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EVOLUTIONARY EFFICIENCY EVALUATION AND INFLUENCING FACTORS OF HIGH-TECH INDUSTRY INNOVATION ECOSYSTEMS

Jianzhao Yang
E-mail: yangjz@ywicc.edu.cn
ORCID: https://orcid.org/0000-0002-2143-4794
Affiliation1: School of Entrepreneurship, Yiwu Industrial & Commercial College, Yiwu, Zhejiang, China
ROR: Not found
Affiliation 2: Zhejiang Provincial Think Tank Alliance for Research on the New Development Pattern, Hangzhou, Zhejiang, China
ROR: Not found
Affiliation 3: School of Economics and Management, Harbin Engineering University, Harbin, Heilongjiang, China
ROR: https://ror.org/03x80pn82

Jingwei Zhu
E-mail: zjw@ywicc.edu.cn
ORCID: https://orcid.org/0009-0001-9950-5011
Affiliation: Center of Industry-Education Integration Ecosystem for Vocational Education, Yiwu Industrial & Commercial College, Yiwu, Zhejiang, China
ROR: Not found

Hairong Zhou
E-mail: 362962922@qq.com
ORCID: Not found
Affiliation: School of Entrepreneurship, Yiwu Industrial & Commercial College, Yiwu, Zhejiang, China
ROR: Not found

Annotation. As a core driver of economic restructuring and technological innovation, the high-tech industry plays a crucial role in enhancing regional innovation capacity and industrial competitiveness. However, existing studies lack a systematic and phased evaluation of the evolutionary efficiency of high-tech industry innovation ecosystems. To explore the efficiency and influencing mechanisms of such evolution, drawing on ecosystem evolution and complex systems theory, a two-stage DEA–Tobit analytical framework was constructed.

Using the panel data from 30 national high-tech industrial parks in China for 2018, the evolutionary efficiency of the innovation ecosystem in two stages (innovation generation and achievement transformation) was measured, and the effects of input factors as well as policy, economic, social, and technological environments on system efficiency were further identified. Results reveal that the innovation ecosystem exhibits relatively high efficiency in the intermediate output stage but shows significant inefficiency in the final output stage. Talent quality, number of enterprises, economic development, and technological factors exert significant positive effects on efficiency, whereas policy interventions and energy inputs exhibit inhibitory effects. Regional heterogeneity is also evident: eastern regions outperform others in achievement transformation efficiency, while certain central and western regions achieve breakthroughs in the intermediate stage through organizational innovation. The conclusions enrich the theoretical framework for evaluating the evolutionary efficiency of innovation ecosystems and provide empirical evidence and policy implications for optimizing regional innovation environments, improving policy systems, and promoting the high-quality development of high-tech industries.

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JEL classification: O36, M21, C52.

Introduction

In the 1960s, the term "high technology" appeared in the United States, which began the process of rapid development. A high-tech industry usually refers to a collection of enterprises that master high-level core technologies for core competitiveness and that transform these technologies into high-tech products or services. Innovation refers to the practical process of human beings' re-creation of the material world and the conscious world. It is a material re-engineering process that realizes material innovation through conscious innovation. From a practical perspective, "innovation" refers to the process in which enterprises break the existing model to increase profits by restructuring production factors, changing production conditions, and designing production systems (Bengt-Ake *et al.*, 2002). The path of high-tech industry innovation is the change process of the high-tech industry, which begins with technological development, gains competitive advantage through technological innovation, and then realizes innovation technology diffusion.

The concept of a high-tech industry innovation ecosystem is defined by the coupling of a high-tech industry innovation system and an innovation ecosystem (Adner, 2006), based on ecological theory (Iansiti *et al.*, 2004). The innovation technology in the system is in the core position (Su and Fan, 2022), the system constitutes the network structure, and knowledge flows at a high speed in the network to facilitate the transmission of innovation technology (Kim *et al.*, 2010; Li, 2009), supplemented by policy (Hong *et al.*, 2016), the market (Fukuda and Watanabe, 2008) and so on. Many kinds of environments work together. The core enterprise is the leading force in the establishment of an innovation ecosystem (Adomavicius and Zhang, 2012). It organizes and allocates cooperation and resources to promote the evolution of the whole system (Bogliacino and Pianta, 2013; Van *et al.*, 2012). Core technology enterprises are at the center of the network structure formed with related technology enterprises, and the core enterprise is composed of the system environment (Boschma and Ter Wal, 2007; Su *et al.*, 2021). An innovation ecosystem can help enterprises quickly obtain a living environment and market relations (Goktan and Miles, 2011; Sun *et al.*, 2017), and the knowledge interaction and knowledge expansion between enterprises are greatly enhanced (Boschma and Wal, 2007; Kang *et al.*, 2021). An innovation ecosystem helps system members realize resource interaction, achieve goal sharing, enter new markets and create value through collaborative innovation. The network structure and inter-enterprise collaboration are the basis of innovation ecosystem. Environmental factors must also be included in the influencing factors of the innovation ecosystem (Chen *et al.*, 2020; Liu *et al.*, 2018).

The evolutionary process of innovation ecosystem is a complex nonlinear process (Song, 2016). Thus, it is difficult to establish a definite explicit expression between the input and output of innovation ecosystem evolution. The evolution is still a multi-output process. Its output indicators can be reflected in the number of intellectual property authorizations and the growth in innovative product income, as well as process improvement innovation and even management system reform, regional economic development and social benefit improvement. Therefore, the problem that we need to solve is from the perspective of the evolutionary practice. What kind of efficiency model can be used to evaluate the evolutionary efficiency? How can a corresponding evaluation index system be constructed? In addition to the significant influence of input factors and influencing factors, the evolutionary process is disturbed by other uncontrollable factors. How can various interference factors be eliminated in the evaluation process? The two-stage data envelopment analysis (DEA)-Tobit model selected in this study has a high level of pertinence and applicability for evaluating the efficiency of high-tech industry innovation ecosystems and analyzing its influencing factors.

The main contributions of this study are reflected in three aspects. First, at the methodological level, this study introduces a two-stage DEA model to systematically depict the multi-stage efficiency of the evolutionary process, thereby overcoming the limitations of traditional single-stage efficiency evaluations. Second, at the theoretical level, it integrates the logic of ecosystem evolution with the analytical perspective of complex systems, deepening the understanding of the internal mechanisms underlying the evolution of innovation ecosystems. Third, at the practical level, by using empirical data from 30 high-tech industrial parks across China, this study identifies the key factors constraining the evolutionary efficiency of innovation ecosystems and proposes targeted policy recommendations. Overall, this research enriches the theoretical framework for evaluating the efficiency of innovation ecosystems and provides a quantitative basis and policy insights for promoting the high-quality development of the high-tech industry.

This study is organized as follows. Section 1 conducts the literature review. Section 2 introduces the efficiency method. Section 3 presents results of the empirical analysis. Section 4 discusses the results. Section 5 provides the discussion and conclusion.

1. Literature Review

1.1 High-Tech Industry Innovation

Su *et al.* (2021) used Chinese provincial panel data and the spatial Durbin model (SDM) to analyze the positive effect of technological innovation on regional development and discussed the impact of technological innovation and industrial structure upgrading on regional development. Goktan and Miles (2011) examined the innovation relationship within the high-tech industry by using hierarchical multiple regression analysis. The results showed that radical product innovation and radical process innovation are positively correlated with their innovation speed. Radical product innovation and radical process innovation are also highly correlated. Wang (2022) paid special attention to the impact of the intellectual property operation mode on enterprise innovation and clarified the characteristics and differences of different modes through case studies. Yuan *et al.* (2023) analyzed the formation mechanism of emerging technology “multi-core” innovation networks, studied the knowledge growth mechanism of emerging technology innovation networks, and constructed a dual two-way formation model of emerging technology “multi-core” innovation networks.

