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Evaluation and application of local fiscal science and technology expenditure efficiency in the Yangtze River Delta urban agglomeration based on AHP-TOPSIS and SOM clustering

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Abstract

This study selected 18 indicators from four dimensions: the scale of regional fiscal science and technology expenditure, the social impact of science and technology, the efficiency of science and technology expenditure, and the environment for scientific and technological innovation, and constructed an evaluation index system for the efficiency of local fiscal science and technology expenditure in the Yangtze River Delta urban agglomeration. The AHP-TOPSIS model was used to determine the weights of evaluation indicators, and the efficiency ranking of fiscal science and technology expenditures in various cities of the Yangtze River Delta urban agglomeration was quantified. Furthermore, using the SOM algorithm for clustering analysis, the level division of innovation capability in the Yangtze River Delta urban agglomeration was clarified. This study provides a scientific tool and method for evaluating the efficiency of local financial science and technology expenditure in the Yangtze River Delta urban agglomeration, and provides solid theoretical support and practical guidance for promoting the coordinated development of regional science and technology innovation.

Keywords

Evaluation of science and technology expenditure efficiency; Yangtze River Delta urban agglomeration; AHP-TOPSIS model; SOM clustering.

1. Introduction

With the increasingly fierce global technological competition, technological innovation has become the core driving force for promoting regional economic development. To promote the integrated development of the Yangtze River Delta, on December 1, 2019, the Central Committee of the Communist Party of China and the State Council issued the Outline of the Development Plan for Regional Integration of the Yangtze River Delta, elevating the integrated development of the Yangtze River Delta to a national strategy. However, due to geographical and resource limitations, there is a significant development gap between cities at all levels within urban agglomerations, and the main gap still stems from technological innovation. Government technology investment has a significant promoting effect on technological innovation [1]. Local governments, as important entities in the construction of regional innovation systems, play an important guiding and fundamental role in improving the innovation environment and promoting innovation development [2]. Local fiscal technology expenditure, as an important means of supporting technological innovation, directly affects the quality and efficiency of technological innovation. Therefore, scientifically evaluating the efficiency of local fiscal science and technology expenditure is of great significance for optimizing the structure of fiscal expenditure and enhancing the level of scientific and technological innovation.

With the continuous deepening of technological innovation and the promotion of regional integration, the research on the efficiency evaluation and application of local financial science

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and technology expenditure in the Yangtze River Delta urban agglomeration has become particularly important. Most studies use data envelopment analysis models and stochastic frontier analysis [3,4]. Wang Qian et al. [5] used a three-stage super efficiency SBM-DEA model to measure the efficiency of fiscal science and technology expenditure in 30 provinces and cities in China, and analyzed the factors that affect the efficiency of fiscal science and technology expenditure; Luo Weiping et al. [6] used Data Envelopment Analysis (DEA) method to evaluate the performance of financial technology investment in 21 cities in Guangdong Province; Miao Hui [7] used the TOPSIS method to establish an improved DEA model that eliminates the impact of environmental factors, calculated the efficiency of financial technology investment in Liaoning Province, and discussed its influencing factors; Pan Juan et al. [8] studied the innovation efficiency of 30 provinces in China using the PP-SFA analysis method, and analyzed the impact of different R&D investment variables in the production function model on innovation efficiency; Xu Yingqi et al. [9] used a combination model of Projection Pursuit (PP) and Transcendent Logarithmic Production Function (Translog SFA) to analyze panel data on input-output variables related to scientific and technological innovation in Sichuan Province from 2014 to 2018, as well as external environmental factors that affect innovation efficiency.

