90.0%, income from ITA surged by 228.9%, and TBV increased more than tenfold. The trends observed in all these indicators are consistent with the principles of production theory in economics.

4.2. Calculation of RIE

Considering the presence of lag effects and the division of regional innovation into two stages - technology development and achievement transformation - this paper introduces a one-year lag between these stages (Fan *et al.*, 2020). Using model (2), we compute the RIE under the influence of the digital economy, as shown in Table 2.

Table 2
Calculation results of RIE scores.

DMU/Year	2014	2015	2016	2017	2018	2019
Beijing	1	1	1	0.9964	1	0.9964
Tianjin	0.5661	0.5623	0.5893	0.6749	0.7104	0.7436
Hebei	0.4907	0.5009	0.5001	0.6097	0.6978	0.7029
Shanxi	0.4814	0.5356	0.5110	0.5959	0.5978	0.6223
Inner Mongolia	0.4261	0.4981	0.4662	0.6491	0.7237	0.8272
Liaoning	0.7355	0.8508	0.7329	0.6986	0.6975	0.7096
Jilin	1	0.9129	0.9099	0.9234	0.9463	0.8838
Heilongjiang	1	1	1	1	1	1
Shanghai	0.8511	0.8566	0.7600	0.7892	0.8053	0.8346
Jiangsu	0.6754	0.6940	0.6056	0.6036	0.6624	0.6041
Zhejiang	0.6655	0.6751	0.6418	0.6434	0.6746	0.6541
Anhui	0.5386	0.5422	0.5304	0.5837	0.6135	0.5998
Fujian	0.6657	0.7273	0.6529	0.6382	0.6326	0.6063
Jiangxi	0.5878	0.5923	0.5633	0.6023	0.5780	0.5572
Shandong	0.6369	0.5943	0.5513	0.5634	0.6403	0.6954
Henan	0.4657	0.4717	0.4519	0.5139	0.5661	0.5397
Hubei	0.6805	0.6926	0.6916	0.6834	0.6426	0.6299
Hunan	0.5968	0.5662	0.5196	0.5651	0.5664	0.5577
Guangdong	0.6657	0.7386	0.6790	0.6690	0.6854	0.6670
Guangxi	0.5500	0.6021	0.5901	0.7270	0.8095	0.9122
Hainan	0.8216	0.8918	0.8048	0.8411	0.8688	0.9186
Chongqing	0.8147	0.8102	0.6993	0.6523	0.7061	0.6586

DMU/Year	2014	2015	2016	2017	2018	2019
Sichuan	0.7939	0.8267	0.7759	0.7313	0.7834	0.7204
Guizhou	0.7501	0.7628	0.7043	0.9081	0.9322	0.7903
Yunnan	0.8451	0.8651	0.5828	0.8117	0.7642	0.6672
Shaanxi	0.9725	1	1	1	0.8372	0.8104
Gansu	0.9912	0.9078	0.8738	0.9187	0.9247	0.8827
Qinghai	0.5772	0.7324	0.6016	0.7931	0.9552	0.8478
Ningxia	0.5205	0.5714	0.5094	0.6402	0.6701	0.6527
Xinjiang	0.7612	0.6672	0.6410	0.8599	1	1
Mean	0.7042	0.7216	0.6713	0.7259	0.7564	0.7431

From 2014 to 2019, RIE showed an initial increase followed by a slight decline, with the lowest point in 2016, before gradually recovering. This trend could be attributed to several factors: in 2016, China implemented policies such as the *Several Provisions on Promoting the Transformation of Scientific and Technological Achievements* and the *Action Plan for Promoting the Transfer and Transformation of Scientific and Technological Achievements*. These new policies required time to be effectively implemented and produce results, with varying responses and execution across different regions. A potential mismatch between technological development and market demand might have contributed to the reduction in innovation efficiency. However, with the continuous increase in input indicators and improvements in management practices, the effective allocation and utilization of scientific resources were achieved, leading to an enhancement in innovation efficiency. Despite these fluctuations, China's overall innovation capacity continued to grow and remained at a high level from 2014 to 2019. Nonetheless, there was a noticeable disparity in innovation efficiency across different regions during these six years. Heilongjiang consistently maintained high innovation efficiency, with Beijing and Shaanxi also performing well. The relatively high innovation efficiency in the two provinces and Beijing municipality reflects the stability of their innovation environments and policies during this period. In contrast, other regions experienced fluctuations in innovation efficiency, possibly due to factors such as changes in regional policies, economic development levels, shifts in technological innovation capabilities, and other external environmental influences.

