

Retraction

Retracted: Evaluation of Innovation Efficiency of High-Tech Enterprise Knowledge Supply Chain Based on AHP-DEA

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] H. Han and X. Gu, "Evaluation of Innovation Efficiency of High-Tech Enterprise Knowledge Supply Chain Based on AHP-DEA," *Journal of Mathematics*, vol. 2022, Article ID 3210474, 9 pages, 2022.

Research Article

Evaluation of Innovation Efficiency of High-Tech Enterprise Knowledge Supply Chain Based on AHP-DEA

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This paper introduces a qualitative analysis on the efficiency evaluation of the knowledge supply chain by combining the analytic hierarchy process (AHP) with data envelopment analysis (DEA), drawing on existing literature to determine the index weight through the scoring of industry experts, and selecting appropriate input and output indicators to construct a knowledge supply chain efficiency evaluation system. The system was then applied to the supply chain of a number of high-tech enterprises. The results identified innovation efficiency differences of the knowledge supply chain in these enterprises, along with best practices and suggestions for the current knowledge supply chain efficiency.

1. Introduction

In the supply chain, there is not only logistics, information flow, and capital flow, but also knowledge flow based on products. The intensification of market competition has broken the original competition mode among enterprises and has gradually formed competition among supply chains. Previous academic research has also focused mainly on supply chain management, such as integrating the concept of environmental protection into the supply chain by studying “low-carbon supply chain” [1, 2]; combining natural environmental risks and economic political risks into the supply chain, studying the impact of external factors on the food supply chain [3, 4]; integrating knowledge management into the supply chain and some papers and a conference proceedings previously been published studying the “knowledge supply chain” [5–7].

The supply chain is centered on core enterprises, and it forms a network chain structure model around the R&D, manufacturing, warehousing, logistics, distribution, and sales of commodities. Suppliers not only undertake production and manufacturing operations, but also conduct different types of knowledge exchange and knowledge

transfer with customers [8, 9]. In today’s rapid digital development of industry, the use of knowledge management to enhance the digital performance of the supply chain plays a crucial role in the digital transformation of the supply chain [10].

The knowledge supply chain was proposed by the “Next Generation Manufacturing Project” in the United States. It refers to the adjacent knowledge nodes in the process of supply, innovation, dissemination [6] and the use of knowledge through the relationship between demand and supply. Link up and convert the concept into a knowledge product and then to a functional network chain for the end user. J. Recharad Hall and Pierpaolo Andfiam put forward the concept of a knowledge chain from the perspective of the supply chain. The knowledge supply chain extends and deepens the traditional physical supply chain.

Compared to the traditional entities that form the supply chain, high-tech enterprises are knowledge-intensive entities. Knowledge-based products and technologies flow through the supply chain upstream and downstream of the enterprise, forming a knowledge supply chain which promotes the supply and dissemination of knowledge and scientific research results. It plays a key role in the landing

transformation of scientific research results [11]. Therefore, improving knowledge conversion, or the efficiency of knowledge flow in the supply chain, and maximizing the benefits of the knowledge economy have become the main problems of enterprises today.

In terms of supply chain performance evaluation, Ramish and Aslam [12] determined indicators for measuring knowledge management in the supply chain, including resource utilization, output measurement, new process performance evaluation, etc. based on the principle of double-loop and three-loop learning. Murata et al. [13] constructed two knowledge supply chain subsystems for Japanese SMEs, including the team building process subsystem and the team management subsystem. The team building process subsystem includes the execution, consulting, and demonstration phases. The team management system includes three steps of management experience accumulation: attention, memorization, and confirmation. Wiig [14] believed that the key to the performance evaluation of the knowledge supply chain lies in the assessment of knowledge management. The indicators should include the promotion of knowledge activities, the infrastructure related to knowledge activities, accumulated knowledge assets, and knowledge learning.

From the perspective of the research index system, there are many ways to evaluate supply chain management and knowledge management, which involve many comprehensive economic indicators. However, the current research aims to build an index system based on the research experience of scholars, which is highly subjective. This study intends to use AHP to screen the efficiency evaluation indicators of the knowledge supply chain. It would effectively draw on the subjective knowledge and experience of experts, while maintaining good objectivity at the same time. In the construction of evaluation models, previous studies mainly used factor analysis and fuzzy synthesis evaluation [15], the entropy method, etc. While using a certain method alone may have certain drawbacks, a combined evaluation method can effectively solve those disadvantages. Thus, it is now trending in comprehensive evaluation research.