Traditional evaluation methods such as data envelopment analysis and stochastic frontier analysis, although able to evaluate the efficiency of fiscal science and technology expenditures to a certain extent, often find it difficult to comprehensively consider multiple evaluation indicators and require high data requirements. Therefore, some scholars have begun to attempt to introduce comprehensive evaluation methods such as Analytic Hierarchy Process and Approximation Ideal Solution Sorting into the efficiency evaluation of local fiscal science and technology expenditures. Zhu Mengfei et al. [10] used the AHP-TOPSIS method to determine the evaluation value of regional innovation policy source capacity, and used the SOM algorithm for cluster analysis to determine the level of regional innovation capacity. Guo Chong [11] conducted empirical research on the high-quality development of 19 new areas in China using TOPSIS from four dimensions: structural optimization, innovation driven, open collaboration, and quality improvement. The AHP-TOPSIS model can comprehensively consider multiple evaluation indicators [12,13] to objectively evaluate the efficiency of local financial science and technology expenditures in various cities. This method not only considers the weight of evaluation indicators, but also calculates the relative closeness between each city and the ideal solution and negative ideal solution to obtain the comprehensive ranking of each city. At the same time, self-organizing mapping neural networks, as an unsupervised learning algorithm, have also played an important role in evaluating the efficiency of local fiscal science and technology expenditures. The SOM algorithm maps similar data to neighboring nodes of the neural network through self-organizing learning of input data, thereby achieving clustering analysis of data [14].

In summary, the evaluation and application research of local fiscal science and technology expenditure efficiency in the Yangtze River Delta urban agglomeration based on AHP-TOPSIS and SOM clustering has important theoretical significance and practical value. By comprehensively applying these two methods, we can comprehensively and objectively evaluate the efficiency of local financial science and technology expenditure in various cities, providing strong support for optimizing the structure of financial expenditure and enhancing the level of scientific and technological innovation.

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2. Relevant theoretical basis

2.1. Analytical Hierarchy Process (AHP)

Analytic Hierarchy Process (AHP) is an American operations researcher and T L. Professor Saaty proposed a qualitative and quantitative, systematic, and hierarchical analysis method in the early 1970s [15].

The general steps of the analytic hierarchy process are as follows:

[Step1] Establish a hierarchical structure model: including target layer, criterion layer and plan layer.

[Step2] Construct all judgment matrices in each level: for n evaluation indicators, use the binary relative comparison method to judge the relative importance between each indicator, and form a matrix based on the pairwise comparison results, that is, the judgment matrix X, The judgment matrix X is used to determine the relative importance between n sub-factors at a certain level.

[Step3] Perform hierarchical single sorting and consistency testing:

$$\mathrm{CI} = \frac{\lambda_{\max} - \mathrm{n}}{\mathrm{n} - 1}$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}$$

In the formula: CI is the consistency index; n is the number of evaluation factors; RI is the average random consistency index; CR is the consistency ratio. When CR<0.1, the consistency of the judgment matrix is considered acceptable and does not meet the needs of experts. Readjust the matrix until you know it's acceptable.

2.2. Sorting method approaching ideal solution (TOPSIS)

TOPSIS is a commonly used comprehensive evaluation method. The basic idea of the TOPSIS method is to assume positive and negative ideal solutions, measure the distance between each sample and the positive and negative ideal solutions, obtain its relative closeness to the ideal solution, and rank the merits of each evaluation object.

The TOPSIS solution steps are as follows:

[Step1]Construct a decision matrix:

$$b_{ij} = a_{ij} / \sqrt{\sum_{i=1}^{m} a_{ij}^2}\ , \ \ i = 1,2,\cdots m, j = 1,2,\cdots n$$

(where a_{ij} is the decision matrix and b_{ij} is the normalized matrix)

[Step2]Calculate the weighted matrix:

$$c_{ij} = w_j * b_{ij}$$

[Step3] Determine the positive ideal solution and negative ideal solution of the evaluation object:

$$\text{Positive solution} c_j^* = \begin{cases} max c_{ij}, & j \text{ is a benefit attribute} \\ min c_{ij}, & j \text{ is a cost attribute} \end{cases}$$

$$\text{Negative ideal solution} c_j^0 = \begin{cases} min c_{ij}, & j \text{ is a benefit attribute} \\ max c_{ij}, & j \text{ is a cost attribute} \end{cases}$$