1.2 The Evolution of Innovation Ecosystems

The innovation ecosystem was first proposed by Moore (1993). From the enterprise perspective, he argued that the innovation ecosystem can be defined as an “economic consortium based on organizational interaction”. Mercan and Autioa (2011) argued that the interior is a symbiotic process of participants, but the symbiotic mode and evolutionary characteristics of innovation subjects are at different stages of development. Adner (2016) argued that an innovation ecosystem is a collection of multilateral cooperating entities that need to concretize the central value of alliance goals. An innovation ecosystem redefines the business strategy model so that it completes the multi-dimensional transformations from simple joint operation to collaborative and systematic cooperation, from product competition to platform competition, and from the independent development of enterprises to “symbiotic evolution”. Symbiotic evolution has also become an effective way to promote ecological alliances (Annanperä *et al.*, 2015; Van *et al.*, 2012). Randhawa *et al.* (2021) studied the relationship between the innovation motivation, ecological strategy and innovation output of different enterprises and explored their evolution over time. Dagnino *et al.* (2021) tracked and deconstructed the evolutionary process of innovation ecology and found that the R&D stage is the key input period of core resources, integrating the value creation efficiency of external resources. Nedkov *et al.*, (2022) revealed the evolutionary mechanism and profitability of enterprise development under an innovative ecological environment by constructing a complex system model of the relationship between innovation behaviour and the goal expectations of different types of innovation subjects.

1.3 Efficiency of Industrial Innovation Ecosystems

Hansen and Pihl-Thingvad (2019) constructed an industrial innovation ecosystem from the three levels of core technology, competitive technology and matching technology. Hansen divided industrial innovation ecosystems into three parts: research, development and application. Cohende *et al.*, (2021) had a similar view according to which the cooperative innovation performance of core enterprises and an innovation ecosystem depends on the interaction between ecosystem members. Yang (2022) studied the impact of the symbiotic structure on innovation efficiency of China's high-tech industry innovation ecosystem. Chen *et al.* (2020) introduced a conceptual model of research and development (R&D) and the commercialization efficiency of China's high-tech industry. Empirical research shows that there are regional differences in China's high-tech industry, and the R&D sub-process is not closely related to the commercial sub-process in terms of efficiency.

Overall, existing studies have provided a solid theoretical foundation for understanding the formation mechanisms, structural characteristics, and evolutionary patterns of high-tech industry innovation ecosystems, yet several limitations remain. First, in terms of research perspective, most studies focus on static structural analysis or single-stage efficiency measurement, paying insufficient attention to the dynamic evolutionary process of innovation ecosystems and lacking a systematic evaluation framework that reflects the entire process of "innovation generation–transformation–diffusion". Second, from the methodological standpoint, current research mainly adopts single-stage DEA models, regression analysis, or system dynamics simulations. Although these approaches reveal certain influencing relationships, they are inadequate in capturing the multi-stage efficiency transformation, nonlinear characteristics, and inter-stage linkages within high-tech industry innovation ecosystems. Third, regarding research content, few studies have quantitatively examined how multidimensional external factors-such as policy, technology, society, and economy-jointly affect evolutionary efficiency, and the coupling effects and regional heterogeneity of these factors across different stages remain under-explored. Therefore, future studies should integrate ecosystem theory with efficiency analysis methods from a dynamic perspective, and develop multi-stage, quantitative analytical frameworks to uncover the intrinsic mechanisms and influencing paths of high-tech industry innovation ecosystem evolution. Building on prior research, this study employs a two-stage DEA-Tobit model to systematically measure and compare the evolutionary efficiency and influencing factors of high-tech industry innovation ecosystems, thereby addressing existing gaps in stage division, mechanism identification, and efficiency evaluation.

2. Methodology

2.1 Methods Selection

In natural ecosystems, biological evolution refers to the process of survival of the fittest through genetic reproduction, variation and natural environment selection (Engler, Kusiak, 2011; Marzucchi, Montresor, 2017). The evolution of natural ecosystems is mainly based on biological heredity, which is continuous. However, the process is random, greatly affected by the selection of the natural environment, and it is highly uncontrollable. The evolutionary process of high-tech industry innovation ecosystems also has a similar process, but differently, the evolution of high-tech industry innovation has the following characteristics:

2.1.1 Proactiveness

The innovation gene guarantees the maintenance of continuous innovation activities. The embodiment of human initiative makes system evolution have a clear purpose and continuous or discontinuous behavior guided by experience. It is not just passive acceptance of selection and random variation.

2.1.2 Inheritance

Innovative genes, such as innovative technology, innovative knowledge, innovative resources, innovative culture, innovative spirit and innovative organization, that have been formed can withstand the test of the innovation environment and gain the competitive advantage of innovation. They will not only be retained but also be passed on through knowledge spillover and technology diffusion as well as in other ways.

2.1.3 Subversion

When the original innovation gene no longer has innovation advantages, it will mutate. It should break through the existing innovation dilemma by searching for an innovation paradigm that is more suitable for the innovation environment. This is similar to the mutation process of innovation genes, but this kind of subversive mutation is not necessarily realized immediately and may also occur through multiple mutations to realize innovation ability, innovation resource optimization, and an innovation environment.

2.1.4 Selectivity

The diversity of innovation species and innovation populations determines the diversity of innovation gene evolution. Based on the results of innovation variation, innovation variation can be divided into beneficial innovation variation, ineffective innovation variation and harmful innovation variation. Based on the form of variation, it can also be divided into routine innovation variation and deviant innovation variation. The innovation environment will receive the feedback of innovation variation and select the innovation variation that adapts to the innovation environment, which reflects the selectivity of the innovation environment with regard to system innovation variation.

The evolutionary efficiency based on the evolutionary efficiency of the innovation subjects in the innovation system. The evolutionary output has multi-dimensional characteristics. Therefore, this study chooses the DEA method, which can evaluate multi-output decision-making units (DMUs), to evaluate the evolutionary efficiency. However, because the DEA method cannot measure the influencing factors of the evolutionary stage in a "one-step" way, other methods need to be introduced to evaluate the influencing factors. Based on the characteristics of influencing factors, this study introduces a multiple linear regression method to evaluate the role of influencing factors.

Taking into account the stage characteristics of the generation and transformation of scientific and technological achievements in the evolutionary process of high-tech innovation ecosystems, based on the two-stage evaluation method, this study establishes an evaluation index system to evaluate the evolutionary efficiency from four aspects: evolutionary intermediate output, evolutionary final output, evolutionary input and evolutionary influencing factors.

2.2 Evolutionary Output Factor Evaluation Index

Evolutionary intermediate output is mainly reflected in three aspects: patent output, technology output and system structure optimization.

Patent output is evaluated based on the number of patent applications (*PA*) in a year. The number of patent applications in a year refers to the total number of patents applied for by all enterprises in a year, including domestic patents and Patent Cooperation Treaty (*PCT*) patents (in units). The greater the number of patent applications is, the more frequent the enterprise innovation activities and the greater the possibility of obtaining independent intellectual property rights.

Technology output is evaluated based on the output technological turnover (*TT*). The output technology trading volume refers to the total monetary value of output technology contract transactions (in units of ten thousand RMB). The larger the transaction volume of an output technology contract, the higher the degree of enterprise cooperation and technology diffusion and transfer.

System structure optimization is evaluated based on the proportion of innovative enterprises (*IE*). The proportion of innovative enterprises refers to the proportion of innovative enterprises identified by relevant government departments in the total number of enterprises (in percentage units). The higher the proportion of innovative enterprises is, the stronger the innovation vitality and innovation strength of enterprises in the innovation ecosystems of high-tech industries and the greater the driving effect on other enterprises and the contribution to scientific and technological innovation.

Evolutionary final output is mainly reflected in two aspects: the output value of new products and new high-tech enterprises.

Output value of new products refers to the total output value of new products realized by high-tech industry innovation ecosystem enterprises (in units of ten thousand RMB). The greater the output value of new products is, the more the high-tech industry innovation ecosystem can continuously develop new products and the better the evolutionary performance.

New high-tech enterprises reflects the number of new main elements formed by the evolution of the system through the continuous interaction of the elements in the system during the evolution of a high-tech industry innovation ecosystem. The larger the number of new high-tech enterprises is, the better the evolutionary effect of the high-tech industry innovation ecosystem, and vice versa.

The evolutionary input factors are evaluated based on three aspects: human resources, capital and material. Evolutionary human resource investment mainly uses two indicators: the amount of innovative personnel input and the quality of innovative personnel input. Evolutionary capital investment mainly uses two indicators, innovation investment and ecological construction investment, for evaluation. Evolutionary material input is mainly evaluated based on three indicators: the number of enterprises, the number of scientific and technological public service platforms, and the energy consumption per ten thousand RMB of output value.