Fig. 4 illustrates the annual changes in average efficiency scores for all regions in China, with a specific focus on the Eastern, Central, Western, and Northeastern regions[1]. In the Eastern region, the average innovation efficiency was 0.704 in 2014 and increased to 0.742 by 2019, indicating a stable upward trend. The Central region's average innovation efficiency started at 0.558 in 2014, experienced fluctuations, but ultimately rose to 0.584 by 2019, showing a gradual improvement despite the variability. The Western region demonstrated significant progress, with its average innovation efficiency increasing from 0.728 in 2014 to 0.797 by 2019, particularly during 2017 and 2018. The Northeastern region, which had the highest average innovation efficiency in 2014 at 0.912, saw a steady decline to 0.864 by 2019. However, despite this decrease, the Northeastern region maintained relatively high innovation efficiency throughout the period. Overall, the

[1] The eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan; the central region includes Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan; the western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang; the northeast region includes Liaoning, Jilin and Heilongjiang. Tibet, Hong Kong, Macao and Taiwan are not included in this study.

Eastern and Western regions showed notable improvements in innovation efficiency over these six years, while the Central region, despite some fluctuations, also exhibited an overall upward trend. The Northeastern region, though experiencing a decline, sustained a high level of innovation efficiency. These changes reflect the varying innovation capabilities and developmental trends across different regions in China.

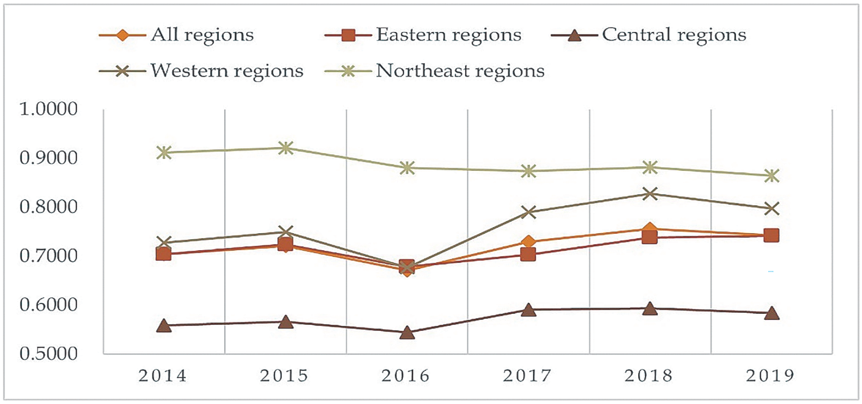

Fig. 4. Annual changes in the average innovation efficiency of the four major economic regions.

Fig. 5 illustrates the annual changes in the Theil Index of average efficiency scores across China, including the Eastern, Central, Western, and Northeastern regions. Nationally, the Theil Index showed an overall downward trend from 2014 to 2019, indicating that regional disparities in innovation efficiency are narrowing. In the Eastern region, the Theil Index fluctuated between 2014 and 2019 but generally showed a slight decrease, suggesting a reduction in regional disparities in innovation efficiency over this period. The Central region's Theil Index also trended downward, particularly between 2017 and 2019, reflecting a significant reduction in inequality of innovation efficiency in this region during these years. Similarly, the Western region's Theil Index decreased overall from 2014 to 2019, with a more pronounced decline after 2017, indicating a decrease in inequality in innovation efficiency. In contrast, the Northeastern region's Theil Index fluctuated considerably over these six years, with a notable decrease in 2015 followed by an increase in subsequent years. Overall, despite fluctuations in the Northeastern region, the Theil Index in the other three major economic regions and across all regions showed a downward trend, indicating a reduction in inequality of innovation efficiency between 2014 and 2019.