Therefore, this study focuses on the efficiency evaluation of the knowledge supply chain, combining the AHP analytic hierarchy process with the DEA data envelopment analysis, and using the authoritative expert scoring method in the industry to determine the key indicators and their weights that need to be considered in the knowledge supply chain efficiency evaluation. Drawing lessons from existing literature research and expert scoring methods, the article screens appropriate input indicators and output indicators, constructs a knowledge supply chain efficiency evaluation system, and further combines supply chain data to calculate the efficiency value. Finally, this article takes the supply chains of high-tech enterprises in four provinces and cities in the Yangtze River Delta as examples to study their innovation efficiency in the process of knowledge and technology innovation, provide certain references for knowledge supply chain management, and put forward relevant policy recommendations.

2. Construction Method of Evaluation Index System

2.1. Knowledge Supply Chain Model. American scholars Holsapple and Singh [16] constructed a systematic knowledge supply chain model from the relationship between organizational knowledge and organizational core competitiveness. The model includes the main part of the knowledge chain and the output of the knowledge chain. The main part of the knowledge chain includes five primary knowledge activities and four advanced high-level activities. The five primary knowledge activities are knowledge acquisition, knowledge selection, knowledge generation, knowledge internalization, and knowledge externalization. The four high-level knowledge activities are leadership, cooperation, control, and measurement. While managing knowledge (output of the knowledge chain) in the supply chain adds additional complexity to the supply chain management process, knowledge sharing between supply chain partners is nonetheless an important element of the supply chain knowledge management (SCKM) system [17].

In the supply chain of high-tech enterprises, the spatial agglomeration effect between enterprises in the industrial park will accelerate the acquisition and generation of knowledge, while the government, financial institutions, and enterprises' own technological R&D investment will promote knowledge transfer, thereby promoting technological innovation and conversion. Once the process of internalization and externalization of knowledge is over, new technologies and processes suitable for the long-term development of the enterprise will be introduced to the consumer, which will bring economic benefits to the enterprise. Therefore, based on the knowledge supply chain model, combined with the process of knowledge acquisition and creation of high-tech enterprises, this study establishes the following knowledge supply chain model (Figures 1 and 2).

2.2. Construction of the Innovation Efficiency Evaluation System of the Knowledge Supply Chain. When selecting supply chain efficiency evaluation indicators, they are usually selected from the two dimensions of input and output. This article will select indicators from the two dimensions of input and output elements based on existing relevant research and evaluation. The input elements include organizational input, human input, and financial input. The output elements include the measurement of innovation output and economic benefits.

Input elements: Since the technological innovation process is an integrated system, all partners involved in this process must group together to establish mutual trust and promote the transfer of tacit knowledge such as experience and technical know-how, thus effectively playing their role in the system. The spirit of collaboration can lead to better acquisition of high-quality tacit and complex knowledge [18]. Therefore, for the supply chain of high-tech enterprises, the spatial agglomeration effect between enterprises in the industrial park can accelerate the acquisition of knowledge

