ICIC Express Letters
Part B: Applications
Volume **14**, Number **1**, January **2023**

ICIC International ©2023 ISSN 2185-2766
pp. **109–116**

EVALUATION METHOD OF COMPREHENSIVE COMPETITIVENESS OF HIGH-TECH INDUSTRY BASED ON KNOWLEDGE ELEMENT

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Received May 2022; accepted July 2022

Abstract. *High-tech industry, which reflects the comprehensive ability of scientific and technological innovation among countries, has become the leading industry in the era of knowledge economy. The existing studies have some problems that the evaluation index system is not detailed enough and the model analysis is not reasonable to some extent. This paper establishes an evaluation index system of high-tech industry competitiveness based on knowledge element model from four dimensions, namely the input, output, technology and innovation, and policy environment of high-tech industry. Subsequently the factor analysis method that many variables are reduced to a few unrelated comprehensive factors is utilized to evaluate the competitiveness of high-tech industry. To verify the feasibility of this study, a case study is proposed to rank the competitiveness of high-tech industry in eleven northern provinces and cities of China, focusing on the competitive situation of Liaoning high-tech industry and putting forward corresponding countermeasures that can be represented as decision knowledge. This method refines the evaluation index system and constructs a common knowledge element framework of high-tech industrial competitiveness, which provides effective support for intelligent decision-makings based on knowledge base.*

Keywords: High-tech industry, Competitiveness evaluation, Knowledge element, Factor analysis

1. **Introduction.** With the changes of economic situation at home and abroad, knowledge and technology-intensive high-tech industries play a vital role in accelerating economic transformation and so on. Constructing a knowledge element system of competitiveness of high-tech industries based on common knowledge and evaluating of competitiveness can improve high-tech industries' core technological capabilities, provide intelligent support for comprehensive analysis and decision-making of industrial competition situation, and improve their core competitiveness [1].

The existing research on the competitiveness assessment of high-tech industry has made great progress in the domains of empirical analysis of evaluation index system, as well as the application of dynamic shift-share space model. However, the lack of research is mainly reflected in the refinement of evaluation index system and the rationality of model analysis. In addition, there is still a gap in related research on how to build a common knowledge framework of industrial competitiveness for knowledge discovery, so as to provide intelligent support for comprehensive analysis and decision-making of industrial competition situation. In view of this, this paper constructs an evaluation index system, which consists of four primary indexes and twenty-nine secondary indexes based on the knowledge element model, and then makes an empirical analysis by using factor analysis method.

DOI: 10.24507/icicelb.14.01.109

The rest of this paper is organized as follows. Section 2 reviews the related works of knowledge element and competitiveness evaluation. Section 3 introduces factor analysis method after building the evaluation index system of high-tech industry competitiveness based on knowledge element model. Taking Liaoning Province as an example, Section 4 carries out a case study on the factor analysis and evaluation of high-tech industry competitiveness by using the relevant data index of eleven major northern provinces in 2019. Some suggestions to promote the competitiveness of high-tech industry in Liaoning Province are also proposed as decision knowledge. Finally, Section 5 draws a conclusion and puts forward future research.

2. **Related Works.**

2.1. **Knowledge element model.** Knowledge element (KE) is considered as the basis of knowledge management. At present, the understandings and technical methods of KE are different due to diverse application fields [2]. Professor Wang put forward a knowledge element model (KEM) which uses triples to represent the features of things, which gets rid of the limitations of text unit and model knowledge representation, and can realize the implicit description of the association relationship between KE attributes [3].

Let N be the concept and attribute name of a thing, A denote the attribute state set, and R denote the relation set on $A \times A$ to describe the change and interaction of attribute states. Then the framework of KEM can be expressed as

$$K = (N, A, R)$$

Let $a \in A$, if the attribute state is quantifiable, it is measurable and has a measurement dimension d_a. In this case, if the change of the attribute state is identified, $a_t = f_a(a_{t-1}, t)$ can be defined where a_t is the state value at time t, so the attribute can be represented as the triples where p_a is the description of the measurable attribute.

$$K_a = (p_a, d_a, f_a)$$

In view of the original and fine-grained characteristics of KEM, it is helpful to represent the common knowledge framework of industry competitiveness for relation mining among evaluation index as well as intelligent decision-making [4].

