Research on the Competitiveness of China's High-Tech Industry Based on Entropy-TOPSIS Method

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Abstract: The technology content, product-added value, and labor productivity of high-tech industry are significantly higher than those of traditional industry, so the strong competitiveness of high-tech industry is important for optimizing the industrial structure and improving the quality of economic development. In this paper, we design the high-tech industry competitiveness evaluation system from four dimensions: business environment, R&D investment, innovation achievements, and policy support, and we use the Entropy-TOPSIS method to calculate the high-tech industry competitiveness of Chinese provinces. The conclusion is as follows: (1) The competitiveness of high-tech industry is on an upward trend, and shows a pattern of "the strongest competitiveness in the east, the second in the west, and the weaker in the middle". (2) The results of high-tech industry competitiveness can be divided into three levels according to the hierarchical clustering method. (3) By comparing the gap of each province in the four dimensions, we find that there are obvious differences in the competitiveness of high-tech industry and unbalanced development in different provinces.

Keywords: High-Tech Industry, Competitiveness Evaluation, Entropy-TOPSIS Method.

1 INTRODUCTION

High-tech industry is an economic entity with knowledge-intensive, capital-intensive, and technology-intensive. Compared with traditional industries, high-tech industry has been greatly improved in terms of production, operation, and technology. As a strategic leading industry to promote the development of national economy, high-tech industry can drive sustained and rapid economic growth and promote industrial upgrading. Therefore, expanding and strengthening high-tech industry is the priority choice for local government to promote economic development. However, due to the differences in economic development level and high-tech industry policies, the regional competitiveness of China's high-tech industry is unbalanced.

At present, the research on the competitiveness of high-tech industry mainly focuses on constructing an evaluation system and calculating it. Chen and Sun (2011) used factor and cluster analysis to evaluate the competitiveness of China's provincial high-tech industry from the perspective of project organization, capital, output, and efficiency [1]. Wang (2014) and Chen (2010) used separately the optimized TOPSIS method and k-means clustering method to calculate the competitiveness of high-tech industry [2][3]. He (2018) compared the

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competitiveness of high-tech industry in 31 provinces based on factor analysis and analyzed the competitiveness differences of four economic regions [4]. Deng (2022) used principal component analysis (PCA) to measure the regional competitiveness of Hunan Province from five dimensions: innovation, coordination, green, openness, and sharing [5].

Based on previous studies, we found those common methods such as factor analysis, clustering method, and PCA are applied to measure the competitiveness of high-tech industry, which is a single measurement method and the results may be inaccurate. To improve the accuracy of the results, we use the comprehensive evaluation method to study the competitiveness of China's high-tech industry, and mainly answer the following questions in this paper: (1) How are the competitiveness of high-tech industry in different provinces? (2) What are the shortcomings of each province in the competitiveness of high-tech industry?

2 THE EVALUATION SYSTEM OF THE COMPETITIVENESS OF HIGH-TECH INDUSTRY

The evaluation system of high-tech industry competitiveness is formed from four dimensions: business environment, R&D investment, innovation achievements, and policy support, and we mainly consider the following aspects:

2.1 Business Environment

The business factors such as a sound legal system, stable macroeconomy, and green ecological environment are the guarantee for the sustainable development of high-tech industry. Therefore, we take the business environment as the most basic dimension to construct the evaluation system of high-tech industry competitiveness.

2.1.1 Marketization Index

The marketization process has significantly promoted the technological progress of China's high-tech industry [6], and we select the marketization index (x1) to characterize the marketization process which comes from [7].

2.1.2 External Openness

We measure the degree of openness of each province with the index of external openness (x2), which is constructed from two dimensions of trade openness and investment openness, as shown in Table 1, including export and import dependence [8][9], tourism openness [10], foreign direct investment(FDI), and outward foreign direct investment(OFDI), and calculate openness scores of each province using the entropy method. The data are obtained from the People's Bank of China and the China Statistical Yearbook.

