Comprehensive Evaluation of Provincial New Quality Productivity in China Based on TOPSIS and K-means Methods

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Abstract: In the current context of global economic integration and rapid technological development, the enhancement of new quality productivity is seen as a key factor driving regional economic growth. Based on the formula of the new quality productivity theory, this paper constructs a comprehensive evaluation system that includes six Primary indicators: science and technology, Factors of Production, Estate, labor force, objects of labor, and tools of labor. Corresponding to these Primary indicators, the paper further subdivides 26 second-level indicators, which can fully reflect the level of new quality productivity in a region. The TOPSIS method is applied to rank and evaluate the new quality productivity of all provinces across the country. By calculating the scores of each province's indicators, the relative position of each province in terms of new quality productivity is clarified. Through K-means cluster analysis, the distribution of new quality productivity in different provinces over the years is further explored, effectively classifying all provinces nationwide. The Pearson correlation coefficient method is used to analyze the relationship between each Primary indicator and new quality productivity, in order to identify the key factors affecting productivity.

1. Introduction

The concept of new-quality productivity was first introduced in 2023, and in the following year, one of the ten key tasks proposed at the Second Session of the 14th National People's Congress held at the Great Hall of the People was "to vigorously advance the construction of a modern industrial system and accelerate the development of new-quality productivity." Studying and developing new-quality productivity is of great significance for China's development in today's information age. With the continuous advancement of technology and the acceleration of digital transformation, new technologies such as artificial intelligence, big data analytics, and the Internet of Things are profoundly influencing corporate production methods and efficiency. Studying new-quality productivity can help companies better address the challenges and opportunities brought about by technological changes[1].Studying new-quality productivity can help companies discover and leverage new opportunities to enhance productivity and competitiveness. In the context of limited resources and increasing environmental pressures, improving production efficiency and resource utilization is critical for achieving sustainable development. Studying new-quality productivity can promote more sustainable production methods for companies.In the current era and under the prevailing circumstances, the purpose of studying new-quality productivity is to deeply understand the theoretical formula of new-quality productivity proposed by the China Productivity Promotion Center Association and to further explore the relationships between the various indicators in the formula and their mutual influences on new-quality productivity itself. The aim is to analyze the theoretical formula of new quality productivity, explore the relationships between indicators, and their impact on the economy Integrate innovative resources to lead the development of strategic emerging industries and future industries, accelerating the formation of new-quality productive forces[2].This paper is the first time to apply the TOPSIS+entropy weight method in the evaluation of new quality productivity.

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2. Establishment of a Comprehensive Evaluation Model for New Quality Productivity

2.1 Research Agenda

To explore the driving factors of new-quality productivity, we developed the technical route shown in Figure 1:

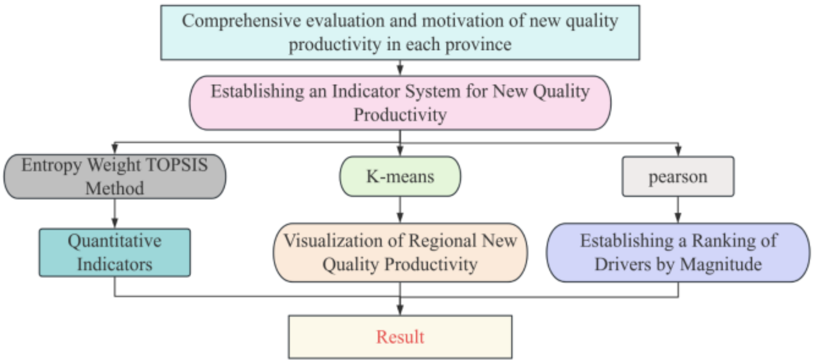

Figure 1. Technical Framework

From Figure 2, we can see that to complete this study, we first established an indicator system for new-quality productivity, which includes quantitative indicators. Then, we utilized the entropy-weighted TOPSIS method to quantitatively evaluate the new-quality productivity of various provinces. Following that, we applied the K-means clustering algorithm to visualize the distribution of new-quality productivity within regions. At the same time, we used the Pearson correlation coefficient method to identify the main driving factors of new-quality productivity. Finally, we summarized these results to draw our conclusions.