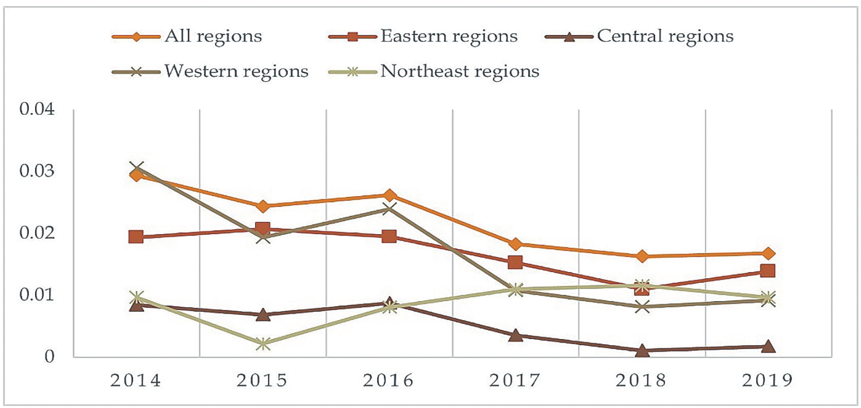

Fig. 5. Annual changes in the Theil index of the four major economic regions.

4.3. Analysis of regional resource allocation under inverse DEA

In this section, we use Jiangsu's regional innovation performance in 2019 as an example, with an innovation efficiency of 0.6041, to analyze how to optimize and adjust resource allocation using the inverse DEA model. Jiangsu was chosen because it ranks first in China in both development and the Daily Life Index, making it the province with the highest comprehensive development level and leading economic competitiveness. Additionally, it has the largest manufacturing industry cluster in the country and attracts numerous high-quality talents. However, its innovation efficiency is relatively low. First, we examine how the corresponding output changes when input indicators increase by 1%, 3%, and 5%, while maintaining Jiangsu's current efficiency level (0.6041). Next, we explore how the corresponding output changes when Jiangsu's efficiency improves to 0.8000, 0.9000, and 0.9900, with input indicators unchanged. Finally, we analyze how the outputs of the entire system change when both inputs and efficiency are adjusted. Our analysis is based on Model (4), where the output of the technology development stage is considered equally important as the output of the achievement transformation stage. The results are presented in Table 3.

Table 3
Resource optimization and adjustment in Jiangsu.

Initial efficiency	Inputs increased by	Efficiency increased to	ΔNVP (piece)	ΔNPP (piece)	ΔITA (million yuan)	ΔTBV (million yuan)	ΔSBR (million yuan)
0.6041	1%	/	-348,966.0	-3,811.9	+782,255.2	+262,636.6	+64,172.7
0.6041	3%	/	-326,494.4	-2,115.7	+802,906.1	+290,384.2	+68,074.7
0.6041	5%	/	-304,022.8	-419.5	+823,557.0	+318,131.8	+71,976.8
0.6041	/	0.8000	+4,083.1	+22,836.9	+1,550,009.1	+1,294,227.7	+209,242.0
0.6041	/	0.9000	+190,066.1	+36,875.3	+2,030,956.5	+1,940,451.8	+300,118.4
0.6041	/	0.9900	+357,450.8	+49,509.8	+2,512,186.9	+2,587,056.0	+391,048.3
0.6041	1%	0.8000	+18,961.8	+23,960.0	+1,568,115.3	+1,318,556.1	+212,663.2
0.6041	1%	0.9000	+206,804.6	+38,138.8	+2,053,872.3	+1,971,242.4	+304,448.4
0.6041	1%	0.9900	+375,863.2	+50,899.6	+2,539,914.9	+2,624,312.7	+396,287.6
0.6041	3%	0.8000	+48,719.0	+26,206.2	+1,604,327.9	+1,367,213.0	+219,505.7
0.6041	3%	0.9000	+240,281.6	+40,665.7	+2,099,703.7	+2,032,823.8	+313,108.4
0.6041	3%	0.9900	+412,687.8	+53,679.2	+2,595,371.0	+2,698,826.1	+406,766.2
0.6041	5%	0.8000	+78,476.3	+28,452.3	+1,640,540.4	+1,415,869.8	+226,348.1
0.6041	5%	0.9000	+273,758.5	+43,192.6	+2,145,535.2	+2,094,405.1	+321,768.4
0.6041	5%	0.9900	+449,512.4	+56,458.8	+2,650,827.1	+2,773,339.6	+417,244.7