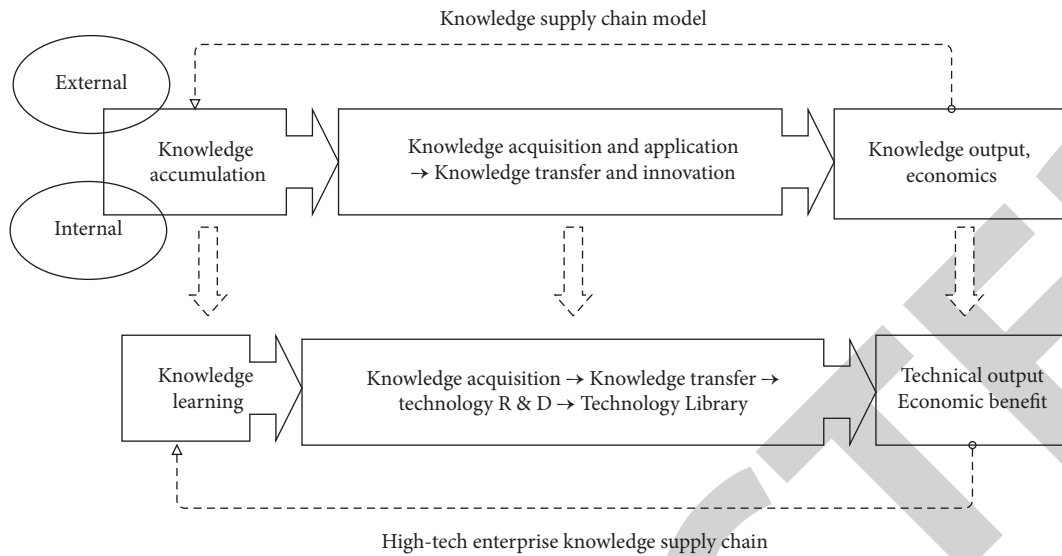


FIGURE 1: Knowledge supply chain model.

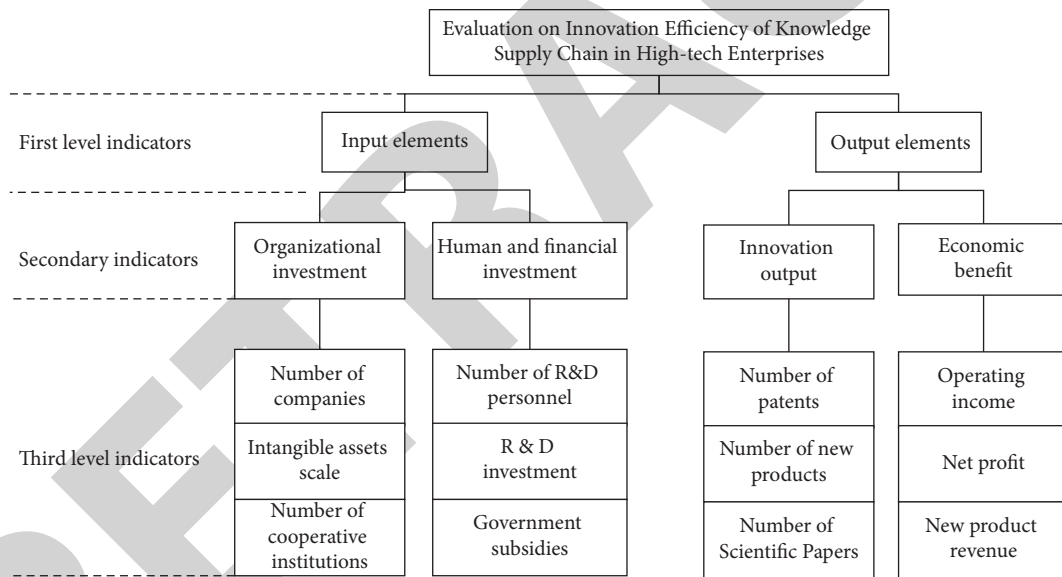


FIGURE 2: Innovation efficiency evaluation system.

to a certain extent. In addition, cooperation between external institutions and the intangible assets owned by the enterprises within the organization can also accelerate the flow of knowledge. This has an important impact on the dissemination and transformation of knowledge. Carneiro [19] also suggested that, in addition to using financial indicators, organizations can use nonfinancial personnel to measure knowledge management. Based on this, this study considers the number of technical R&D personnel as one of the factors to measure human and financial inputs.

Output elements: In traditional supply chain performance evaluation, financial indicators are often selected to measure economic benefits. However, using only economic benefits to measure performance may lead to bias in the results. In the knowledge supply chain of high-

tech industries, the flow of commodities has nothing to do with physical commodities, but with the flow of R&D commodities. R&D products include patents, technologies, research services, and research projects, etc. In high-tech industries, their development and commercialization are considered just as important as real products [20]. Therefore, based on the research of scholars such as Alessandra Alletto, this study uses the number of new patent application and development as the measurement index of knowledge output elements in the measurement of technology output in addition to traditional financial indicators such as the changes in operating income and net profit.

Based on the above analysis, this paper establishes the following level analysis model.