Table 1. Evaluation index system of China's regional openness.

Dimension	Indicator	Indicator description
Trade openness	Export dependency	Export value/regional output value
	Import dependence	Import value /regional output value
	Tourism openness	International tourism foreign exchange earnings/regional output value

Investment openness	FDI	Actual utilization of foreign capital/regional output
	OFDI	Non-financial OFDI/Regional Output

2.1.3 Digital Financial Inclusion Index

As a representative of the new financial model, the development of digital inclusive finance can reduce the financing cost [11], and effectively stimulate technological innovation of small and medium-sized enterprises [12][13]. We use the digital financial inclusion index (x3) to represent the availability of financial services [14].

2.1.4 Nighttime Light

Nighttime light data record artificial light on the earth's surface and can characterize the intensity of human activities and the urbanization process, which is a good data source for studying human activities [15]-[17]. It has been shown that the trend of nighttime lighting data coincides with the trend of GDP to a certain extent and correlates with the urbanization rate, the ratio of three industries, and the number of the population [18]. At present, nighttime lighting data have been widely used in many fields, such as monitoring economic development [19], urban development [20], and energy consumption [21]. The nighttime light data (x4) used in this paper comes from the "NPP-VIIRS-like NTL Data" produced by Chen et al. (2021) [22].

2.1.5 Pollutant Emission Index

A good ecological environment is one of the factors that enhance competitiveness and contribute to sustainable development. We use the pollutant emission index (x5) to characterize the environmental quality. The main components of environmental pollutants are industrial wastewater emissions, industrial sulfur dioxide emissions, and industrial smoke emissions, so the pollutant emission index is calculated based on them and the calculation method refers to [23] and [24]. The larger this index indicates more pollution emissions and worse environmental quality, so this index is a negative indicator. This data comes from China Statistical Yearbook and China Environmental Statistical Yearbook.

2.2 R&D Investment

The development of high-tech industry is based on continuous R&D, and there is a correlation between R&D investment and the competitiveness of high-tech industry [25]. The intensity of R&D investment is much higher than other industries, and elements such as talent reserve and research funding can influence the development of high-tech industry. We select R&D personnel full-time equivalent (x6), technology investment acquisition and transformation share (x7), and average R&D project funding (x8) to characterize the R&D investment size of talent, technology, and capital.

2.3 Innovation Achievements

The development of high-tech industry is driven by innovation, and the indicators selected for the innovation achievements dimension in this paper are shown in Table 2. The higher the revenue ratio of high-tech industry (x9) is, the better the development of high-tech industry is in the region. The profit ratio of high-tech industry (x10) reflects the direct economic output of

R&D in high-tech industry. The innovation activities carried out by enterprises are only a means to enhance the competitiveness of the industry, and their ultimate goal is to obtain high profits. The high-tech new product expenditure-to-income ratio (x11) reflects the efficiency of new product R&D, which is a negative indicator, that is, the lower this index, the higher the R&D efficiency of new products.

The change in high-tech product exports (x12) reflects the international market competitiveness of high-tech industry. High-tech products expand the scale of output at low cost which has become a new growth point for China. R&D patents per capita (x13) and trademark applications per enterprise (x14) reflect the indirect economic output of R&D in high-tech industry.

2.4 Policy Support

Policy support is an important means for the government to stimulate the development of high-tech industry. The government encourages enterprises to carry out innovation activities and increase R&D investment from the aspects of R&D support policy (x15) and intellectual property protection (x16).

The proportion of government funds in the internal expenditure of R&D funds in high-tech industry reflects the willingness and ability of the government in promoting special expenditure in high-tech industry. Due to the public goods attribute of high-tech products, the optimal allocation of resources in high-tech industry cannot be achieved only by the market mechanism. In the case that individuals or enterprises cannot afford the huge risk brought by investment in basic research, the government directly sponsors the development of basic research through financial allocation, and enterprises make breakthroughs by reinventing products on basic research results. The proportion of technology market turnover to GDP not only reflects the strength of intellectual property protection but also reflects the marketization of high-tech industry.