2.2. **Competitiveness evaluation.** Great progress has been made in studying on the competitiveness of high-tech industry. For example, Ye and Zhang established an evaluation index system based on the four dimensions, calculating results by entropy method [5]. Fan and Du calculated the results by TOPSIS grey relational projection method from three aspects, i.e., technological innovation input, output and environment [6]. Yin et al. constructed an evaluation index system of GTI capability under multi-agent cooperation [7]. Dai et al. studied the competitiveness by dynamic shift-share space model and economic weight matrix method [8]. Yang and He proposed an algorithm of coordinated expert weights based on fixed point iteration and used an improved TOPSIS method to rank the alternatives [9].

Summing up the above academic achievements, it is found that some scholars chose to construct the evaluation index system of high-tech industry competitiveness from the influencing factors, and then used cluster analysis, regression analysis and correlation analysis to make empirical analysis. Whereas some others used the dynamic deviation-share space model to study the competitiveness of high-tech industries.

Generally speaking, although the research domain, content and methods are comprehensive, there are still some shortcomings. First, the process of establishing the index evaluation system has not formed a systematic theoretical method, so the establishment of the index system for high-tech industry evaluation is not detailed enough. Secondly, whether the analysis method, which sets the spatial weight by using the dynamic deviation-share space model, is reasonable for high-tech industry competitiveness analysis still needs further discussion. Thirdly, few studies have been carried out on how to build a standard representation framework of industrial competitiveness based on common knowledge, so as to provide intelligent support for comprehensive analysis and decision-making of industrial competition situation.

3. Index System and Comprehensive Evaluation Method of High-Tech Industry Competitiveness Based on KEM.

3.1. Evaluation index system based on KEM.

With the consideration of the characteristics of high-tech industry, an evaluation index system is established based on KEM and Chen's study [10], so that the index can comprehensively cover the dominant factors.

The evaluation indexes, which are regarded as the attributes of the KE industry competitiveness, are shown as Table 1, where all four primary indexes are marked as K_a^1, K_a^2, K_a^3, K_a^4 respectively, and the secondary indexes are regarded as the descriptions of single measurable attributes, i.e., $p_a^1 = \{x_1, \ldots, x_9\}$, $p_a^2 = \{x_{10}, x_{11}, x_{12}, x_{13}\}$, $p_a^3 = \{x_{14}, \ldots, x_{21}\}$, and $p_a^4 = \{x_{22}, \ldots, x_{29}\}$.

1) High-tech industry is a knowledge-intensive and technology-intensive industry, which needs a large amount of capital and technology investment to achieve rapid development. The corresponding secondary index is mainly scientific research investment, including capital and manpower investment.

2) The essence of assessing the competitiveness of high-tech enterprises is to find out whether the quality and quantity of output can occupy a certain competitive advantage in the market, which can be expressed by operating income and profits.

3) The fundamental driving force for the continuous development of high-tech industries comes from technological innovation and progress, which are mainly reflected in the number of patents and new product research and development, etc.

4) The government can give preferential policies to the scientific research investment of high-tech industries, as well as certain financial support to enterprises in some fields. The ability to measure policy environment mainly includes government investment, capital flow in technology market and capital investment in colleges.

3.2. Evaluation method.

1) Selection of evaluation methods

Compared with other analysis methods, factor analysis can realize objective weighting, which makes the economic meaning of factors clear and easy to explain. Therefore, factor analysis method is selected as the evaluation method of high-tech industry competitiveness. Factor analysis is to decompose each original variable into two parts: one part is composed of a few factors common to all variables, that is, the common factor part; the other part is the unique factor of each variable, that is, the unique factor part. There are p measurement variables like $x_1, x_2, \ldots, x_p$ and each variable can be decomposed as follows:

$$
\begin{aligned}
x_1 &= \alpha_{11} f_1 + \alpha_{12} f_2 + \cdots + \alpha_{1m} f_m + \alpha_1 \varepsilon_1 \\
x_2 &= \alpha_{21} f_1 + \alpha_{22} f_2 + \cdots + \alpha_{2m} f_m + \alpha_2 \varepsilon_2 \\
&\cdots \\
x_p &= \alpha_{p1} f_1 + \alpha_{p2} f_2 + \cdots + \alpha_{pm} f_m + \alpha_p \varepsilon_p
\end{aligned}
$$

The above formula is a factor model, where $f_1, f_2, \ldots, f_m$ is called common factor, which are factors that occur together in each variable. ε_i $(i = 1, 2, \ldots, p)$ represents unique factor influencing x_i. α_{ij} is called factor load, which indicates the load of the i variable on the j principal factor, which reflects the relative importance of the i variable on the j principal