[Step4] Calculate the distance between each evaluation object and the positive and negative ideal solutions. The distance between the evaluation object and the ideal solution is:

$$d_i^* = \sqrt{\sum_{j=1}^{n} (c_{ij} - c_j^*)^2}$$

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The distance between the evaluation object and the negative ideal solution is:

$$d_i^0 = \sqrt{\sum_{j=1}^{n} (c_{ij} - c_j^0)^2}$$

[Step5] Calculate the relative closeness of each evaluation object to the ideal solution based on the Euclidean distance, and sort the merits according to the proximity value, that is

$$f_i^* = d_i^0 / (d_i^0 + d_i^*)$$

In the formula, $f_i^* \in [0,1]$ the closer f_i^* is to 1, the closer the i-th evaluation object is to the optimal level; the closer f_i^* is to 0, the closer the i-th evaluation object is to the worst level.

2.3. Self-organizing map neural network (SOM)

Self Organizing Mapping Neural Network (SOM) is a neural network based on unsupervised learning methods, first proposed by Kohonen from Helsinki University of Technology in Finland in 1981 [16]. The SOM network consists of an input layer and an output layer.

Its main algorithm flow is as follows:

[Step1] Initialize the network and select random values for the initial weight vector;

[Step2] Calculate distance: Calculate the similarity between each input data and the node neurons in the competition layer, usually using Euclidean distance.

$$d_j(x) = \sqrt{\sum_{i=1}^{D} (x_i - w_{ji})^2}$$

(where D is the input vector dimension; w_{ji} is the connection weight of the node neuron)

[Step3] Select the winning neuron: Select the neuron with the smallest distance from the weight vector. This neuron is called the winning neuron (Best Match Unit, BMU). At the same time, the set of adjacent neurons of the winning neuron is determined.

[Step4] Adjust weights: Adjust the weights of the winning neuron and its neighbor neurons to reduce the distance between these weight vectors and the current input sample. This process helps maintain the topological structure of the input data. The weight update formula is:

$$w_{ji}(t+1) = w_{ji}(t) + \Delta w_{ji} = w_{ji}(t) + \eta(t) T_{j,i(x)}(t)(x_i - w_{ji})$$

(In the formula, Δw_{ji} is the weight update amount; η is the learning rate. It decreases exponentially with the number of training times t)

The training process of the SOM network is based on a competitive learning strategy, and neurons gradually optimize the network through competition with each other. At the same time, it uses the neighbor relationship function to maintain the topology of the input space and ensure that the two-dimensional map contains the relative distances between data points. This feature enables adjacent input samples to be assigned to adjacent output neurons during the mapping process.

3. Construction of an evaluation index system for the efficiency of local fiscal science and technology expenditures

Indicator selection is the core link of evaluation work. Due to the complexity of local fiscal science and technology expenditure efficiency and the diversity of influencing factors, this article needs to ensure that the selected evaluation indicators can comprehensively and accurately reflect the efficiency of local fiscal science and technology expenditure in the Yangtze River Delta urban agglomeration. Based on the existing classic evaluation system indicators, this article carefully selects 18 indicators to evaluate the efficiency of local fiscal science and technology expenditure from four dimensions: science and technology expenditure scale,

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science and technology social impact, science and technology expenditure efficiency, and science and technology innovation environment. The established evaluation index system for local fiscal science and technology expenditure efficiency is shown in Table 1.