In summary, we construct the evaluation index system of high-tech industry competitiveness from four dimensions, as shown in Table 2.

Table 2. Evaluation index system of high-tech industry competitiveness.

Dimension	Index	Formula	Var
Business environment	Marketization index	Marketization index of China’s provinces: NERI report 2021	x1(+)
	External openness	Calculated by entropy method	x2(+)
	Digital financial inclusion index	Digital Finance Research Center of Peking University	x3(+)
	Nighttime Light	NPP-VIIRS-like NTL Data	x4(+)
	Pollutant emission index	Weights of three pollutants and standardized product	x5(-)
R&D investme	R&D personnel full-time equivalent	The sum of the workload of full-time and part-time personnel	x6(+)

nt	Technology investment acquisition and transformation share	Total expenditure on technology introduction, transformation, purchase, and absorption / Internal expenditure on R&D funds	x7(+)
	Average R&D project funding	R&D Project Funding / Number of R&D Projects	x8(+)
Innovation achievements	High-tech industry revenue ratio	High-tech industry main business income/GDP high-tech industry	x9(+)
	Profit margin	High-tech industry profits/main business income	x10(+)
	High-tech new product expenditure-to-income ratio	Expenditure on R&D of new products of high-tech products/new product sales revenue	x11(-)
	High-tech export ratio	The export trade volume of high-tech products / total export trade volume	x12(+)
	R&D patents per capita	Number of patent applications/number of R&D personnel	x13(+)
	Trademark applications per enterprise	Number of trademark registration applications/number of high-tech enterprises	x14(+)
Policy support	R&D support policy	Proportion of government funds in internal R&D expenditure	x15(+)
	Intellectual property protection	Technology Market Turnover/GDP	x16(+)

3 COMPREHENSIVE EVALUATION MODEL

3.1 Entropy Method

The entropy method determines the weight of the evaluation index. If the weight is higher, the more discrete the data set is and the more information it contains. The calculation steps are as follows.

Step 1: Positive standardization of data.

Establishing a decision matrix D of n evaluation indexes and m evaluation object:

$$D = \left[x_{ij}\right]_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}_{m\times n} \tag{1}$$

To avoid the influence caused by unit differences between different indicators, the data are standardized before the weights are determined, and the normalization matrix R=[rij]m×n is calculated. The formulas are as follows:

$$r_{ij} = \frac{x_{ij} - min\{x_j\}}{max\{x_j\} - min\{x_j\}} \tag{2}$$

or

$$r_{ij} = \frac{max\{x_j\} - x_{ij}}{max\{x_j\} - min\{x_j\}} \tag{3}$$

where rij is the standardized value in the range [0,1]. If rij is positive, formula (2) is used to standardize the data set. If rij is negative, formula (3) is used.

Step 2: Calculate the proportion Yij :

$$Y_{ij} = \frac{X_{ij}}{\sum X_{ij}}\ , 1 \leq \mathrm{i} \leq \mathrm{m}, 1 \leq \mathrm{j} \leq \mathrm{n} \tag{4}$$

Step 3: Calculate the entropy ej :

$$e_j = -\frac{1}{lnm}\sum(Y_{ij} * lnY_{ij})\ , 1 \leq \mathrm{i} \leq \mathrm{m}, 1 \leq \mathrm{j} \leq \mathrm{n}, 0 \leq e_j \leq 1 \tag{5}$$

Step 4: Calculate the variance coefficient dj :

$$d_j = 1 - e_j, 0 \leq d_j \leq 1 \tag{6}$$

Step 5: Calculate the objective weight wj :

$$w_j = \frac{d_j}{\sum d_j}, 0 \leq d_j \leq 1, \sum_{j=1}^{n} w_j = 1 \tag{7}$$

3.2 TOPSIS Method

The TOPSIS method selects the solution whose objective value is with the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution as the best alternative [24]. The specific steps are as follows:

Step 1: The standardized matrix R=[rij]m×n and the weight vector w=(w1,w2,…,wn)T constitute the weighted decision matrix Z=[zij]m×n as follows, where zij=rij×wj， 1≤i≤m, 1≤j≤n and wj are determined based on the entropy method.

$$Z = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ w_1 r_{m1} & x_{m2} & \cdots & w_n r_{mn} \end{bmatrix}_{m \times n} \tag{8}$$

Step 2: Calculate the positive ideal solution Z+ and the negative ideal solution Z-:

$$Z^{+} = \left\{max\, z_{ij} \middle| j \in J\right\} = (z_1^{+}, z_2^{+}, \cdots, z_n^{+}) \tag{9}$$

$$Z^{-} = \left\{min\, z_{ij} \middle| j \in J\right\} = (z_1^{-}, z_2^{-}, \cdots, z_n^{-}) \tag{10}$$

Step 3: Calculate the distance from each evaluation target to Z+ and Z- and obtain the maximum distance S i+ and the minimum distance Si-:

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} \left(z_{ij} - z_j^{+}\right)^2} \tag{11}$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} \left(z_{ij} - z_j^{-}\right)^2} \tag{12}$$

Step 4: Calculate the relative closeness Di:

$$D_i = \frac{S_i^{-}}{S_i^{-} + S_i^{+}} \tag{13}$$

It can be seen that the relative closeness Di is between 0 and 1 from the formula (13). The greater the Di, the closer the evaluation objective is to the optimal solution.

3.3 Data Sources and Processing

The research object of this paper is provinces in China, but Hong Kong, Macao, Taiwan, and Tibet have a large amount of missing data, so they are not included in this study, and the research time range is 2011-2019. The data of the selected indicators in three dimensions of R&D investment, innovation achievements, and policy support are mainly from China Statistical Yearbook (2011-2019), and China High Technology Industry Statistical Yearbook (2011-2019). For the missing data, we used interpolation to fill in the data.

4 ESTIMATION RESULTS OF REGIONAL HIGH-TECH INDUSTRY COMPETITIVENESS

4.1 Competitiveness Score of High-Tech Industry in Each Province of China

The competitiveness score of high-tech industry in each province from 2011 to 2019 is measured based on Entropy-TOPSIS method, and the results are shown in Table 3.

Table 3. Competitiveness score of high-tech industry in each province from 2011 to 2019.