2.3. Calculating Method of Innovation Efficiency of Knowledge Supply Chain. Because there are many supply chain innovation performance evaluation indicators of high-tech enterprises, we needed to ensure the operability of the methods and the simplicity of the indicators and to reduce the complexity of calculations. The many types of indicators present have to be screened and the input and output cover a wide range. The indicators are difficult to screen solely based on the data, so they require the judgment of experts with many years of industry experience. The pairwise comparison method provided by AHP can effectively reduce the difficulty of expert judgment and reduce errors. At the same time, the DEA method has advantages in handling multi-input and multioutput effectiveness evaluation and is widely used in financial resource operation efficiency [21], risk performance evaluation, etc.

Therefore, this study uses the AHP method to screen the established high-tech enterprise knowledge supply chain evaluation indicators and the DEA method to evaluate and rank the innovation efficiency of the knowledge supply chain in the Yangtze River Delta. This calculation method effectively integrates AHP and DEA methods and can reasonably evaluate multiattribute problems. The analytic hierarchy process can fully reflect the preferences of decision makers, while the DEA model can objectively evaluate the efficiency of technological innovation, technological effectiveness, and scale effectiveness. This research uses comprehensive AHP and DEA modeling to evaluate the innovation efficiency of the knowledge supply chain of high-tech enterprises and effectively realize horizontal comparison and sorting, which is beneficial to knowledge management-related research on the supply chain.

3. Model Principles

This article combines analytic hierarchy process (AHP) and data envelopment analysis (DEA) to evaluate and rank the innovation efficiency of the knowledge supply chain. The AHP combines qualitative analysis and quantitative analysis and selects the most representative evaluation indicators by comparing the importance of the elements. The DEA method can be used to calculate the innovation efficiency value based on the objective observation and carry out a numerical evaluation. Therefore, this article first selects representative indicators and then further collects data based on representative indicators, uses data envelopment analysis methods to calculate indicators, and finally calculates the efficiency value comprehensively and realizes the efficiency ranking.

3.1. Principles of Analytic Hierarchy Process. The analytic hierarchy process (AHP) was formally proposed by the American operations researcher T. L. Saaty in the mid-1970s. It is a systematic and hierarchical analysis method that combines both qualitative and quantitative analyses. It compares the importance of each element in pairs, calculates the relative weight of each element through mathematical methods, and finally sorts the importance of the elements

based on their relative weight. Because of its practicality and effectiveness in dealing with complex decision-making problems, it quickly gained attention worldwide [22, 23]. Its applications have spread throughout the fields of economic planning and management, energy policy and distribution, behavioral science, military command, transportation, agriculture, education, human resources, medical care, and the environment. The main steps of the analytic hierarchy process are as follows.

3.1.1. Weight Calculations. To establish a quantitative judgment matrix based on input and output indicators, we invited 10 technical field supply chain management experts to compare n indicators at each level in pairs and give a judgment matrix $A = (a_{ij})_{m \times n}$, a_{ij} represents the importance of element i relative to element j , and each element of the judgment matrix satisfies $a_{ij} > 0$, $a_{ij} = 1/a_{ji}$, $a_{ii} = 1$. The arithmetic average method is used to calculate the maximum eigenvalue λ_{\max} of each judgment matrix and its corresponding eigenvector $(W_1, W_2, W_3, \dots, W_n)$, which is the weight of the index.

3.1.2. Consistency Inspection. Calculate the consistency index CI and random consistency ratio CR of each judgment matrix:

$$\begin{aligned} CI &= \frac{\lambda_{\max} - n}{n - 1}, \\ CR &= \frac{CI}{RI}. \end{aligned} \tag{1}$$

RI represents the average consistency index of the judgment matrix. If the consistency ratio is $CR < 0.10$, the consistency test is passed. The eigenvector obtained above is the weight vector reflecting the relative importance of the indicators. The experts are invited to adjust the judgment against the value of the matrix until satisfactory consistency is achieved.