Table 1 Evaluation indicator system for efficiency of local fiscal science and technology expenditures

target layer A	Criterion layer B	Indicator layer C
Evaluation of the efficiency of local fiscal science and technology expenditures in the Yangtze River Delta urban agglomeration	Science and technology expenditure scale B1	Science and technology expenses C11
		Education expenditure C12
		R&D expenditure C13
	Social Impact of Science and Technology B2	Public library book collection C21
		Urban green space area C22
		Number of hospitals C23
		Number of beds in nursing homesC24
		The number of employees in urban non-private units at the end of the periodC25
	Technology Spending Benefit B3	Patent authorization amount C31
		Invention quantity C32
		Gross regional productC33
		The proportion of tertiary industry in regional GDP C34
		Total profits of industrial enterprises above designated size C35
	Science and Technology Innovation Environment B4	Number of industrial enterprises C41
		Number of general colleges and universities C42
		The number of students enrolled in general undergraduate and junior college programs is C43
		Number of mobile phone users at the end of the year C44
		Number of Internet broadband access users C45

4. Evaluation of the efficiency of local fiscal science and technology expenditures in the Yangtze River Delta urban agglomeration based on AHP-TOPSIS

4.1. Data sources

Since 2010, with the support of major national strategies and policies, the regional integration of the Yangtze River Delta has experienced a transformation from planning integration and multi-center integration to high-quality integration and digital economy integration. Among them, the "Yangtze River Delta Urban Agglomeration Development Plan" It has become a guiding and binding document for the integrated development of the Yangtze River Delta region. Therefore, taking into account the scientific nature, accessibility and operability of the data [17], this article selects relevant data reflecting the level of scientific and technological innovation at the 27 prefecture-level cities in the Yangtze River Delta urban agglomeration in 2021 for

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empirical analysis. The data comes from the " China Science and Technology Statistical Yearbook, China City Statistical Yearbook, statistical yearbooks of various provinces, EPS database, etc. Some missing data were mainly filled using the mean substitution method.

4.2. Weight determination and assignment based on AHP

After combining the actual situation and discussing with relevant experts, the importance ranking of the first level indicators is as follows: B4 focuses on the policy environment, talent team construction, innovation platform construction, and other aspects of scientific and technological innovation. A good scientific and technological innovation environment is an important guarantee for improving the efficiency of scientific and technological expenditure, helping to stimulate innovation vitality and enhance innovation capabilities. Therefore, the environment for technological innovation is the most important and comes first; B1 mainly examines the investment level of local finance in science and technology. A larger scale of science and technology expenditure often indicates the government's attention and support for scientific and technological development, which is conducive to promoting scientific and technological innovation and enhancing scientific and technological strength. Therefore, it is placed in the second place; B2 focuses on the impact of technology expenditure on social, economic, and environmental aspects. The social impact of technology expenditure is an important aspect of measuring its efficiency, which helps to achieve coordinated development between technology and social economy. Therefore, it is placed in the third place; B3 mainly examines the output and benefits of technology expenditure. Efficient technology expenditure should be able to bring significant benefits, promote sustained economic growth and industrial upgrading, therefore it is ranked fourth. B1 is more important than B2, so the score is 3. B3 is slightly less important than B1, with a score of 1/4, indicating that the latter is extremely important than the former. B4 is the most important among the four dimensions, so its ratings for the other three dimensions are relatively low, indicating that it is extremely important or significantly important compared to the other dimensions. Based on the above research, the initial judgment matrix for the first level indicators constructed is as follows:

$$\mathrm{A} = \begin{bmatrix} 1 & 3 & 4 & 5 \\ 1/3 & 1 & 2 & 3 \\ 1/4 & 1/2 & 1 & 2 \\ 1/5 & 1/3 & 1/2 & 1 \end{bmatrix}$$

The analytic hierarchy process is used to calculate the eigenvector W, maximum eigenvalue λ_{max} ,consistency test index CI and CR of matrix A as follows:

$$W = [2.169,0.933,0.559,0.339]^T$$

λ_{max}=4.051; CI=0.017; since n=4, RI=0.890, and CR=CI/RI= <0.1. The consistency of the matrix is acceptable, which means the weight is reasonable.