Evolutionary human resource input is manifested in the quantity (*HS*) and quality of personnel (*HZ*). The number of innovative personnel is used to measure the total number of innovative personnel invested in innovation ecosystems of high-tech industries. It is the talent base of enterprise innovation activities in innovation ecosystems of high-tech industries and is evaluated based on the full-time equivalent of R&D personnel. The quality of innovative personnel is the guarantee of innovative talent in the evolution of high-tech industry innovation ecosystems, and it is evaluated based on the total number of personnel with a master's degree or above.

Evolutionary capital investment mainly includes two aspects: innovation investment (*IF*) and ecological construction investment (*EI*). Innovation investment refers to the investment of enterprises in innovation ecosystems of high-tech industries in basic research, applied research and experimental development to carry out innovation activities, which is evaluated based on R&D expenditure. Innovation funds are the financial guarantee for the continuous development of technology R&D activities and the basis for the upgrading of innovation ecosystems of high-tech industries. Ecological construction investment is the investment of high-tech industry innovation ecosystems in ecological construction, including the construction of circulation systems, pollution control systems, greening, power generation systems, industrial ecological chain construction and so on. The higher the ecological construction investment is, the more perfect the ecological circulation system.

Evolutionary material input is mainly reflected in innovative enterprises (*ES*), science and technology public service platforms (*PS*) and innovative energy (*EC*). The investment of innovative enterprises is evaluated by the number of innovative enterprises. The number of enterprises refers to the total number of all enterprises in an innovation ecosystem of high-tech industries (unit is headquarters). The larger the number of enterprises is, the stronger the incubation function of the high-tech industry innovation ecosystem, the greater the attractiveness to enterprises, and the higher the possibility of industrialization. The input of science and technology public service platforms is evaluated based on the number of science and technology public service platforms. The number of science and technology public service platforms refers to the number of science and technology public service platforms (including basic condition platforms, public technology service platforms, etc.) with basic, open and public welfare characteristics (unit is one). The more scientific and technological public service platforms there are, the more powerful support can be obtained for high-tech research, technological innovation, science and technology innovation and entrepreneurship, and the internal and external resource integration activities of enterprises in the high-tech industry innovation ecosystem. Innovative energy input is evaluated based on energy consumption per ten thousand RMB of output value. Energy consumption per ten thousand RMB of output value refers to the energy consumed per ten thousand RMB of output value, namely, where energy consumption per ten thousand RMB of output value = total energy consumption (tons of standard coal) / output value (ten thousand RMB) (unit is tons of standard coal). The index reflects the level of energy consumption, energy savings and consumption reduction in the development of high-tech industry innovation ecosystems. The higher the index value is, the higher the energy utilization efficiency.

It is necessary to note that evolutionary intermediate output can be used as the input of final output. The reason is that some scientific and technological achievements are not the final market-oriented output, and the further transformation of these scientific and technological achievements can produce the final output. For example, intermediate output patents need to be further transformed into new products supported by patents and enable enterprises to obtain greater profits, which is also the economic and social value.

In addition to the direct impact of evolutionary input and output factors on the evolutionary efficiency, evolutionary efficiency will be indirectly affected by factors such as the economic development level and policy status. This study uses the classic political, economic, social, and technological (PEST) theoretical framework to analyse the influencing factors of the evolutionary efficiency of high-tech industry innovation ecosystems.

In terms of evolutionary policy factors (*PI*), the index of government investment is used to evaluate the influence of policy on the evolution of high-tech industry innovation ecosystems.

In terms of evolutionary economic factors (*SR*), the sales revenue of new products that can reflect the scale of market demand is used for evaluation.

In terms of evolutionary social factors (*LA*), the number of innovative and entrepreneurial activities that can reflect the degree of social acceptance of and support is selected as the evaluation index of social factors.

In terms of evolutionary technological factors (*TM*), the technology transaction volume, which is directly related to the evolutionary activity and evolutionary results of high-tech industry innovation ecosystems, is selected to evaluate technological factors.

2.3 Evaluation Model

When evaluating the evolutionary efficiency, the generation and transformation of innovation achievements are not produced by one stage. They undergo an intermediate process, and each stage needs to be regarded as an input process and as an output process. These two stages can be regarded as the stage of innovation achievement generation and the stage of innovation achievement transformation. Then, a two-stage DEA model can be established based on these two stages. Each stage uses the DEA-C^2R model for calculation and analysis. The DEA-C^2R model for evaluating the efficiency of the innovation evolutionary stage of high-tech industry innovation ecosystems is as follows:

$DMU_j(j=1,2,\cdots,n)$ is a decision-making unit. *x* is the input of the system. $x_j=(x_{1j},x_{2j},\cdots,x_{mj})^T$, where $(j=1,2,\cdots,n)$. *y* is the output of the system, and $y_j=(y_{1j},y_{2j},\cdots y_{sj})^T$, where $(j=1,2,\cdots,n)$. x_{ij} is the input to the *i-th* input of DMU_j, and $x_{ij}>0$. y_{rj} is for the output of the *r-th* output of DMU_j, and $y_{rj}>0$. v_i is a measure (or weight) of the input of the *i*-th type, and $i=1,2,\cdots,m$. u_r is a measure (or weight) of the second output, and $r=1,2,\cdots,s$.

The following efficiency evaluation index is defined:

$$h_j=\frac{y_i{}^Tu}{x_j{}^Tv},\ j=1,2\cdots,n; \tag{1}$$

Clearly, the smaller the input is, the larger the output efficiency of DMU_j. We can always select the coefficients v and u appropriately so that $h_j\le 1$. Taking the efficiency index of one DMU as the objective function and the efficiency index of all DMUs $(j=1,2,\cdots,n)$ as the constraint, we obtain the fractional programming problem (C^2R model) of equation (2):

$$\begin{cases}\max\dfrac{y_j{}^Tu}{x_j{}^Tv}=E_j\\ s.t.\ \dfrac{y_j{}^Tu}{x_j{}^Tv}\le 1\ (1\le j\le n),\ u\ge 0,\ v\ge 0\end{cases} \tag{2}$$

Equation (2) can be transformed into an equivalent linear programming form by using C^2 transformation. Let $t=\dfrac{1}{x_j{}^Tv}$, $\omega=tv$, $\mu=tu$. Then, equation (2) can be transformed into the following equation (3):

$$\begin{cases}\max y_j{}^T\mu=E_j\\ s.\ \mathrm{t.}\ y_j{}^T\mu-x_j{}^T\omega\le 0\quad (1\le \mathrm{j}\le \mathrm{n}),\ \mathrm{x_j}{}^\mathrm{T}\omega=1,\quad \omega\ge 0,\ \mu\ge 0\end{cases} \tag{3}$$

This study uses this model to evaluate the evolutionary efficiency of the innovation ecosystems of different high-tech industries. When the measured technical efficiency or scale efficiency value is 1, it is called technical or scale effective. Technology effectiveness refers to the technology adopted by an innovation ecosystem of high-tech industries (refers to generalized technology, including the management status of the system) that can ensure that the innovation ecosystem can achieve the maximum output of the production frontier production function, which means that the current input factors and factor combination of the innovation ecosystem are reasonable. Through the current organization and management, an innovation ecosystem of high-tech industries can achieve the level of the production frontier, that is, the maximum output. Scale efficiency refers to the scale when the marginal output is equal to the marginal input. At this scale, various resources of a high-tech industry innovation ecosystem can be well allocated. Comprehensive efficiency is defined as technical efficiency × scale efficiency. When the comprehensive evolutionary efficiency of a high-tech industry innovation ecosystem is 1, the evolution of the innovation ecosystem is considered efficient.

On the basis of calculating the value of the evolutionary efficiency, a multiple linear regression Tobit model is constructed with the value of evolutionary efficiency as the dependent variable and the evolutionary input and influencing factors as the independent variable. The specific form of the Tobit model is shown in equation (4):

$$Y_k = \begin{cases} X_k^{'}\beta + \mu_k, X_k^{'}\beta + \mu_k > 0 \\ 0,\ others \end{cases} \tag{4}$$

Where Y_k is the first dependent variable of the k -th observation value of the sample data, X_k is the explanatory variable, β is the unknown parameter variable, $\mu_k \sim N(0,\sigma^2)$, and $k = 1,2,3,\Lambda$.