Table 3 reveals that changes in the inputs (RDE, RDP, and ICTC) affect the system's efficiency. Specifically, a 1%, 3%, and 5% increase in RDE, RDP, and ICTC, respectively, leads to a decrease in NVP and NPP, while ITA, TBV, and SBR increase. As the input proportions grow, the declines in NVP and NPP gradually lessen, while the increases in ITA, TBV, and SBR become more pronounced. In this scenario, the system maintains an overall efficiency of 0.6041 by reducing the efficiency of the technology development stage and enhancing the efficiency of the achievement transformation stage. Therefore, if Jiangsu aims to increase investment while maintaining the current efficiency level, it must focus on enhancing the transformation of scientific and technological achievements while reducing the output of 'low-quality' patents and papers. Additionally, when the original inputs remain constant, increasing system efficiency to 0.8000, 0.9000, and 0.9900 results in higher values for NVP, NPP, ITA, TBV, and SBR. Thus, Jiangsu needs to address both aspects simultaneously: improving the high-quality output of patents and papers and accelerating the transformation and implementation of scientific and technological achievements. This should be done alongside efforts to enhance the efficiency of both technology development and achievement transformation. Finally, when both input indicators and efficiency are increased, the gains in NVP, NPP, ITA, TBV, and SBR are even more significant. Other regions can similarly optimize their resource allocation following this analysis.

5. Conclusion, Discussion, and Recommendations

5.1. Conclusion and discussion

This study constructs a RIE evaluation system driven by the digital economy and employs a two-stage inverse DEA model to provide a comprehensive measurement of RIE across China. Through an empirical analysis of Jiangsu Province, the study not only demonstrates the advantages of this model in optimizing resource allocation but also offers practical insights for enhancing regional innovation in the context of the digital economy.

The results indicate that from 2014 to 2019, China's overall RIE improved steadily, with the eastern and western regions experiencing significant growth in innovation efficiency. This is due to factors such as policy support, abundant innovation resources, and strong economic foundations in these regions. However, the northeastern region faced a slight decline, reflecting challenges related to traditional industries and talent outflow (Lan and Zhao, 2020; Guo *et al*., 2023). In terms of resource allocation in Jiangsu Province, the study highlights that maintaining innovation efficiency requires reducing output in the technology development stage while enhancing output in the transformation stage when input increases. To further improve RIE, output in both stages must be optimized simultaneously. This underscores the importance of not only focusing on technological development but also enhancing mechanisms for the commercialization of technological achievements (Irtyshcheva *et al*., 2022; Cao *et al*., 2023; Guo *et al*., 2023).

The theoretical significance of this study is reflected in two key innovations. First, traditional RIE research mainly relies on economic factors such as physical capital, labor, and R&D investment as core indicators for evaluation. These models fail to fully capture the complexity of innovation activities in the digital economy era. For example, many traditional studies (Bai, 2013; Chen *et al*., 2018; Wang and Zhang, 2022) adopt singular innovation input and output indicators, overlooking the impact of digitalization on innovation activities. In contrast, this study expands the scope of RIE evaluation by incorporating indicators such as digital capital, digital industrialization, and industrial digitization, ensuring that the evaluation is more timely and relevant. This improvement not only makes the assessment more comprehensive but also addresses the gap in existing studies that neglect the digital economy's influence.

Second, most existing literature uses traditional DEA models to evaluate RIE, primarily focusing on measuring innovation efficiency while lacking correlation analysis in multi-stage resource allocation (Wang and Zhang, 2022; Guo *et al*., 2023). In contrast, this study is the first to apply the inverse DEA model to the production system of regional innovation evaluation, proposing a new pathway for optimizing resource allocation by dividing the technological development stage and the transformation stage. This method helps identify resource bottlenecks in regional innovation and provides a theoretical basis for resource distribution across different stages.