3.2. Principles of DEA Data Envelopment Analysis. The data envelopment analysis (DEA) method is the most widely used nonparametric performance evaluation method, which was jointly proposed by Charnes and Cooper [24]. The DEA method is widely used in many fields, such as production management of industrial enterprises and efficiency evaluation of scientific research institutions. The DEA algorithm treats each object to be evaluated as a decision-making unit (DMU) and multiple decision-making units together as the evaluated group. The efficiency and effectiveness of each decision-making unit are determined by dividing the indicators into two types of input and output indicators and then using the weight of the input and output indicators as variables to perform optimization calculations.

Commonly used DEA models include the CCR and BCC models. The former is used to evaluate the overall effectiveness of the decision-making unit, and the latter is used to evaluate the technical effectiveness of the decision-making

unit. The use of the CCR model is based on the assumption of constant return to scale (CRS), which assumes that the decision-making unit can increase their output scale return by increasing their input in equal proportions. In practical application, as the input elements increase, the return to scale gradually saturates before entering the stage of diminishing returns to scale. Therefore, this study chooses to incorporate the variable returns to scale (VRS) DEA-BCC model instead.

The basic principle is that, for each decision unit, $DMU_k (k = 1, 2, \dots, n)$. Each decision-making unit has m inputs and outputs. The i -th input of DMU_k is $X_k = \{X_{ik}, i = 1, 2, \dots, m\}$, and the j -th output is $Y_k = \{Y_{rk}, r = 1, 2, \dots, s\}$. The BCC model is established as follows:

$$\begin{cases} \min \Theta = V_{D1} \\ \text{s.t.} \sum_{j=1}^n \lambda_j x_j \leq \Theta X_0 \\ \sum_{j=1}^n \lambda_j = 1 \\ \lambda_j \geq 0, j = 1, 2, \dots, n. \end{cases} \quad (2)$$

Its dual formula is

$$\begin{cases} \text{Max}(u^T Y_0 + u_0) = V_{P1} \\ \text{s.t.} w^T X - u^T Y_j - u_0 \geq 0, j = 1, 2, \dots, n \\ w^T X_0 = 1 \\ w \geq 0, u \geq 0 \end{cases} \quad (3)$$

If there is an efficiency optimal solution w_0, u_0, \hat{u}_0 in the formula which satisfies $V_{P1} = u_0^T Y_0 + \hat{u}_0 = 1$, it is a weakly valid unit of DEA. If there is $w_0 > 0, u_0 > 0$ in the formula, it is called DMU_{j0} is a fully effective unit of DEA. Finally, after the introduction of non-Archimedean infinitesimal ε , input slack variable S^- , and output slack variable S^+ , the final BCC model is as follows:

$$\begin{cases} E_{BCC} = \min \Theta - \varepsilon(s^- + s^+) \\ \text{s.t.} \sum_{k=1}^n \lambda_k x_k + S^- = \Theta X_0 \\ \sum_{k=1}^n \lambda_k x_k - S^+ = Y_0 \\ \sum_{k=1}^n \lambda_k = 1 \\ \lambda_k \geq 0, k = 1, 2, \dots, n \\ s^- \geq 0, s^+ \geq 0 \end{cases} \quad (4)$$

The goal of the BCC model is to maximize the efficiency of decision-making units. This study uses the BCC model to evaluate the innovation efficiency of multiple decision-making units in the input and output of the high-tech enterprise knowledge supply chain. DEA's comprehensive technical efficiency is composed of pure technical efficiency and scale efficiency. Pure technical efficiency comes from the influence of management and technology on the efficiency of output units, and scale efficiency comes from the influence of scale factors on the efficiency of output units. When the

pure technical efficiency is 1, technical efficiency is completely effective. When the scale efficiency is 1, the scale efficiency of the decision-making unit is completely effective. If both are 1, the decision-making unit is a fully effective DEA unit. If only the technical efficiency or scale efficiency is 1, the DEA of the unit is weakly effective. If both are not 1, the DEA of the decision-making unit is invalid.

4. Sample Analysis

This article selects high-tech enterprises in the Yangtze River Delta region of China as the research sample. The Yangtze River Delta region includes four provinces, Shanghai, Jiangsu, Zhejiang, and Anhui, and contains many high-tech enterprises. It is an important strategic economic belt in China, and the integration of the Yangtze River Delta is one of China's national strategies. Therefore, the economic development and various data indicators in this area are representative. As the 2019-nCoV in 2020 will have an impact on the economy, this article selects a sample of knowledge supply chain data from 75 listed high-tech companies in the Yangtze River Delta in 2019 for analysis.