To ensure the effectiveness of the Tobit model constructed in this study, in addition to the multicollinearity test of the model independent variables when constructing the evaluation index system for the evolutionary efficiency, this study analyses and diagnoses the outliers and robustness of the model independent variables. The test results show that the Tobit regression model constructed in this study has high effectiveness.

3. Result Analysis

To evaluate the evolutionary efficiency, this study needs to select the empirical object for verification. Therefore, how to find the appropriate sample plays a crucial role in the verification of research topics. This study believes that the empirical object should not only reflect the core position of high-tech enterprises but also fully consider the heterogeneous characteristics of other subjects to form a multi-dimensional complex network structure. Considering the above requirements and conditions, this study finds 156 national high-tech industrial parks through the "China Statistical Yearbook 2018" and divides them by province, which can ensure the unity of high-tech enterprises and related support organizations and has wide industry coverage, with the basic conditions for innovation ecosystems of high-tech industries.

3.1 High-Tech Industry Innovation Ecosystem Evolutionary Efficiency Calculation

3.1.1 High-tech Industry Innovation Ecosystem Evolutionary Intermediate Output Efficiency Calculation

Using the model constructed above, the intermediate output efficiency is calculated without considering the influencing factors. The results are shown in *Table* 1.

Table 1. Intermediate Output Efficiency of 30 Regions without Considering the Influencing Factors

Region	Overall efficiency	Pure technical efficiency	Scale efficiency	Scale benefits
Beijing	0.728	1.000	0.728	drs
Tianjin	0.404	0.682	0.593	drs
Hebei	0.673	0.719	0.936	drs
Shanxi	0.568	0.692	0.821	drs
Inner Mongolia	0.722	0.753	0.959	irs
Liaoning	0.640	0.706	0.906	drs
Jilin	0.799	0.887	0.901	drs
Heilongjiang	0.916	0.925	0.99	drs
Shanghai	1.000	1.000	1.000	-
Jiangsu	1.000	1.000	1.000	-
Zhejiang	0.789	0.801	0.985	drs
Anhui	0.937	0.937	1.000	-
Fujian	0.969	0.983	0.986	irs
Jiangxi	0.989	0.992	0.997	irs
Shandong	1.000	1.000	1.000	-
Henan	0.586	0.614	0.955	drs
Hubei	0.899	0.976	0.921	drs
Hunan	0.938	0.947	0.99	irs
Guangdong	0.952	1.000	0.952	drs
Guangxi	0.839	0.854	0.982	irs
Hainan	0.911	0.911	1.000	-
Chongqing	0.709	0.737	0.962	drs
Sichuan	0.971	0.979	0.992	irs
Guizhou	0.739	0.762	0.970	irs
Yunnan	1.000	1.000	1.000	-
Shanxi	0.804	1.000	0.804	drs
Gansu	0.736	0.75	0.981	irs
Qinghai	0.953	0.961	0.992	irs
Ningxia	0.913	0.921	0.991	drs
Xinjiang	0.993	1.000	0.993	irs

Source: authors' own results.

On this basis, the model constructed above is used to further calculate the intermediate output efficiency considering the influencing factors. The results are shown in *Table* 2.

Table 2. Intermediate Output Efficiency of 30 Regions without Considering the Influencing Factors

Region	Overall efficiency	Pure technical efficiency	Scale efficiency	Scale benefits
Beijing	0.510	0.779	0.655	drs
Tianjin	0.328	0.614	0.534	drs
Hebei	0.545	0.647	0.842	drs
Shanxi	0.460	0.623	0.739	drs
Inner Mongolia	0.585	0.678	0.863	irs
Liaoning	0.518	0.635	0.815	drs
Jilin	0.647	0.798	0.811	drs
Heilongjiang	0.742	0.833	0.891	drs
Shanghai	1.000	1.000	1.000	-
Jiangsu	1.000	1.000	1.000	-
Zhejiang	0.639	0.721	0.887	drs
Anhui	0.759	0.843	0.900	drs
Fujian	0.785	0.885	0.887	irs
Jiangxi	0.801	0.893	0.897	irs
Shandong	0.716	0.806	0.888	drs
Henan	0.475	0.553	0.860	drs
Hubei	0.728	0.878	0.829	drs
Hunan	0.759	0.852	0.891	irs
Guangdong	0.844	0.986	0.857	drs
Guangxi	0.679	0.769	0.884	irs
Hainan	0.738	0.820	0.900	drs
Chongqing	0.574	0.663	0.866	drs
Sichuan	0.787	0.881	0.893	irs
Guizhou	0.599	0.686	0.873	irs
Yunnan	0.820	0.925	0.887	drs
Shanxi	0.724	1.000	0.724	irs
Gansu	0.596	0.675	0.883	irs
Qinghai	0.772	0.865	0.893	drs
Ningxia	0.739	0.829	0.892	drs
Xinjiang	0.894	1.000	0.894	irs

Source: authors' own results.

3.1.2 High-tech Industry Innovation Ecosystem Evolution Final Output Efficiency Calculation

Using the model constructed above, the final output efficiency in 30 regions of China is calculated without considering the influencing factors. The results are shown in *Table* 3.

Table 3. Final Output Efficiency of 30 Regions without Considering the Influencing Factors

Region	Overall efficiency	Pure technical efficiency	Scale efficiency	Scale benefits
Beijing	1.000	1.000	1.000	-
Tianjin	0.292	0.580	0.504	drs
Hebei	0.486	0.611	0.796	drs
Shanxi	0.410	0.588	0.698	drs
Inner Mongolia	0.522	0.640	0.815	irs
Liaoning	0.462	0.600	0.770	drs
Jilin	0.577	0.754	0.766	drs
Heilongjiang	0.662	0.786	0.842	drs
Shanghai	1.000	1.000	1.000	-
Jiangsu	0.784	0.811	0.967	drs
Zhejiang	0.570	0.681	0.837	drs
Anhui	0.677	0.796	0.850	drs
Fujian	0.700	0.836	0.838	irs
Jiangxi	0.715	0.843	0.847	irs
Shandong	0.518	0.837	0.619	drs
Henan	0.424	0.522	0.812	drs
Hubei	0.650	0.830	0.783	drs
Hunan	0.677	0.805	0.842	irs
Guangdong	1.000	1.000	1.000	-
Guangxi	0.606	0.726	0.835	irs
Hainan	0.658	0.774	0.850	drs
Chongqing	0.512	0.626	0.818	drs
Sichuan	0.702	0.832	0.843	irs
Guizhou	0.534	0.648	0.825	irs
Yunnan	0.599	0.740	0.809	drs
Shanxi	0.471	0.689	0.683	irs
Gansu	0.532	0.638	0.834	irs
Qinghai	0.689	0.817	0.843	drs
Ningxia	0.659	0.783	0.842	drs
Xinjiang	0.577	0.683	0.844	irs

Source: authors' own results.

On this basis, the previous model is used to further calculate the final output efficiency in 30 regions of China considering the influencing factors. The results are shown in *Table* 4.

Table 4. Final Output Efficiency of 30 Regions Considering the Influence Factors

Region	Overall efficiency	Pure technical efficiency	Scale efficiency	Scale benefits
Beijing	1.0000	1.000	1.000	-
Tianjin	0.264	0.551	0.479	drs
Hebei	0.439	0.580	0.756	drs
Shanxi	0.370	0.559	0.663	drs
Inner Mongolia	0.470	0.608	0.774	irs
Liaoning	0.417	0.570	0.732	drs
Jilin	0.521	0.716	0.728	drs
Heilongjiang	0.597	0.747	0.800	drs
Shanghai	1.000	1.000	1.000	-
Jiangsu	0.708	0.770	0.919	drs
Zhejiang	0.514	0.647	0.795	drs
Anhui	0.611	0.756	0.808	drs
Fujian	0.632	0.794	0.796	irs
Jiangxi	0.644	0.801	0.805	irs
Shandong	0.467	0.795	0.588	drs
Henan	0.383	0.496	0.771	drs
Hubei	0.587	0.789	0.744	drs
Hunan	0.612	0.765	0.800	irs
Guangdong	0.599	0.777	0.772	drs
Guangxi	0.547	0.690	0.793	irs
Hainan	0.594	0.735	0.808	drs
Chongqing	0.462	0.595	0.777	drs
Sichuan	0.633	0.790	0.801	irs
Guizhou	0.482	0.616	0.784	irs
Yunnan	0.540	0.703	0.769	drs
Shanxi	0.425	0.655	0.649	irs
Gansu	0.480	0.606	0.792	irs
Qinghai	0.622	0.776	0.801	drs
Ningxia	0.595	0.744	0.800	drs
Xinjiang	0.520	0.649	0.802	irs

Source: authors' own results.