2.2 Construction of the Indicator System

(1) Establishing Indicators

Referring to the Fourteenth National People's Congress and relevant literature, this paper directly uses the various components of the new quality productivity theory formula as the primary indicators, which are: science and technology, Factors of Production, Estate, labor force, labor objects, and labor tools . The specific indicators are as follows in the Table.1.

Table.1. New Quality Productivity Indicators

Level 1 indicators	Secondary indicators	Code
Estate	Number of new material enterprises	Est1
	Number of R&D organizations in high-tech enterprises	Est2
	Number of artificial intelligence companies	Est3
Science and Technology	Number of invention patent applications by industrial enterprises	Sci &Tech1
	Number of effective invention patents of industrial enterprises	Sci &Tech2
	Number of patent applications by industrial enterprises	Sci &Tech3
	Number of new product projects of industrial enterprises	Sci &Tech4
	Technology market turnover	Sci &Tech5
	Sales revenue of new products of industrial enterprises	Sci &Tech6
	Funding for the development of new products by industrial enterprises	Sci &Tech7
Factors of Production	Local finance expenditure on science and technology	Fact1
	General public service expenditures of local finances	Fact2
	General budget expenditures of local finances	Fact3
	Local financial expenditure on education	Fact4
	Persons employed in scientific research and technological services urban units	For1

Labor Force	Number of degrees conferred by general institutions of higher education at the undergraduate level	For2
	Average years of schooling	For3
	Total number of employees in emerging industries	For4
	Number of R&D personnel in high-tech enterprises	For5
Labor Tool	Robot mounting density	Too1
	Completed investment in industrial pollution control	Too2
	Investment in R&D by high-tech enterprises	Too3
Labor Object	Mobile subscribers	Obj1
	Number of enterprises with e-commerce transactions	Obj2
	New energy efficiency	Obj3
	Revenue from sales of new products by high-tech enterprises	Obj4

(2) Constructing the Entropy Weight TOPSIS Model

This paper employs the Entropy Weight TOPSIS method to conduct an objective evaluation of the selected secondary indicators, generating scores for each primary indicator. According to the theoretical formula of new quality productivity, data calculations are performed to obtain the final scores. Firstly, the calculation of the secondary indicators is carried out based on the model formula.

Firstly, use the entropy weight method to determine the weight of each secondary indicator, with the formula as follows:

$$w_j = \frac{(1-E_j)}{\sum_{i=1}^{m}(1-E_j)} \tag{1}$$

The specific values are as follows in the Table.2-7.

Table.2. The weights of the seven secondary indicators for science and technology are as follows

Secondary indicators	Weight
Sci & Tech1	0.1432
Sci & Tech2	0.1601
Sci & Tech3	0.1417
Sci & Tech4	0.1438
Sci & Tech5	0.1585
Sci & Tech6	0.1252
Sci & Tech7	0.1276

Chinese-style modernization relies on the modernization of science and technology as its support, and achieving high-quality development depends on fostering new drivers through scientific and technological innovation. It is essential to fully recognize the strategic leading role and fundamental supporting role of science and technology, strengthen top-level design and overall planning, and accelerate the realization of high-level self-reliance and strength in science and technology [3].

Table.3. The weights of the four secondary indicators for Factors of Production are as follows

Secondary indicators	Weight
Fact1	0.4469
Fact2	0.1851
Fact3	0.1682
Fact4	0.1998

Through the weight analysis of the secondary indicators for production factors, local government fiscal science and technology expenditure accounts for nearly 0.5, indicating that local government support has a significant impact on new-quality productivity and can, to a certain extent, represent whether the development of new-quality productivity is favorable or not.Technological revolutions have facilitated the qualitative transformation, innovative combination, and optimized allocation of production factors, significantly enhancing total factor productivity. This is objectively manifested as a systematic leap in the quality state of productive forces [4].