As above, this article calculates the weights of the four first-level indicators and their sub-indicators respectively. The calculation results are retained to four decimal places. The final weight results are shown in Table 2:

Table 2 Evaluation results of science and technology expenditure benefit indicator system

	First level indicator	First level indicator weight	Secondary indicators	Secondary indicator weight	Comprehensive weight of secondary indicators
Evaluation of the efficiency of local fiscal science and technology	Technology spending scale	0.5423	Science and technology expenses C11	0.6194	0.3359
			Education expenditure C12	0.2842	0.1541

ISSN: 2710-0170

expenditures in the Yangtze River Delta urban agglomeration			R&D expenditure C13	0.0964	0.0523
	Social impact of science and technology	0.2333	Public library book collection C21	0.4124	0.0962
			Urban green space area C22	0.1606	0.0375
			Number of hospitals C23	0.1248	0.0291
			Number of beds in nursing homesC24	0.2337	0.0545
			The number of employees in urban non-private units at the end of the periodC25	0.0686	0.0160
	Technology Spending Benefits	0.1397	Patent authorization amount C31	0.4671	0.0653
			Invention quantity C32	0.2658	0.0371
			Gross regional productC33	0.1228	0.0172
			The proportion of tertiary industry in regional GDP C34	0.0914	0.0128
			Total profits of industrial enterprises above designated size C35	0.0529	0.0074
	Science and technology innovation environment	0.0847	Number of industrial enterprises C41	0.4337	0.0367
			Number of general colleges and universities C42	0.1277	0.0108
			The number of students enrolled in general undergraduate	0.0739	0.0063

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			and junior college programs is C43		
			Number of mobile phone users at the end of the year C44	0.1556	0.0132
			Number of Internet broadband access users C45	0.2092	0.0177

4.3. Efficiency evaluation and ranking based on TOPSIS

Due to the different dimensions of each indicator in the indicator system, this article adopts Z-Score standardization for dimensionless processing. Multiply the obtained standardized matrix with the comprehensive weights of various indicators calculated by AHP to obtain a weighted standardized decision matrix. By calculating, the relative closeness of each region can be found. The optimal solution should simultaneously satisfy the requirement of being closest to the positive ideal solution, both of which are the farthest distance from the negative ideal solution, that is, the greater the relative closeness, the better. In this article, the strength of technology expenditure efficiency is relatively close. The specific calculation results are shown in Table 3.

Table 3 TOPSIS evaluation calculation results

City	Positive solution distance d_i^*	Negative solution distance d_i^0	Relative proximity f_i^*
Hefei City	3.344	1.382	0.292
Wuhu	4.057	0.532	0.116
Ma'anshan City	4.369	0.183	0.040
Tongling City	4.451	0.090	0.020
Anqing City	4.276	0.343	0.074
Chuzhou City	4.306	0.255	0.056
Chizhou City	4.489	0.070	0.015
xuancheng city	4.383	0.181	0.040
Nanjing City	3.070	1.601	0.343
Wuxi City	3.620	1.050	0.225
Changzhou City	3.993	0.639	0.138
Suzhou City	2.506	2.318	0.481
Nantong city	3.816	0.828	0.178
Yancheng City	4.049	0.569	0.123
Yangzhou	4.174	0.416	0.091
Zhenjiang	4.249	0.331	0.072
Taizhou City	4.231	0.353	0.077

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City	Positive solution distance d_i^*	Negative solution distance d_i^0	Relative proximity f_i^*
Hangzhou City	2.631	2.028	0.435
Ningbo City	3.265	1.408	0.301
Jiaxing City	3.986	0.648	0.140
Huzhou	4.187	0.420	0.091
Shaoxing City	4.006	0.579	0.126
Jinhua City	3.938	0.896	0.185
Zhoushan City	4.427	0.128	0.028
Taizhou	4.014	0.624	0.135
Shanghai	0.215	4.474	0.954

5. Analysis of science and technology expenditure efficiency evaluation results based on SOM clustering

The SOM clustering method is used to group the evaluation results, as shown in Table 4. The clustering method is used to group the evaluation results, and the grouping results are more scientific and objective, which better solves the problem of unclear grouping boundaries due to small differences in data.