3.1.3 Optimization Calculation of the Evolutionary Efficiency of High-Tech Industry Innovation Ecosystems

The analysis of the calculation results of the evolutionary efficiency shows that there are multiple DMUs in the measurement results of the evolutionary efficiency. That is, the efficiency value is 1 in multiple regions, such as Shanghai, Jiangsu, Shandong and Yunnan. In the case of multiple DMUs with an efficiency value of 1, not only is it impossible to effectively analyse their differences but this value also affects the further development of subsequent research work, such as measuring the influencing factors. Therefore, the original DEA model needs to be improved. Based on the traditional C2R model, this study introduces virtual DMUs to improve the model. The specific steps are as follows:

First, virtual DMUs are constructed. The virtual optimal DMU and the virtual worst DMU are constructed and named DMU$_{n+1}$ and DMU$_{n+2}$. The input vectors are $X_{n+1} = (x_{1,n+1},\Lambda\ ,x_{i,n+1},\Lambda\ ,x_{m,n+1})^T$ and $X_{n+2} = (x_{1,n+2},\Lambda\ ,x_{i,n+2},\Lambda\ ,x_{m,n+2})^T$, and the output vectors are $Y_{n+1} = (y_{1,n+1},\Lambda\ ,y_{r,n+1},\Lambda\ ,y_{s,n+1})^T$ and $Y_{n+2} = (y_{1,n+2},\Lambda\ ,y_{r,n+2},\Lambda\ ,y_{s,n+2})^T$. The optimal DMU$_{n+1}$ takes the minimum and maximum values of all the actual DMU indexes as its input and output index values, respectively. The worst DMU$_{n+1}$ takes the maximum and minimum values of all the actual DMU indexes as its input and output index values: $x_{i,n+1} = \min(x_{i1},\Lambda\ ,x_{in})$, $y_{r,n+1} = \max(y_{r1,}\Lambda\ ,y_{rn})$; $x_{i,n+2} = \max(x_{i1},\Lambda\ ,x_{in})$, and $y_{r,n+2} = \min(y_{r1,}\Lambda\ ,y_{rn})$. DMU$_{n+1}$ and DMU$_{n+2}$ may not exist within the production possibility set, and their introduction is used only as a reference to effectively distinguish the efficiency of each DMU.

Second, the efficiency evaluation model of DMU$_{n+1}$ is established. Taking the efficiency evaluation value of n+2 DMUs as the constraint and taking the efficiency evaluation value of the optimal DMU, namely DMU$_{n+1}$, as $V^*{}_{n+1}$, the objective function, a new DEA model is established, as shown in equation (5):

$$\begin{cases} \max \beta^T Y_{n+1} \\ \alpha^T X_j - \beta^T Y_j \geq 0, \quad j = 1,\Lambda\ ,n+2 \\ \alpha^T X_{n+1} = 1 \\ \alpha \geq 0 \quad ,\beta \geq 0 \end{cases} \tag{5}$$

DMU$_{n+1}$ is obviously DEA efficient, yet it has $V^*{}_{n+1} \equiv 1$. However, model (5) has an infinite number of optimal solutions α^* and β^*, which need to be filtered to determine that all DMUs have a public weight vector that meets the requirements.

Third, the public weight vector is determined.

$V^*{}_{n+1} = \dfrac{u^{*T} Y_{n+1}}{v^{*T} X_{n+1}} = \dfrac{\beta^{*T} Y_{n+1}}{\alpha^{*T} X_{n+1}} \equiv 1$, and the optimal DMU, namely DMU$_{n+1}$, satisfies $\beta^{*T} Y_{n+1} - \alpha^{*T} X_{n+1} = 0$. To determine the public weight vector, we build the model as shown in equation (6):

$$\begin{cases} \min \beta^T Y_{n+2} \\ \alpha^T X_j - \beta^T Y_j \geq 0, \quad j \neq n+1 \\ \alpha^T X_{n+2} = 1 \\ \beta^T Y_{n+1} - \alpha^T X_{n+1} = 0 \\ \alpha \geq 0 \quad ,\beta \geq 0 \end{cases} \tag{6}$$

Equation (6) aims to minimize the efficiency evaluation value of the worst DMU DMU$_{n+2}$. Compared with model

(5), it adds constraints $\beta^T Y_{n+1} - \alpha^T X_{n+1} = 0$ to maximize the efficiency evaluation value of DMU_{n+1}. Through model (6), infinite sets of weight vectors of the optimal DMU can be screened to obtain a set of weight vectors that minimize the efficiency value of the worst DMU.
Fourth, the efficiency value of each DMU is calculated.

Based on the optimal solution (α^{**}, β^{**}) of model (6), the efficiency evaluation value of each DMU is obtained by using model (7).

$$V_j^{**} = \frac{\beta^{**T} Y_j}{\alpha^{**T} X_j} \quad (j = 1, \Lambda\ , n) \tag{7}$$

Using the improved DEA model, the comprehensive efficiency of the evolutionary intermediate output of 30 regions in China and the comprehensive efficiency of the evolutionary final output of the two cases of not considering and considering the influencing factors are calculated in turn. The results are shown in *Table* 5.

Table 5 Comprehensive Evolution Efficiency of 30 Regions in China—Based on Improved DEA Model (Intermediate Output Stage and Final Output Stage)

Region	IOE-UC	IOE-C	FOE-UC	FOE-C	Region	IOE-UC	IOE-C	FOE-UC	FOE-C
Beijing	0.066	0.057	0.059	0.053	Henan	0.056	0.048	0.050	0.045
Tianjin	0.038	0.033	0.035	0.031	Hubei	0.085	0.073	0.077	0.069
Hebei	0.061	0.053	0.055	0.050	Hunan	0.087	0.075	0.079	0.071
Shanxi	0.051	0.044	0.046	0.041	Guangdong	0.124	0.107	0.112	0.100
Inner Mongolia	0.068	0.059	0.062	0.055	Guangxi	0.077	0.066	0.069	0.062
Liaoning	0.059	0.051	0.053	0.048	Hainan	0.083	0.071	0.075	0.067
Jilin	0.071	0.061	0.064	0.057	Chongqing	0.070	0.060	0.063	0.057
Heilongjiang	0.078	0.067	0.070	0.063	Sichuan	0.117	0.100	0.105	0.094
Shanghai	0.100	0.086	0.090	0.081	Guizhou	0.066	0.057	0.060	0.054
Jiangsu	0.129	0.111	0.116	0.104	Yunnan	0.078	0.067	0.070	0.063
Zhejiang	0.074	0.064	0.067	0.060	Shanxi	0.072	0.062	0.065	0.058
Anhui	0.088	0.076	0.079	0.071	Gansu	0.064	0.055	0.058	0.052
Fujian	0.115	0.099	0.104	0.093	Qinghai	0.087	0.075	0.078	0.070
Jiangxi	0.088	0.076	0.079	0.071	Ningxia	0.084	0.072	0.075	0.068
Shandong	0.098	0.084	0.088	0.079	Xinjiang	0.084	0.072	0.075	0.068
DMU n+1	1.000	1.000	1.000	1.000	DMU n+2	0.006	0.005	0.005	0.005

Note: IOE-UC stands for intermediate output efficiency without considering the influence factors; IOE-C stands for intermediate output efficiency with considering the influence factors; FOE-UC stands for the efficiency of the final output of factors not considered; FOE-C stands for the efficiency of the final output of factors considered.

Source: authors' own results.

3.2 Analysis of the Influencing Factors of the Evolutionary Efficiency of High-Tech Industry Innovation Ecosystems

Since the "one-step" calculation does not affect the reliability and validity of the calculation results, the impact of influencing factors must be reflected in the innovation results, without the need for step-by-step calculation. Therefore, we can calculate the influencing factors of the evolutionary efficiency in a "one-step" manner.