TABLE 1. Evaluation index system of high-tech industry competitiveness

Primary index		**Secondary index**
Industrial input K_a^1	x_1	Number of enterprises
	x_2	Investment intensity of industrial R&D funds
	x_3	Investment intensity of R&D personnel in industry
	x_4	Investment amount of science and technology activities
	x_5	Total expenditure of technical optimization and upgrading funds
	x_6	Investment in fixed assets
	x_7	Investment amount of human capital
	x_8	Expenditure on new product development
	x_9	Average number of employees in enterprises
Industrial output K_a^2	x_{10}	Main business income
	x_{11}	Industrial added value rate
	x_{12}	Exports of high-tech products
	x_{13}	Total profit of high-tech industry
Technology and innovation capability K_a^3	x_{14}	Number of patent applications
	x_{15}	Number of patents owned by enterprises
	x_{16}	Number of scientific research institutions
	x_{17}	Scientific and technological activity personnel of scientific and technological institutions
	x_{18}	Internal expenditure of scientific and technological activities of institutions
	x_{19}	Publish scientific papers
	x_{20}	Sales revenue of new products
	x_{21}	Number of new products
Policy environment K_a^4	x_{22}	Proportion of government investment
	x_{23}	National industrialization project implementation fund
	x_{24}	Number of contracts concluded by market technology flowing to regions
	x_{25}	Market technology flows to regional transaction contract amount
	x_{26}	Internal expenditure of funds for scientific research activities in colleges and universities
	x_{27}	External expenditure of funds for scientific research activities in colleges and universities
	x_{28}	University R&D institutions
	x_{29}	Gross output value of high-tech park

factor. α_i is the load of unique factor. Note that the basic problem of factor analysis is to determine the factor load.

2) Competitiveness evaluation method based on factor analysis

Step 1: Investigate whether variables are suitable for factor analysis. If Kaiser-Meyer-Olkin value (KMO) is greater than 0.5, there is a strong correlation between target variables, which is suitable for factor analysis.

Step 2: Extract the factors whose characteristic values are greater than 1 as common factors, and get the variance contribution rate of each factor. If the cumulative contribution rate exceeds 85%, the information loss of the original variables will be less, and it is ideal to carry out factor analysis. The factor load matrix is rotated orthogonally by factors, and then each factor is named and explained.

Step 3: Estimate the factor score coefficient by regression method. Calculate the main factor scores of each analysis object and rank separately, then compute the comprehensive competitiveness scores by the main factor weights, so as to judge the competitiveness of objects. The higher the score of industrial competitiveness, the stronger the industrial competitiveness.

4. Case Study.

4.1. **Data collection and processing.** In order to ensure the availability and comparability of the case study, the original data is collected from 2020 China Statistical Yearbook of High-Tech Industries and 2020 China Statistical Yearbook of Science and Technology. Calculations are uniformly carried out to get the corresponding data of each index. The relevant index data of eleven major northern provinces in 2019 are used to carry out factor analysis and evaluation on the competitiveness of high-tech industries in these areas. Limited by space, only Liaoning Province data are listed as shown in Table 2.

TABLE 2. Secondary index data of Liaoning Province

Secondary index	x_1 (unit)	x_2	x_3	x_4 (yuan)	x_5 (yuan)
Attribute state	493	2.04%	0.32%	9,720,470,000	611,730,000
Secondary index	x_6 (yuan)	x_7 (yuan)	x_8 (yuan)	x_9 (person)	x_{10} (yuan)
Attribute state	3,644,110,000	13,577,440,000	4,771,060,000	157,287	192,900,000,000
Secondary index	x_{11}	x_{12} (yuan)	x_{13} (yuan)	x_{14} (item)	x_{15} (item)
Attribute state	5.70%	4,168,090,000	23,500,000,000	2,807	4,879
Secondary index	x_{16} (unit)	x_{17} (person)	x_{18} (yuan)	x_{19} (article)	x_{20} (yuan)
Attribute state	99	4,515	1,326,110,000	4,951	33,281,130,000
Secondary index	x_{21} (unit)	x_{22}	x_{23} (yuan)	x_{24} (item)	x_{25} (yuan)
Attribute state	2,277	14.35%	6,048,570,000	14,351	35,585,360,000
Secondary index	x_{26} (yuan)	x_{27} (yuan)	x_{28} (unit)	x_{29} (yuan)	
Attribute state	6,555,900,000	372,660,000	115	420,999,390,000	

4.2. **Factor analysis process.** In this paper, SPSS software is used for empirical analysis.