Entropy-TOPSIS	2011	2012	2013	2014	2015	2016	2017	2018	2019	average
Liaoning	0.135	0.14	0.127	0.139	0.125	0.137	0.15	0.158	0.161	0.141
Beijing	0.411	0.439	0.444	0.45	0.448	0.457	0.474	0.482	0.485	0.454
Tianjin	0.219	0.224	0.24	0.257	0.244	0.255	0.255	0.254	0.327	0.253
Hebei	0.073	0.077	0.077	0.08	0.086	0.089	0.109	0.127	0.138	0.095
Shanghai	0.365	0.33	0.393	0.389	0.408	0.408	0.426	0.44	0.488	0.405
Jiangsu	0.266	0.273	0.275	0.268	0.271	0.275	0.271	0.279	0.298	0.275
Zhejiang	0.172	0.183	0.188	0.192	0.195	0.195	0.208	0.231	0.239	0.2
Fujian	0.163	0.156	0.16	0.155	0.153	0.191	0.193	0.192	0.183	0.172
Shandong	0.116	0.128	0.141	0.142	0.146	0.149	0.153	0.161	0.173	0.145
Guangdong	0.344	0.376	0.37	0.366	0.363	0.365	0.37	0.438	0.438	0.381
Guangxi	0.11	0.086	0.106	0.101	0.109	0.119	0.129	0.14	0.147	0.116
Hainan	0.201	0.141	0.156	0.154	0.137	0.171	0.224	0.221	0.223	0.181
Eastern	0.215	0.213	0.223	0.224	0.224	0.234	0.247	0.260	0.275	0.235
Shanxi	0.058	0.086	0.105	0.122	0.118	0.135	0.139	0.15	0.194	0.123
Inner Mongolia	0.139	0.056	0.065	0.079	0.09	0.095	0.122	0.154	0.157	0.106
Jiangxi	0.098	0.143	0.118	0.126	0.142	0.129	0.14	0.156	0.164	0.135
Jilin	0.137	0.153	0.169	0.123	0.149	0.128	0.144	0.174	0.222	0.155
Heilongjiang	0.122	0.145	0.152	0.139	0.149	0.143	0.162	0.178	0.192	0.154
Hubei	0.1	0.106	0.118	0.13	0.144	0.152	0.165	0.171	0.177	0.14
Hunan	0.14	0.131	0.127	0.12	0.125	0.134	0.135	0.123	0.134	0.13
Anhui	0.108	0.113	0.122	0.125	0.129	0.134	0.145	0.166	0.17	0.135
Henan	0.106	0.119	0.13	0.131	0.15	0.155	0.158	0.168	0.195	0.146
Middle	0.112	0.117	0.123	0.122	0.133	0.134	0.146	0.160	0.178	0.136
Chongqing	0.118	0.141	0.158	0.165	0.17	0.182	0.187	0.193	0.206	0.169
Sichuan	0.194	0.208	0.173	0.184	0.192	0.193	0.204	0.222	0.219	0.199
Guizhou	0.095	0.096	0.1	0.104	0.124	0.105	0.148	0.142	0.192	0.123
Yunnan	0.117	0.123	0.133	0.127	0.161	0.126	0.141	0.148	0.156	0.137
Shaanxi	0.191	0.198	0.218	0.232	0.249	0.253	0.256	0.263	0.309	0.241
Gansu	0.117	0.126	0.122	0.14	0.132	0.136	0.152	0.174	0.194	0.144
Qinghai	0.081	0.089	0.101	0.099	0.125	0.14	0.148	0.182	0.145	0.123
Ningxia	0.106	0.115	0.078	0.093	0.121	0.107	0.141	0.129	0.138	0.114
Xinjiang	0.129	0.152	0.159	0.165	0.158	0.17	0.185	0.198	0.224	0.171
Western	0.128	0.139	0.138	0.145	0.159	0.157	0.174	0.183	0.198	0.158

We map the high-tech industry competitiveness score of each province with ArcGIS software according to Table 3. As shown in Figure 1(a)-1(c), during the study period, the competitiveness of high-tech industry is on an upward trend. We also conclude from the average score of high-tech industry competitiveness, as shown in Figure 1(d), the competitiveness of high-tech industry in the eastern, middle, and western regions has obvious step-like distribution characteristics, showing the pattern of “the strongest competitiveness in the east, the second in the west, and the weaker in the middle”.