3.2.1 Analysis of the influencing factors of intermediate output efficiency at the evolutionary stage

(1) Calculation of the influencing factors of evolutionary intermediate output efficiency

When considering influencing factors, based on the results of the evolutionary intermediate output efficiency, we use the previous model to calculate the intensity and direction of the influence of the influencing factors of the evolutionary intermediate output efficiency. The results are shown in *Table* 6.

Table 6. Tobit Regression Analysis Results of Influencing Factors of Intermediate Output Efficiency

Influencing factors	Coefficient	Standard error	Z statistic	P value
C	0.859***	0.013	66.376	0
HZ	0.145**	0. 044	2.202	0.028
HS	0.093	0. 142	0.311	0.756
IF	0.093	0.148	-0.628	0.536
EI	0.106	0.151	-0.598	0.491
ES	0.211***	0.082	2.584	0.010
PS	0.038	0.074	-0.522	0.600
EC	-0.146*	0.078	-1.874	0.061
PI	-0.218*	0.082	-1.576	0.071
SR	0.233***	0.081	2.602	0.009
IA	0.042	0.043	-0.986	0.324
TM	0.100**	0.040	2.195	0.031

Note: *, **, *** are statistically significant at 10 %, 5 % and 1 % significance levels.

Source: authors' own results.

(2) Analysis of influencing factors of evolutionary intermediate output efficiency

The quality of innovation personnel input has a significant positive impact on the evolutionary intermediate output efficiency, while the amount of innovation personnel input has a positive but non-significant impact on the evolutionary intermediate output efficiency. In the investment of innovation funds, although R&D investment and ecological construction investment have a positive impact on the evolutionary intermediate output efficiency, they are not significant. The results show the inconsistency between innovation input and output, reflecting the high-risk characteristics of innovation. In terms of material input, the number of enterprises has a significant positive impact on the evolutionary intermediate output efficiency. An increase in innovation subjects can promote the development of the competition mechanism, which has a positive effect on the IE of innovation subjects. It can be inferred that improving the competition mechanism of high-tech industry innovation ecosystems is conducive to improving their innovation intermediate output efficiency. Energy input has a significant negative impact on the evolutionary intermediate output efficiency. The results show at least the following two points. First, the evolutionary intermediate output, such as patents, does not depend on high energy input. Second, high energy-consuming industries generally do not have a high innovation capability, which will inhibit the evolutionary intermediate output efficiency. Therefore, promoting the development of low-carbon high-tech industries is conducive to improving the intermediate output efficiency.

Policy factors have a certain negative impact on the evolutionary intermediate output efficiency. The results show that there are still many industrial control policies in the high-tech industry field, restricting the evolutionary intermediate output efficiency to a certain extent. Economic factors have a high and significant positive impact on the evolutionary intermediate output efficiency. The results show that new product demand can effectively impact IE. Although the social environment has a certain positive impact on the evolutionary intermediate output efficiency, it is not significant. The results indicate that although positive social factors are conducive to improving the evolutionary intermediate output efficiency, their impact is not direct. Technological factors have a significant positive impact on the evolutionary intermediate output efficiency, but the impact intensity is not large. On the one hand, the results show that the efficient flow of technology and other factors is conducive to improving the evolutionary intermediate output efficiency of the system. On the other hand, they also show the importance of technological factors to the evolutionary intermediate output, such as patents, which is highly consistent with the technology-intensive characteristics of high-tech industries.

3.2.2 Analysis of the Influencing Factors of Evolutionary Final Output Efficiency

(1) Calculation of the influencing factors of evolutionary final output efficiency

When considering influencing factors, based on the value of the evolutionary final output efficiency, we use the above model to calculate the intensity and direction of the influence of the influencing factors on the evolutionary final output efficiency. The results are shown in *Table* 7.

Table 7. Tobit Regression Analysis of the Factors Influencing the Final Output Efficiency

Influencing factors	Coefficient	Standard error	Z statistic	P value
C	0.816***	0.012	63.057	0
PA	0.238***	0.079	2.502	0.011
TT	0.256***	0.080	2.496	0.010
IE	0.095**	0.038	2.086	0.029
HZ	0.138	0.137	0.295	0.719
HS	0.088**	0.040	2.091	0.026
IF	0.088	0.141	-0.597	0.509
EI	0.100	0.143	-0.568	0.466
ES	0.200***	0.077	2.454	0.009
PS	0.036	0.070	-0.495	0.570
EC	-0.139*	0.074	-1.780	0.0580
PI	-0.207*	0.077	-1.497	0.067
SR	0.221***	0.077	2.472	0.009
IA	0.040	0.041	-0.937	0.308
TM	0.095**	0.038	2.086	0.029

Source: authors' own results.

(2) Analysis of the influencing factors of evolutionary final output efficiency

Comparative analysis of the factors influencing the evolutionary intermediate output efficiency and evolutionary final output efficiency shows that the direction and intensity of the influence of input factors and influencing factors on evolutionary intermediate output efficiency and evolutionary final output efficiency are highly consistent. Therefore, there is no need to repeatedly analyse the impact of input factors and influencing factors on evolutionary intermediate output efficiency and evolutionary final output efficiency. Accordingly, we focus on the following two aspects: first, the impact of the evolutionary intermediate output on evolutionary final output efficiency; and, second, the difference in the impact of input factors and influencing factors on evolutionary intermediate output efficiency and evolutionary final output efficiency.

First, in terms of the impact of evolutionary intermediate output on evolutionary final output efficiency, innovation patent output, innovation technology output and innovation enterprise output have a significant positive impact on the evolutionary final output efficiency of high-tech industry innovation ecosystems (the high degree of consistency between the two to a certain extent provides a reasonable explanation of the high degree of consistency in the intensity and direction of the influence of influencing factors on evolutionary intermediate output and evolutionary final output efficiency). Among them, the impact of innovation patent output and innovation technology output is greater. The results show that an increase in innovation patent output and innovation technology output can effectively increase the possibilities of the patent or technology portfolio, thus increasing the possibility of the industrialization and transformation of patents and technologies that could not be industrialized in the form of a “patent family” or "technology set", which in turn increases the evolutionary final output efficiency. The positive impact of the output of innovative enterprises on the evolutionary final output efficiency is relatively small, indicating that an increase in high-tech enterprises helps improve evolutionary final output efficiency through the competition mechanism. However, competition will increase the difficulty of patent and technology transformation and squeeze the market space, thus producing a directional impact and inhibiting an improvement in evolutionary final output efficiency. Overall, the development of innovative enterprises will promote their evolutionary final output efficiency.

Second, in terms of the difference in the impact of input factors and influencing factors on evolutionary intermediate output efficiency and evolutionary final output efficiency, the impact of input factors and influencing factors on evolutionary intermediate output efficiency is higher than that on evolutionary final output efficiency. On the one hand, the results show that various resource inputs in the evolutionary stage of China's high-tech industry innovation ecosystem can be effectively converted into intermediate outputs such as patents. However, there is an inefficiency problem when they are converted into final outputs such as new products, which is consistent with the fact that universities and research institutes are important patent producers in innovation ecosystems but have relatively weak industrialization capabilities. On the other hand, the results show that China has not yet formed a macro environment conducive to the industrialization of innovation intermediate output such as patents. Although the country’s current situation is constantly improving, there is still much room for improvement.

4. Discussion

Based on the empirical results of the two-stage DEA–Tobit model, significant differences are observed in the evolutionary efficiency of China’s high-tech industry innovation ecosystems across different stages, regions, and influencing factors. Overall, the evolutionary efficiency of China’s high-tech industry innovation ecosystem is relatively high in the intermediate output stage, while substantial efficiency losses and conversion deficiencies persist in the final output stage, indicating a structural break in the transformation chain from innovation generation to application.

4.1 Characteristics of Intermediate Output Efficiency

Regardless of whether external influencing factors are considered, the overall level of intermediate output efficiency in China’s high-tech industry innovation ecosystem remains high, indicating that innovation activities such as patent output and technological achievements are active. The empirical results show that the average efficiency value is 0.836 without considering influencing factors and declines to 0.692 when they are included, suggesting that external environmental conditions impose certain constraints on system efficiency. This result reflects the strong endogenous momentum in the input–output conversion of the innovation ecosystem, while the synergy among external policies, markets, and social environments remains insufficient (Geels, 2005).