4.1. Expert Scoring and Data Collection. To establish a quantitative judgment matrix based on the input and output element indicators in this study, we invited 10 technical field supply chain management experts to brainstorm and compare indicators at each level in pairs, give a judgment matrix, and calculate the weightage of each index (W represents the weight of the indicator) (Tables 1–3).

Through the weight analysis of the first-level indicators, we can see that, in the measurement of innovation efficiency, the measurement of output elements takes a larger proportion, and the importance of innovation output and economic benefits is equal. In the measurement of input elements, human capital and capital investment are more important. The following is an analysis of the three-level indicator weights contained in the two second-level indicators, as shown in Tables 4–7.

4.2. AHP to Determine the Index Weight. Based on the above index scores, the overall index weights are listed in Table 8.

Based on the results of our analysis, it can be seen that, among the organizational input elements, the weight of the number of enterprises is higher than that of the other indicators, indicating that the greater the number of enterprises in a region, the greater the convergent effect on the acquisition and creation of regional knowledge as well as the rapid flow of knowledge. Among the human and financial input elements, the weight of R&D expenditure and the number of R&D personnel are obviously higher than others, which reflects the importance of human capital and capital investment in knowledge creation. Among the elements of innovation output, the weight of the number of patents is significantly higher than that of new products and papers, indicating that technology creation is an important part of innovation output. Among the indicators of economic benefits at all levels, operating revenue and net profit have a

TABLE 1: Judgment matrix of primary indicators of knowledge supply chain.

Innovation efficiency	Input elements	Output elements	W
input elements	1	1/2	0.333
Output elements	2	1	0.667

TABLE 2: Judgment matrix of secondary indicators of knowledge supply chain-input elements.

Input elements	Organizational investment	Human and financial investment	W
Organizational investment	1	1/3	0.25
Human and financial investment	3	1	0.75

TABLE 3: Judgment matrix of secondary indicators of knowledge supply chain-output elements.

Output elements	Innovation output	Economic benefit	W
Innovation output	1	1	0.50
Economic benefit	1	1	0.50

TABLE 4: Organizational investment judgment matrix.

Organizational investment	Number of companies	Intangible assets scale	Number of cooperative institutions	W
Number of companies	1	3	5	0.648
Intangible assets scale	1/3	1	2	0.230
Number of cooperative institutions	1/5	1/2	1	0.122
Consistency inspection: $CI = 0.0018 < 0.1$ $CR = 0.0032$				

TABLE 5: Human and financial investment judgment matrix.

Human and financial investment	Number of R&D personnel	R&D investment	Government subsidies	W
Number of R&D personnel	1	1	2	0.387
R&D investment	1	1	3	0.443
Government subsidies	1/2	1/3	1	0.169
Consistency inspection: $CI = 0.0091 < 0.1$ $CR = 0.0158$				

TABLE 6: Judgment matrix of innovation output.

Innovation output	Number of patents	Number of new products	Scientific papers	W
Number of patents	1	3	5	0.648
Number of new products	1/3	1	2	0.230
Scientific papers	1/5	1/2	1	0.122
Consistency inspection: $CI = 0.0018 < 0.1$ $CR = 0.0032$				

TABLE 7: Judgment matrix of economic benefit.

Economic benefit	Operating income	Net profit	New product revenue	W
Operating income	1	1/2	3	0.309
Net profit	2	1	7	0.582
New product revenue	1/3	1/7	1	0.110
Consistency inspection: $CI = 0.0013 < 0.1$ $CR = 0.0023$				

TABLE 8: Summary of indicator weights.

First-level indicators	W	Second-level indicators	W	Third-level indicators	W	Code
Input elements	0.333	Organizational input	0.083	Number of companies	0.054	X1
				Intangible assets scale	0.019	X2
				Number of cooperative institutions	0.010	X3
		Human and financial investment	0.250	Number of R&D personnel	0.097	X4
				R&D investment	0.111	X5
				Government subsidies	0.042	X6
Output elements	0.667	Innovation output	0.333	Number of patents	0.216	Y1
				Number of new products	0.077	Y2
				Scientific papers	0.041	Y3
		Economic benefit	0.333	Operating income	0.103	Y4
				Net profit	0.194	Y5
				New product revenue	0.036	Y6

TABLE 9: Output results of innovation efficiency.