Table 4 SOM clustering grouping results

Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
Suzhou City 0.481	Hefei City 0.292	Nantong City 0.178	Wuxi City 0.225	Ma'anshan City 0.040	Wuhu City 0.116
Hangzhou City 0.435	Nanjing City 0.343	Jinhua City 0.185		Tongling City 0.020	Changzhou City 0.138
Shanghai 0.954	Ningbo City 0.301			Anqing City 0.074	Yancheng City 0.123
				Chuzhou City 0.056	Jiaxing City 0.140
				Chizhou City 0.015	Shaoxing City 0.126
				Xuancheng 0.040	Taizhou City 0.135
				Yangzhou City 0.091	
				Zhenjiang City 0.072	
				Taizhou City 0.077	
				Huzhou City 0.091	
				Zhoushan City 0.028	

The SOM clustering results show significant differences and clustering characteristics in the efficiency of science and technology expenditure among cities. The SOM clustering method

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effectively divides the efficiency of science and technology expenditure in the Yangtze River Delta urban agglomeration into several different levels or groups, and the cities within each group have similar characteristics in terms of science and technology expenditure efficiency.

From the results of SOM clustering grouping, it can be seen that Shanghai has the highest efficiency in science and technology expenditure, belonging to the first group, demonstrating its efficiency in science and technology input and output. Suzhou and Hangzhou also have high efficiency values, but there is still a certain gap compared to Shanghai. These cities may have a relatively complete system of technological innovation, high-level scientific research institutions, and good mechanisms for cultivating and introducing scientific and technological talents; The second group of cities, Nanjing, Hefei, and Ningbo, are at a moderate level in terms of science and technology expenditure efficiency. The third and fourth groups of cities have relatively low efficiency in science and technology expenditure, and these cities may face problems such as insufficient science and technology innovation resources and incomplete science and technology innovation systems. The cities in the fifth group generally have lower efficiency in science and technology expenditure. Most of these cities belong to economically underdeveloped areas with weak foundations for scientific and technological innovation, and the efficiency of science and technology expenditure urgently needs to be improved. The cities in the sixth group have slightly higher efficiency in technology expenditure than those in the fifth group, but they are still at a relatively low level. These cities have certain potential in technological innovation, but further investment is needed to optimize resource allocation and enhance technological innovation capabilities.

6. Conclusion and suggestions

This article constructs an evaluation index system for the efficiency of local financial science and technology expenditure in the Yangtze River Delta urban agglomeration. Through the AHP-TOPSIS method, it was found that there are differences in the efficiency of local financial science and technology expenditures among cities in the Yangtze River Delta urban agglomeration. Some cities have performed excellently and reached the level of optimal solutions, while others have lagged behind and are approaching the worst solution. Using the SOM clustering algorithm, the efficiency of local fiscal science and technology expenditure in the Yangtze River Delta urban agglomeration can be divided into different clusters, which reflect the common characteristics and differences of fiscal science and technology expenditure efficiency among different cities. This study provides a scientific tool and method for evaluating the efficiency of local financial technology expenditure in the Yangtze River Delta urban agglomeration.

In response to the differences in fiscal and technological expenditure efficiency among cities within the Yangtze River Delta urban agglomeration, the government should strengthen policy guidance and coordination to promote balanced development of scientific and technological innovation among cities. For cities with lower efficiency, policy support can be increased to optimize the structure of fiscal science and technology expenditure. At the same time, cities within the Yangtze River Delta urban agglomeration should strengthen cooperation and exchange in scientific and technological innovation, share resources, experience, and technological achievements. Through regional cooperation, it is possible to promote the coordinated development of technological innovation and improve the efficiency of fiscal science and technology expenditures in the entire region.

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