From a regional perspective, both developed regions such as Shanghai, Jiangsu, and Shandong, as well as less-developed regions such as Yunnan, have achieved DEA-efficient frontiers. This demonstrates that under the driving force of innovation ecosystems, some regions can realize “leapfrog evolution” through new technological paradigms and innovation models. It also confirms that innovation ecosystems have the potential to overcome resource-based limitations and promote reverse catch-up in regional innovation capacity.

4.2 Characteristics of Final Output Efficiency

Compared with the intermediate output stage, the final output efficiency of China’s high-tech industry innovation ecosystem is generally lower. The average efficiency value is 0.622 without considering influencing factors and decreases to 0.558 when they are included. This finding suggests that while innovation activities yield effective accumulation in knowledge and technology, there remain evident “bottlenecks” in the transformation and market application stages. The reasons for this phenomenon are twofold: first, universities and research institutions face capacity constraints in the commercialization of research achievements, and the university–industry–research collaborative mechanism has not yet been fully developed; second, mismatches between the macro policy system and market mechanisms persist, and distortions in policy-based resource allocation hinder the effective transformation of innovation outcomes.

Such stage-specific inefficiency reveals a “front-hot, back-cold” characteristic of China’s innovation system—that is, high vitality in R&D and knowledge creation but considerable friction losses in commercialization and application.

4.3 Differences in the Effects of Influencing Factors

Regression results further indicate that although the direction of influence of different inputs and external environmental factors on intermediate and final output efficiency is consistent, the intensity varies. Talent quality, enterprise quantity, economic development, and technological factors exert significant positive effects on efficiency, whereas policy factors and energy inputs have negative effects (Russell *et al.*, 2011). The negative impact of policy factors reflects the inhibiting effect of industrial regulations, resource approvals, and administrative inefficiencies on the evolutionary efficiency of innovation ecosystems. The negative impact of energy inputs reveals a structural contradiction between high energy consumption industries and high-tech innovation efficiency (Liu *et al.*, 2015).

Moreover, the promoting effect of influencing factors on intermediate output efficiency is more significant than on final output efficiency, suggesting that resource inputs can be effectively transformed into patents and technologies but suffer from efficiency decay during industrialization. This “high generation–low transformation” pattern indicates the imbalance within the internal innovation chain and highlights a key direction for future policy optimization.

4.4 Verification of the Optimized Efficiency Model and Regional Differences

By introducing virtual DMUs into the optimized DEA model, this study improves the discriminatory power and interpretability of the efficiency evaluation results. The optimized results show that Jiangsu and Shanghai exhibit higher efficiency in the intermediate output stage, whereas Guangdong performs best in the final output stage. These results are consistent with the regional industrial structure and innovation environment, validating the rationality and applicability of the model (Adomavicius *et al.*, 2007; Garnsey and Leong, 2008).

In general, regions with a solid economic foundation and well-developed innovation systems demonstrate advantages in final output efficiency, while some inland regions achieve breakthroughs in intermediate output efficiency through policy-driven and organizational innovations. This difference reflects the regional heterogeneity of China’s high-tech industry innovation ecosystem and underscores the contextual and multi-path nature of ecosystem evolution.

Conclusions and Implications

The empirical analysis based on the two-stage DEA–Tobit model reveals significant differences between the intermediate and final output stages of China's high-tech industry innovation ecosystem, presenting an overall pattern of "high generation and low transformation." The efficiency of the intermediate output stage is relatively high, reflecting strong activity and alignment between input and output in knowledge creation and technological development. However, the final output stage exhibits structural obstacles in transforming innovation achievements into industrial and market outcomes, indicating weak linkages along the innovation chain. Regression analysis further shows that talent quality, enterprise quantity, economic development, and technological factors have significant positive impacts on evolutionary efficiency, while policy factors and energy inputs exert inhibitory effects. Regional comparisons indicate that eastern developed regions enjoy advantages in final output efficiency due to robust economic and institutional foundations, whereas several central and western regions achieve breakthroughs in intermediate output efficiency through institutional and organizational innovation. Overall, China's high-tech industry innovation ecosystem is transitioning from quantitative accumulation to qualitative enhancement, with internal element synergy and external environmental optimization being key to improving overall evolutionary efficiency.

Managerial Implications

The findings offer several managerial and policy implications for governments, industries, and research institutions. First, governments should shift from "direct intervention" to "institutional incentives" by improving intellectual property protection (Leten *et al.*, 2013), strengthening incentives for technology transfer, optimizing fiscal and taxation policies, and enhancing public innovation services. These measures can help create a market-oriented institutional environment conducive to the free flow of innovation resources and reduce policy-induced distortions. Second, enterprises should reinforce innovation collaboration and ecosystem linkages, deepen partnerships with universities and research institutes, and enhance the efficiency of the innovation chain through joint technology development and resource sharing. Third, regional authorities should design differentiated innovation ecosystems that align with local industrial structures and resource endowments, promote the clustering of innovation entities, and optimize resource allocation to facilitate the evolution of ecosystems from "local vitality" to "systemic efficiency." Finally, promoting low-carbon, digital, and intelligent technologies can guide high-tech industries toward sustainable development by synchronizing energy efficiency with innovation upgrading.

Limitations and Future Directions

Although this study contributes to the theoretical and empirical understanding of innovation ecosystem efficiency, it has several limitations. First, due to data availability, the selected indicators are mainly based on provincial or park-level statistics, which may not fully capture micro-level collaboration and knowledge flow among firms. Second, while the two-stage DEA–Tobit model effectively captures stage-specific efficiency, it does not incorporate time dynamics, limiting the exploration of long-term evolutionary trends. Third, the identified influencing factors primarily focus on macro-level dimensions; future research could introduce mediating and moderating mechanisms to examine how institutional environment, organizational learning, and network structures shape efficiency formation. Subsequent studies may employ time-series or multi-level modeling approaches to investigate long-term evolutionary paths and extend the analysis to international comparisons, thereby enriching the theoretical and empirical foundations for innovation ecosystem efficiency evaluation and governance.

Literature

Adner, R. (2006), "Match your innovation strategy to your innovation ecosystem", *Harvard Business Review*, Vol. 84, No 4, pp.98-107, 148.

Adner, R. (2016), "Navigating the leadership challenges of innovation ecosystems", *MIT Sloan Management Review*, Vol. 58, No 1, pp.141-146.

Adomavicius, G., Bockstedt, J.C., Gupta, A., Kauffman, R.J. (2007), "Technology roles and paths of influence in an ecosystem model of technology evolution", *Information Technology and Management*, Vol. 8, No 2, pp.185-202.

Adomavicius, G., Zhang, J. (2012), "Stability of Recommendation Algorithms", *ACM Transactions on Information Systems*, Vol. 30, No 4, pp.1-31.

Annanperä, E., Liukkunen, K., Markkula, J. (2015), "Innovation in evolving business ecosystem: A case study of information technology-based future health and exercise service", *International Journal of Innovation and Technology Management*, Vol. 12, No 4, pp.1550015.

Autio, E., Kenney, M., Mustar, P., Siegel, D., Wright, M. (2014), "Entrepreneurial innovation: The importance of context", *Research Policy*, Vol. 43, No.7, pp.1097-1108.

Bengt-Åke, L., Björn, H.J., Esben, S.A., Bent, D. (2002), "National systems of production, innovation and competence building", *Research Policy*, Vol. 31, No 2, pp.213-231.

Bogliacino, F., Pianta, M. (2013), "Profits, R&D, and innovation: A model and a Test", *Industrial and Corporate Change*, Vol. 22, No 3, pp.649-678.

Boschma, R.A., Wal, A.L.J.T. (2007), "Knowledge networks and innovative performance in an industrial district: The case of a footwear district in the South of Italy", *Industry and Innovation*, Vol. 14, No 2, pp.177-199.

Chen, X., Liu, Z., Zhu, Q. (2020), "Performance evaluation of China's high-tech innovation process: Analysis based on the innovation value chain", *Technovation*, Vol. 94, pp.102094.