Step 1: Investigate whether the original variables (secondary index used here) are suitable for factor analysis. In Bartlett sphericity test, $Sig. = 0.000$, it can be seen that p of the corresponding probability is close to 0, and there is a strong correlation between variables. At the same time, the KMO value is 0.621. According to the KMO value greater than 0.5, the original index variables are suitable for factor analysis.

Step 2: Extract common factors. As shown in Table 3, three common factors are extracted according to the characteristic value greater than 1, and the cumulative contribution rate of these three factors is 90.57%, which is more than 90%. As a result, the proposed factor analysis is ideal.

TABLE 3. Root and cumulative contribution factor

Factor	**Eigenvalue**	**Percentage**	**Percentage of accumulation**
1	16.67	57.483	57.483
2	8.033	27.699	85.182
3	1.562	5.387	90.57

Step 3: The naming explanation of factors. The maximum variance method is used to rotate the factor load matrix orthogonally, so that the factor has naming explanation. Then the rotated factor load matrix is obtained, as shown in Table 4. F_1 among x_{17}, x_{14}, x_{20}, x_8, x_{16}, x_{18}, x_9, x_1, x_{21}, x_{10}, x_{13}, x_{15}, x_5, x_{12}, x_{29}, x_7, x_6, x_{28} has a high load, which mainly reflects the existing input-output capacity of high-tech industries. Therefore, F_1

Table 4. Rotated factor component matrix and component score coefficient matrix

Rotating component matrix				Component coefficient matrix			
	Factor				Factor		
	1	2	3		1	2	3
x_{17}	0.991			x_1	0.062	−0.02	0.013
x_{14}	0.987			x_2	−0.023	0.125	0.022
x_{20}	0.985			x_3	−0.035	0.139	−0.129
x_8	0.984			x_4	−0.041	0.138	0.008
x_{16}	0.981			x_5	0.079	−0.034	−0.111
x_{18}	0.98			x_6	0.02	0.053	0.104
x_9	0.979			x_7	0.028	0.054	0.038
x_1	0.975			x_8	0.071	−0.02	−0.058
x_{21}	0.973			x_9	0.064	−0.022	0.005
x_{10}	0.971			x_{10}	0.063	−0.013	−0.011
x_{13}	0.964			x_{11}	0.058	0.003	−0.537
x_{15}	0.962			x_{12}	0.062	−0.023	0.012
x_5	0.958			x_{13}	0.06	−0.006	−0.005
x_{12}	0.952			x_{14}	0.071	−0.024	−0.049
x_{29}	0.844	0.334		x_{15}	0.073	−0.02	−0.086
x_7	0.78	0.574		x_{16}	0.067	−0.029	−0.004
x_6	0.76	0.554		x_{17}	0.074	−0.032	−0.053
x_{28}	0.506		0.416	x_{18}	0.076	−0.032	−0.079
x_{23}		0.978		x_{19}	−0.039	0.14	0.019
x_{19}		0.951		x_{20}	0.068	−0.021	−0.024
x_4		0.925		x_{21}	0.063	−0.017	−0.001
x_3		0.917		x_{22}	0.054	−0.002	−0.552
x_2		0.903		x_{23}	−0.037	0.144	−0.035
x_{26}	0.46	0.861		x_{24}	0.001	0.096	0.045
x_{27}	0.451	0.84		x_{25}	0.013	0.082	0.03
x_{24}	0.539	0.796		x_{26}	−0.005	0.109	0.027
x_{25}	0.642	0.731		x_{27}	0.003	0.105	−0.037
x_{22}			−0.763	x_{28}	−0.005	0.022	0.268
x_{11}			−0.73	x_{29}	0.04	0.017	0.054

is called the realistic development factor, which reflects 57.483% of the information of all the indicator systems. F_2 is a high load on the indexes of x_{23}, x_{19}, x_4, x_3, x_2, x_{26}, x_{27}, x_{24}, x_{25}, which mainly reflects the R&D input capacity, so it is called R&D factor, which reflects 27.699% of the information of the whole index system. F_3 has a high load on the x_{22} and x_{11}, which reflects the government's support for high-tech industries. It is called the policy support factor, which reflects 5.387% information of all index systems.