From a practical perspective, the findings has many implications for regions aiming to enhance their innovation efficiency. Unlike most existing research that focuses on increasing R&D investment and improving the efficiency of technological development (Bai, 2013; Chen *et al*., 2018; Fan *et al*., 2020), this study emphasizes the coordinated development of both the technology development phase and the transformation stage. Traditional research tends to overemphasize the investment in the technological development stage while neglecting the mechanisms for transforming innovation outcomes into marketable products. These studies recommend increasing R&D input and fostering innovation talent, but they fail to effectively address the real-world challenges in the commercialization of innovation outcomes. Through the analysis of the inverse DEA model, this study points out that when resource input increases, both the technology development stage and the transformation stage must be optimized simultaneously, or else resource waste or delays in the commercialization process will occur. This finding sharply contrasts with traditional views and highlights the need for balance and systematization in the innovation process.

5.2. Recommendations

Based on the above analysis, in order to implement innovation-driven development and enhance RIE, this study provides the following recommendations: First, it is essential to recognize the importance of the digital economy in driving regional innovation. The digital economy, through the widespread application of digital technologies, propels economic growth and transformation. It not only fosters the emergence of new industries and business models but also enhances the efficiency of traditional sectors. To support this, it is necessary to increase investment in digital infrastructure, including the construction of 5G networks, data centers, and cloud computing platforms. Such investments will provide robust support for regional innovation and promote the healthy development of the digital economy. Additionally, policies should be formulated to facilitate the digital transformation of small and medium-sized enterprises (SMEs) and traditional industries. For instance, financial subsidies and tax incentives could encourage businesses to adopt digital technologies, thereby enhancing production efficiency and innovation capabilities. Moreover, support should be provided for the comprehensive application of digital technologies across various industries, particularly in manufacturing, agriculture, and services. Establishing pilot projects and demonstration zones can effectively showcase how digital technologies can drive industrial upgrading and innovation (Chen, 2022; Liu and Zheng, 2022; Wang and Cen, 2024).

Second, we should focus on producing high-quality results and promoting the transfer and transformation of scientific and technological achievements. This can be achieved by establishing more technology innovation incubators, accelerators, and technology transfer centers to provide market-oriented support and services for research outcomes. Additionally, it's essential to establish and optimize processes and mechanisms for technology transfer, which includes simplifying patent application procedures and strengthening intellectual property protection. Simultaneously, we must promote collaboration between industry and academia to facilitate the commercialization of research achievements. Encouraging corporate R&D investment through tax incentives and subsidy policies will motivate companies to increase their R&D spending, particularly in high-tech fields. Furthermore, supporting partnerships among businesses, universities, and research institutions will help in jointly developing innovative results with significant market potential (Su and Yan, 2020; Xiong *et al*., 2020; Lou *et al*., 2024).

Third, we should optimize resource allocation among different regions. This involves developing differentiated resource allocation policies based on each region's innovation potential and development needs. For regions with weak innovation foundations, we should increase investment in infrastructure and R&D; conversely, for regions with strong innovation capabilities, the focus should be on supporting technology transfer and market application. We must encourage innovation cooperation between developed eastern regions and the central, western, and northeastern regions by sharing technology resources and innovative experiences. Establishing cooperation mechanisms and platforms between regions will promote the exchange and sharing of resources and information. Additionally, it is essential to implement targeted support policies that consider the specific development stages and characteristics of each region. For instance, eastern regions could prioritize support for high-end technology R&D, while central and western regions might focus on industrial transformation and infrastructure construction. Meanwhile, northeastern regions should address talent retention and the upgrading of traditional industries (Xiong *et al*., 2020; Wu *et al*., 2023; Lou *et al*., 2024).

This study also has some limitations: First, regional innovation is a complex system, and this paper only considers representative input-output indicators to measure innovation efficiency. Future research could further refine the connotations of the digital economy and improve the evaluation system for RIE driven by the digital economy. Second, this paper uses a simple two-stage system to evaluate the regional innovation process. In practice, there are also production structures involving input sharing between the two stages, as well as output feedback structures from the second stage to the first stage. This will be a direction for future research.

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