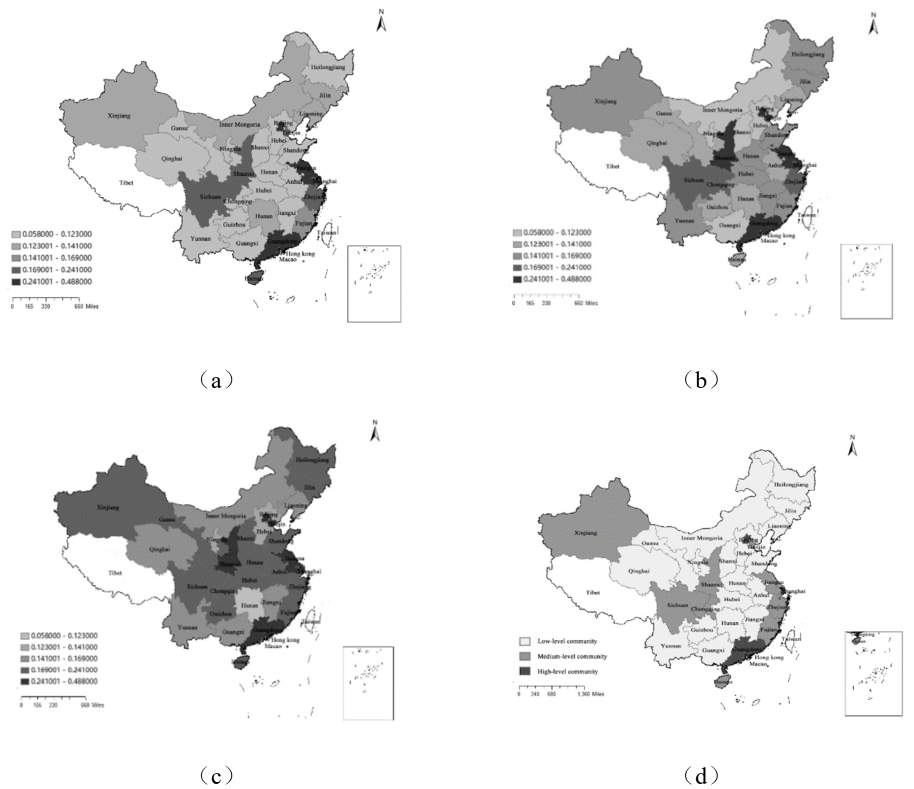

Figure 1. Evolution of high-tech industry competitiveness in 2011, 2015, 2019 and average score

4.2 The Hierarchical Clustering Analysis of High-Tech Industry Competitiveness in China's Provinces

The main purpose of hierarchical clustering is to identify variables on some similar or dissimilar features and to divide the variables into several categories according to these features, so that the individuals within the clusters are as similar as possible, while individuals between clusters are as different as possible. We apply SPSS 22.0 analysis tool to cluster the high-tech industry competitiveness score levels of 30 provinces from 2011-2019 based on Euclidean distance and use the Ward method to obtain the distance between different categories. The hierarchical clustering results are shown in Table 4.

Comparing the results of hierarchical clustering analysis with the results obtained by the Entropy-TOPSIS method, it is found that among the three groups of results divided by hierarchical clustering, the scores within each group are similar, and there are no exceptions. Therefore, the clustering results further verify the rationality of using the Entropy-TOPSIS method to evaluate the competitiveness of high-tech industry.

Table 4. Hierarchical clustering results.

Level	Province
Strong competitiveness	Beijing, Shanghai, Guangdong
General competitiveness	Hainan, Fujian, Xinjiang, Chongqing, Sichuan, Zhejiang, Jiangsu, Shaanxi, Tianjin
Weak competitiveness	Hunan, Qinghai, Ningxia, Guangxi, Guizhou, Shanxi, Inner Mongolia, Hebei, Jilin, Liaoning, Shandong, Heilongjiang, Yunnan, Jiangxi, Gansu, Anhui, Hubei, Henan,

According to Table 1, The clustering results of the competitiveness of high-tech industry are divided into three levels which include strong competitiveness, general competitiveness, and weak competitiveness. Among 30 provinces, the ranking of Beijing, Shanghai, and Guangdong is always in the top three from 2011 to 2019, and they are classified into strong competitiveness cluster which has an absolute leading edge. And these three provinces are the core city of the Beijing-Tianjin-Hebei urban agglomeration, the Yangtze River Delta urban agglomeration, and the Pearl River Delta urban agglomeration. Tianjin, Shaanxi, Jiangsu, Zhejiang, Sichuan, Chongqing, Xinjiang, Fujian, and Hainan are classified into the middle-level cluster whose competitiveness of high-tech industry performs generally. In this cluster, Tianjin, Shaanxi, and Jiangsu are slightly better than other regions, but there is still a certain gap compared with the strong competitive cluster. The remaining regions have weaker competitiveness in high-tech industries.