Step 4: Estimate the factor score coefficient by regression method and output this coefficient. According to Table 4, the functional form of each principal factor is shown in the following formula:

$$F_1 = 0.062x_1 - 0.023x_2 + \cdots + 0.040x_{29}$$
$$F_2 = -0.020x_1 + 0.125x_2 + \cdots + 0.017x_{29}$$
$$F_3 = 0.013x_1 + 0.022x_2 + \cdots + 0.054x_{29}$$

The score of each principal factor can be calculated by substituting the standard value of the original variable into the principal factor function and each factor is ranked. Then, according to the weight of each main factor, the comprehensive scores of each province

Table 5. Each factor and comprehensive ranking table

	F_1	Rank of F_1	F_2	Rank of F_2	F_3	Rank of F_3	Comprehensive score	Comprehensive rank
Beijing	−0.364	6	4.632	1	−0.186	8	0.984	1
Shandong	0.050	1	0.150	3	1.781	1	0.184	2
Shaanxi	−0.059	2	0.597	2	−2.673	11	−0.014	3
Henan	−0.062	3	−0.339	9	0.860	2	−0.092	4
Hebei	−0.390	8	0.044	4	0.666	3	−0.195	5
Liaoning	−0.347	4	0.030	6	0.126	7	−0.204	6
Tianjin	−0.351	5	0.031	5	0.139	6	−0.205	7
Heilongjiang	−0.372	7	−0.323	8	−0.282	10	−0.352	8
Jilin	−0.450	11	−0.311	7	0.389	5	−0.358	9
Shanxi	−0.420	10	−0.523	10	0.596	4	−0.391	10
Inner Mongolia	−0.410	9	−0.614	11	−0.252	9	−0.463	11

can be calculated by $F = 57.483/90.570 * F_1 + 27.699/90.570 * F_2 + 5.387/90.570 * F_3$, ranking as shown in Table 5.

4.3. **Suggestions and decision KEs generation.** From Table 5, we can see that the scores of industrial technology development factor, R&D factor and policy support factor of Liaoning Province rank 4th, 6th and 7th respectively among these northern provinces. The overall ranking is 6th, which shows that the competitiveness of Liaoning's high-tech industry is at the middle level in the northern provinces. The existing input-output capacity is good, but the R&D and policy support are weak, so there is much room for improvement.

Some measures are proposed from three aspects to help Liaoning Province enhance the comprehensive competitiveness of high-tech industries based on the above assessment in this case study.

1) Promote the dynamic mechanism of enterprise technological innovation

Although Liaoning Province's policy support factor ranks low, its score is 0.126, which is higher than that of the real development factor. It shows that Liaoning's policy support has no obvious effect on its input and output. Therefore, by transforming government functions and formulating relevant policies, an external incentive and restraint mechanism for enterprises to strengthen their technological innovation consciousness and behavior is created.

2) Improve the talent introduction and training mechanism

The R&D factor score of Liaoning Province is only 0.030, which shows that the R&D ability is weak. As a result, funds and talents should be invested to improve the R&D ability. Introduce more favorable policies, provide talent introduction funds, and improve the local employment rate of Liaoning graduates, such as: strengthen the cultivation of innovative talents and teams, focus on major science and key laboratories, engineering technology centers and other innovative bases, vigorously cultivate talents with innovative consciousness and ability.

3) Explore the establishment of venture capital mechanism

The real development factor of Liaoning Province ranks 4th in the northern provinces, but the factor score is only −0.347, which means that there is still much room for improvement in the input-output capacity. Therefore, increasing capital investment, gradually establishing and introducing the venture capital mechanism should be considered carefully. Furthermore, the government may stimulate and attract domestic and foreign investment companies, financial institutions and private capital investment by injecting seed funds to form high-tech venture capital companies.

Note that, all the above measures can be stored as decision knowledge units from the perspective that the decision knowledge based on common representation can be reused.

Especially, if all these pieces of countermeasure knowledge in the domain of high-tech industry competitiveness assessment can be described as decision KEs, intelligent decision support based on think tanks will get great development in the near future. This is the original intention of introducing KEM into competitiveness evaluation method in the proposed paper.

5. **Conclusion and Future Research.** To sum up, this paper constructs the evaluation index system of high-tech industry competitiveness based on KEM, calculating comprehensive score to judge the competitiveness by using factor analysis method, focusing on the analysis of Liaoning high-tech industry competitiveness, which finds out that technological innovation and investment restrict the development of Liaoning high-tech industry, and provides three measures as decision-making knowledge represented as decision KEs for intelligent decision support. The evaluation of regional high-tech industry competitiveness can be further deepened in the future work.

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