Firm	Crste	Vrste	Scale		Firm	Crste	Vrste	Scale	
1	0.467	0.921	0.507	irs	39	0.489	0.904	0.541	irs
2	0.778	0.903	0.861	irs	40	0.681	0.949	0.717	irs
3	0.447	0.864	0.517	irs	41	0.603	0.899	0.671	irs
4	0.646	0.907	0.712	irs	42	1	1	1	—
5	0.473	0.904	0.523	irs	43	0.837	0.935	0.895	irs
6	0.67	0.918	0.729	irs	44	1	1	1	—
7	0.553	0.961	0.576	irs	45	0.506	0.854	0.592	irs
8	0.777	0.933	0.833	irs	46	0.309	0.844	0.367	irs
9	0.719	0.927	0.776	irs	47	0.424	0.882	0.481	irs
10	0.508	0.85	0.597	irs	48	1	1	1	—
11	0.451	0.9	0.5	irs	49	0.388	0.875	0.444	irs
12	0.712	0.91	0.782	irs	50	0.599	0.863	0.694	irs
13	0.828	0.959	0.863	irs	51	0.461	0.908	0.508	irs
14	0.468	0.871	0.537	irs	52	0.651	0.921	0.707	irs
15	0.07	0.839	0.084	irs	53	0.582	0.921	0.632	irs
16	0.314	0.848	0.371	irs	54	0.942	1	0.942	irs
17	0.531	0.974	0.545	irs	55	0.395	0.929	0.425	irs
18	0.832	0.938	0.887	irs	56	0.591	0.929	0.635	irs
19	0.728	0.95	0.765	irs	57	0.546	0.906	0.603	irs
20	0.506	0.906	0.559	irs	58	0.612	0.921	0.664	irs
21	0.397	0.86	0.462	irs	59	0.758	0.938	0.809	irs
22	0.494	0.899	0.55	irs	60	0.681	0.973	0.7	irs
23	0.592	0.917	0.646	irs	61	1	1	1	—
24	0.827	0.97	0.852	irs	62	0.806	0.934	0.863	irs
25	0.936	1	0.936	irs	63	0.728	0.934	0.78	irs
26	0.105	0.866	0.121	irs	64	0.726	0.901	0.806	irs
27	0.53	0.901	0.588	irs	65	1	1	1	—
28	0.414	0.886	0.467	irs	66	0.553	0.878	0.63	irs
29	0.469	0.883	0.531	irs	67	0.927	0.977	0.948	irs
30	0.408	0.921	0.443	irs	68	0.598	0.885	0.676	irs
31	1	1	1	—	69	0.619	0.887	0.698	irs
32	0.648	0.934	0.694	irs	70	0.783	0.941	0.832	irs
33	0.411	0.887	0.463	irs	71	0.503	0.884	0.569	irs
34	0.703	0.941	0.747	irs	72	0.979	0.981	0.997	irs
35	0.365	0.933	0.391	irs	73	0.448	0.971	0.461	irs
36	0.683	0.925	0.739	irs	74	0.645	0.976	0.661	irs
37	0.744	0.891	0.834	irs	75	0.909	0.953	0.954	irs
38	0.534	0.91	0.587	irs	Mean	0.627	0.922	0.673	

Note: irs: increasing benefits of scale, constant benefits of scale, and diminishing returns of scale.

TABLE 10: The efficiency value of the Yangtze River Delta region.

Region	Code	Crste	Vrste	Scale
Shanghai	D1	0.74	0.938	0.782
Zhejiang	D2	0.828	0.965	0.854
Jiangsu	D3	0.787	0.967	0.808
Anhui	D4	0.963	1	0.963

significantly higher weight. It is not difficult to understand that revenue and profit are the most obvious indicators reflecting the actual capital flow and operating conditions of the supply chain. Therefore, this study selects the economic indicators (X4, X5, Y1, Y4, Y5) with significantly higher weights among all levels of indicators for subsequent DEA analysis.