Engler, J., Kusiak, A. (2011), "Modeling an innovation ecosystem with adaptive agents", *International Journal of Innovation Science*, Vol. 3, No 2, pp.55-68.

Fukuda, K., Watanabe, C. (2008), "Japanese and US perspectives on the National Innovation Ecosystem", *Technology in Society*, Vol. 30, No 1, pp.49-63.

Garnsey, E., Leong, Y.Y. (2008), "Combining resource-based and evolutionary theory to explain the genesis of bio-networks", *Industry and Innovation*, Vol. 15, No 6, pp.669-686.

Geels, F.W. (2005), "Processes and patterns in transitions and system innovations: Refining the co-evolutionary multi-level perspective", *Technological Forecasting and Social Change*, Vol. 72, No 6, pp.681-696.

Goktan, B.A., Miles, G. (2011), "Innovation speed and radicalness: Are they inversely related?", *Management Decision*, Vol. 49, No 4, pp.533-547.

Hansen, J.A., Pihl-Thingvad, S. (2019), "Managing employee innovative behaviour through transformational and transactional leadership styles", *Public Management Review*, Vol. 21, No 6, pp.918-944.

Hong, J., Feng, B., Wu, Y., Wang, L. (2016), "Do government grants promote innovation efficiency in China's high-tech industries?", *Technovation*, Vol. 57, pp.4-13.

Iansiti, M., Levien, R. (2004), "Strategy as ecology", *Harvard Business Review*, Vol. 82, No 3, pp.68-81.

Kang, X., Yang, J., Yu, L. (2021), "Function mechanism of knowledge lattice in gazelle enterprises' relay innovation: Using knowledge matching and knowledge transfer as conducting variables", *Managerial and Decision Economics*, Vol. 42, No 7, pp.1782-1792.

Kin H., Lee, J. N., Han, J. (2010), "The role of IT in business ecosystems". *Communications of the Acm*, Vol. 53, No 5, pp.151-156.

Leten, B., Vanhaverbeke, W., Roijakkers, N., Clerix, A., Helleputte, V.J. (2013), "IP models to orchestrate innovation ecosystems: IMEC, a public research institute in nano-electronics", *California Management Review*, Vol. 55, No 4, pp.51-64.

Li, Y.R. (2009), "The technological roadmap of Cisco's business ecosystem", *Technovation*, Vol. 29, No 5, pp.379-386.

Liu, J., Kauffman, R.J., Ma, D. (2015). "Competition, cooperation, and regulation: Understanding the evolution of the mobile payments technology ecosystem", *Electronic Commerce Research and Applications*, Vol. 14, No 5, pp.372-391.

Liu, Z., Chen, X., Chu, J., Zhu, Q. (2018), "Industrial development environment and innovation efficiency of high-tech industry: Analysis based on the framework of innovation systems", *Technology Analysis & Strategic Management*, Vol. 30, No 4, pp.434-446.

Marzucchi, A., Montresor, S. (2017), "Forms of knowledge and eco-innovation modes: Evidence from Spanish manufacturing firms", *Ecological Economics*, Vol. 131, pp.208-221.

Mercan, B., Goktas, D. (2011), "Components of innovation ecosystems: A cross-country study", *International Research Journal of Finance and Economics*, Vol. 76, No 16, pp.102-112.

Moore, J.F. (1993), "Predators and prey: A new ecology of competition", *Harvard Business Review*, Vol. 71, No 3, pp.75-86.

Nedkov, S., Campagne, S., Borisova, B., Krpec, P., Prodanova, H., Kokkoris, I. P., Hristova, D., Le Clec'h, S., Santos-Martin, F., Burkhard, B. (2022), "Modeling water regulation ecosystem services: A review in the context of ecosystem accounting", *Ecosystem Services*, Vol. 56, pp.101458.

Randhawa, K., West, J., Skellern, K., Josserand, E. (2021), "Evolving a value chain to an open innovation ecosystem: Cognitive engagement of stakeholders in customizing medical implants", *California Management Review*, Vol. 63, No 2, pp.101-134.

Russell, M.G., Still, K., Huhtamäki, J., Yu, J.C., Rubens, N. (2011), "*Transforming innovation ecosystems through shared vision and network orchestration*", Proceedings of the Triple Helix IX International Conference: Silicon Valley: Global Model or Unique Anomaly , pp.1-21.

Song, J. (2016), "Innovation ecosystem: Impact of interactive patterns, member location and member heterogeneity on cooperative innovation performance", *Innovation*, Vol. 18, No 1, pp.13-29.

Su, Y., Fan, Q. (2022), "Renewable energy technology innovation, industrial structure upgrading and green development from the perspective of China's provinces", *Technological Forecasting and Social Change*, Vol. 180, pp.121727.

Su, Y., Jiang, X., Lin, Z. (2021), "Simulation and relationship strength: Characteristics of knowledge flows among subjects in a regional innovation system", *Science, Technology and Society*, Vol. 26, No 3, pp.459-481.

Sun, S.L., Chen, V.Z., Sunny, S.A., Chen, J. (2017), "*Venture capital as an ecosystem engineer for regional innovation in an emerging market*", 2017 IEEE Technology & Engineering Management Conference (TEMSCON), pp.13-18.

Van, D.B., Cloodt, M., Romme, A.G.L. (2012), "Value creation by knowledge-based ecosystems: Evidence from a field study". *Research & Development Management*, Vol. 42, No 2, pp.150-169.

Yang, J. (2022). "An empirical study evaluating the symbiotic efficiency of China's provinces and the innovation ecosystem in the high-tech industry", *Complexity*, No 1, pp.1391415.

AUKŠTŲJŲ TECHNOLOGIJŲ PRAMONĖS INOVACIJŲ EKOSISTEMŲ EVOLIUCINIS EFEKTYVUMO VERTINIMAS IR ĮTAKOS VEIKSNIAI

Jianzhao Yang, Jingwei Zhu, Hairong Zhou

Santrauka. Aukštųjų technologijų pramonė, kaip pagrindinė ekonomikos restruktūrizavimo ir technologinių inovacijų varomoji jėga, yra itin reikšminga didinant regioninius inovacijų pajėgumus ir pramonės konkurencingumą. Tačiau moksliniuose tyrimuose trūksta sistemingo ir etapinio aukštųjų technologijų pramonės inovacijų ekosistemų evoliucinio efektyvumo vertinimo. Siekiant ištirti tokios evoliucijos efektyvumą ir įtakos mechanizmus, remiantis ekosistemų evoliucija ir sudėtingų sistemų teorija, buvo sukurtas dviejų pakopų DEA-Tobit analitinis modelis. Pasitelkus 30 nacionalinių aukštųjų technologijų pramonės parkų Kinijoje 2018 m. panelinius duomenis, buvo išmatuotas inovacijų ekosistemos evoliucinis efektyvumas dviem etapais (inovacijų generavimas ir pasiekimų transformacija). Buvo nustatytas įvesties veiksnių, taip pat politinės, ekonominės, socialinės ir technologinės aplinkos poveikis sistemos efektyvumui. Rezultatai atskleidė, kad inovacijų ekosistema pasižymi santykinai dideliu efektyvumu tarpiniame produkcijos etape, tačiau rodo didelį neefektyvumą galutiniame produkcijos etape. Talentų kokybė, įmonių skaičius, ekonominis vystymasis ir technologiniai veiksniai reikšmingai teigiamai veikia efektyvumą, o politikos intervencijos ir energijos sąnaudos pasižymi slopinamuoju poveikiu. Taip pat akivaizdus regioninis heterogeniškumas: rytiniai regionai lenkia kitus siekdami transformacijos efektyvumo, o tam tikri centriniai ir vakariniai regionai pasiekia proveržio tarpiniame etape per organizacines inovacijas. Išvados praturtina teorinį inovacijų ekosistemų evoliucinio efektyvumo vertinimo pagrindą, jose pateikta empirinių įrodymų ir politikos implikacijų, skirtų regioninei inovacijų aplinkai optimizuoti, tobulinti politikos sistemas ir skatinti aukštos kokybės aukštųjų technologijų pramonės plėtrą.

Reikšminiai žodžiai: aukštųjų technologijų pramonė; inovacijų ekosistema; evoliucinis efektyvumas; dviejų pakopų DEA modelis; Tobito regresija.