4.3 Dimensional Analysis of High-Tech Industry Competitiveness

We can clearly understand the shortcomings of the province in terms of high-tech industry competitiveness by comparing the gaps in the four dimensions, which will help the province to find and fill gaps. To observe the differences between the four dimensions of high-tech industry competitiveness of each province more intuitively, a radar chart is drawn in this section and shown in Figure 2.

(a)High-tech industry competitiveness

(b) Business environment

(c) R&D investment

(d) Innovation achievements

(e)Policy support

Figure 2. The competitiveness dimension of high-tech industry

In Figure 2, the closer the point is to the center of the circle, the smaller the corresponding value is. With the increase of the year, each point gradually spreads outward, which means the corresponding value is getting larger. According to Figure 2(a), it can be seen that the competitiveness of high-tech industry in various provinces showed a trend of increasing year by year from 2011 to 2019, and there were four extreme points in spatial distribution: Beijing-Tianjin-Hebei region, Yangtze River Delta region, Guangdong and Shaanxi.

The business environment is the premise to ensure the sustainable and stable development of high-tech industry. As can be seen from Figure 2(b), the development of the business environment in various provinces in China is extremely unbalanced, with a standard deviation of 0.1290. Shanghai, Beijing, and Tianjin rank at the forefront while Gansu, Guizhou, and Qinghai have the worst business environment. In addition, as the business environment is highly valued in China, many provinces have introduced policies to provide enterprises with more efficient and convenient government services and preferential measures which lead to significant growth in the business environment indicator dimension.

From Figure 2(c), it can be seen that the level of R&D investment in Guangdong is significantly higher than that in other provinces, followed by Jiangsu and Zhejiang, while Hainan, Gansu, and Qinghai have the lowest level of R&D investment. The same problem of uneven development among provinces exists in the dimension of R&D investment, with a standard deviation of 0.1521. In addition, Gansu, Heilongjiang, Ningxia, Jiangxi, Guangxi, Yunnan, Jilin, Shanxi, and Shaanxi have achieved large growth in R&D investment in the past few years, and these provinces have relatively high potential in the future development of high-tech industry.

It can be seen from Figure 2(d) that the innovation achievements of Guangdong, Jiangsu, and Shanghai are among the top three, and the innovation achievements of Chongqing, Xinjiang, Beijing, Sichuan, Henan, Shaanxi, Tianjin, Shanxi, Zhejiang are also high, and their standard deviation is 0.0836, the development imbalance of innovation achievements is weaker than other dimensions.

It can be seen from Figure 2(e) that Beijing, Shaanxi, Shanghai, and Sichuan have the highest degree of policy support. The standard deviation of this dimension is 0.1599, and the development of the policy support dimension is the most uneven. Given this, for provinces with weak high-tech industry competitiveness, the local government can refer to the relevant policies of provinces with strong competitiveness to improve the competitiveness of high-tech industry.

5 MAIN CONCLUSIONS AND SUGGESTIONS

In this paper, we design a high-tech industry competitiveness evaluation index system from four dimensions, including business environment, R&D investment, innovation achievements, and policy support. The scores of each province are calculated by Entropy-TOPSIS method. The conclusion is as follows:

(1) The competitiveness of high-tech industry is on an upward trend, and the pattern is presented as "the strongest competitiveness in the east, the second in the west, and the weaker in the middle".

(2) According to the hierarchical clustering method, the clustering results of high-tech industry competitiveness can be divided into three grades: strong competitiveness, general competitiveness, and weak competitiveness.

(3) By comparing the gap of each province in the four dimensions, we find that there are obvious differences in the competitiveness of high-tech industry and unbalanced development in different provinces.

According to the research conclusions, we put forward the following suggestions: in terms of policy support, the government should encourage enterprises to deduct tax proportionally with the transformation of innovative achievements and reduce the cost of land use for scientific research; in terms of scientific research innovation, the government should set up special financial funds to reward and support related industries; in terms of talent team construction, the government should increase the force of the high-tech talents introduction, and give preference to senior talents in employment subsidies and housing subsidies.

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