4.3. Analysis and Evaluation Based on DEA. In actual production activities, input factors can often be controlled artificially, while the output factors are not highly controllable, which makes them more appropriate for the measurement of efficiency values from the perspective of input. Therefore, this study selects an input-oriented DEA model to examine the knowledge supply chain of 75 listed high-tech enterprises in the Yangtze River Delta in 2019, which includes 34 in Shanghai, 20 in Zhejiang, 18 in Jiangsu, and 3 in Anhui. With the help of Deap 2.1 software, we use the input-output indicators selected above to calculate and comprehensively calculate DEA efficiency by province, and the results are as follows. In Table 9, Crste represents the overall efficiency of the knowledge supply chain, Vrste represents pure technical efficiency, and Scale represents scale efficiency.

Further, we grouped and calculated the supply chain of each region to obtain the innovation efficiency of the regional knowledge supply chain (Table 10).

We can see that the overall efficiency (Crste) of the regional knowledge supply chain is ranked as follows: $D4 > D2 > D3 > D1$. When considering the return to scale (VRS perspective), the order of pure technical efficiency (vrste) is $D4 > D3 > D2 > D1$. From the overall efficiency level, the indicators of the four regions were higher than the overall average. Anhui's supply chain innovation efficiency is relatively high, while Shanghai's is relatively low. Jiangsu was slightly better than Zhejiang in terms of pure technical efficiency.

5. Conclusions and Policy Recommendations

5.1. Research Conclusion. This paper combines AHP with DEA to introduce qualitative analysis in the efficiency evaluation of the knowledge supply chain by combining relevant research in the existing literature before selecting and determining the appropriate input products through the scoring method of authoritative experts in the industry. After that, the index weights were calculated, and an efficiency evaluation system for the knowledge supply chain was constructed, which was later used to measure the supply chain efficiency of high-tech enterprises in four provinces

and cities in the Yangtze River Delta in 2019. The results of this study are as follows:

- (1) All indicators in the four regions are higher than the overall average, indicating that the innovation vitality of the Yangtze River Delta region remains at a high level and that there is no significant difference in development between the four provinces and cities.
- (2) In terms of specific ranking, Anhui's supply chain innovation efficiency is relatively high, while Shanghai's is relatively low. In terms of overall economic situation, while Shanghai is the leader in the Yangtze River Delta, their innovation efficiency remains low, which could be a reflection on their use of resources or internal limitations in deployment, which requires further attention from relevant management.
- (3) In terms of pure technical efficiency, the Jiangsu region is slightly better than the Zhejiang region. Overall, both regions were at the middle level of overall development. Therefore, stabilizing the current development trend and seeking future innovation efficiency improvement is an issue worthy of attention.

5.2. Policy Recommendations. This study focuses on the knowledge supply chain of the Yangtze River Delta, which is an important economic belt in China. The integration of regional talent, technology, capital, and other resources is relatively complete. The problems reflected in the various economic data are forward-looking and reference. Based on the above research conclusions, this article puts forward the following policy recommendations:

First, improvements in innovation efficiency can be achieved by improvement in both input and output elements. In terms of input, attention should be paid to the cooperative innovation and technological exchanges between enterprises in the industrial park and the utilization of upstream and downstream knowledge accumulation in the supply chain. In addition, high-tech talent should also be strengthened. Strengthening the cultivation of knowledge and research investment in important fields can maximize the input of human capital and social capital within the knowledge supply chain. In terms of output, it is necessary to strengthen the assessment model that pays equal attention to the output of technology patents and economic benefits, which can promote the transformation of knowledge and the application of technology.

Second, at the level of regional development, Shanghai should further look at the limiting factors of innovation efficiency and further coordinate the rational use of economic, political, and technological resources while strengthening the formulation of incentive policies related to technological innovation. Provinces and cities in the Yangtze River Delta should also strengthen in-depth cooperation, use their regional advantages, and explore deep-seated mechanisms for resource sharing at the technical level, such as the establishment of innovation platforms, industry incubators, government innovation funds, and so on.

Data Availability

The data that support the findings of this study are available in China Stock Market; Accounting Research Database (CSMAR) (<https://www.gtarsc.com/>), among which the number of enterprise technical personnel comes from Wind database.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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