Table.4. The weights of the three secondary indicators for estate are as follows

Secondary indicators	Weight
Est1	0.2517
Est2	0.4371
Est3	0.3112

Innovation-driven future industries fully embody new development concepts and play a significant role in achieving high-quality development. Future industries help accelerate the formation of new types of productive forces, build a coordinated and high-quality development pattern, promote green development, realize high-level opening up to the outside world, meet people's aspirations for a better life, and advance modernization of national governance capabilities [5].

Table.5. The weights of the five secondary indicators for the labor force are as follows

Secondary indicators	Weight
For1	0.1843
For2	0.1087
For3	0.0139
For4	0.2401
For5	0.4530

The introduction of talent attraction policies has prompted businesses to increase investment in industrial robots, promoting the intelligent transformation of manufacturing. These policies have significantly increased the supply of highly skilled labor without raising the cost of labor for companies, enabling them to hire more skilled workers[6].

Table.6. The weights of the three secondary indicators for labor tools are as follows

Secondary indicators	Weight
Too1	0.3389
Too2	0.4395
Too3	0.2217

The core element of new-quality productive forces is 'innovation.' In response to the challenges and opportunities presented by new-quality productive forces, we can optimize technical processes, introduce new equipment, leverage new devices, and enhance 'new' development momentum, injecting powerful drive into development [7].

Table.7. The weights of the four secondary indicators for labor objects are as follows:

Secondary indicators	Weight
Obj1	0.0937
Obj2	0.1879
Obj3	0.3447
Obj4	0.3737

As times and the objectification of our activities evolve, basic objects of labor have changed. Along with these changes, some labor values have also been altered [8].

This paper employs the Entropy Weight TOPSIS method to conduct an objective evaluation of the selected secondary indicators, generating scores for each Primary indicator. According to the theoretical formula of new quality productivity, data calculations are performed to obtain the final scores. The specific values are as follows in the Table.8.

Table.8. Quantitative Scoring Table for Primary Indicators (a part of the whole) are as follows:

Region Year	Science and Technology Score	Estate Score	Labor Object Score
Guangdong 2018	67.24804915	67.24804915	78.83977091
Guangdong 2019	77.75509811	77.75509811	83.89348971

(continuation of previous table)

Guangdong 2020	87.21677658	87.21677658	86.50720639
Guangdong 2021	98.04289151	98.04289151	89.11707358
Guangdong 2022	100	100	86.46381633
...	...	...	...

From the table above, we obtain specific values. By substituting these values into the theoretical formula for new quality productivity, we can calculate the specific quantitative values of new quality productivity for various regions in different years.

The specific values are shown in the Table.9.below (partial):

Table.9. Quantitative Values of New Quality Productivity for Various Regions in Different Years

Region	Year	New Quality Productivity
Anhui	2014	1173.022933
Anhui	2015	1376.815446
Anhui	2016	1726.016446
Anhui	2017	1862.438154
Anhui	2018	2383.626483
Anhui	2019	2916.892988
Anhui	2020	3324.658406
Anhui	2021	4421.278529
Anhui	2022	6030.198579
...	...	...

From the above table, we can obtain the quantified scores of new-quality productivity for different regions of China across various years, allowing us to more intuitively see the differences between regions. This provides favorable numerical parameters for our subsequent K-means clustering analysis.

2.3 Constructing the K-means Clustering Model to Analyze Regional Differences

(1) Perform clustering visualization on the new quality productivity of various regions from 2014 to 2022.

Objective Function

The goal of the K-means algorithm is to minimize the sum of the distances from all points within each cluster to their respective cluster centers, which is to minimize the cost function:

$$J=\sum_{j=1}^{k}\sum_{i=1}^{n_j}\| x_i^{(j)}-\mu_j \|^2 \tag{2}$$

The three cluster centers are as follows:

1:15603   2:61447   3:1267

The specific clustering is shown in the following figure 2:

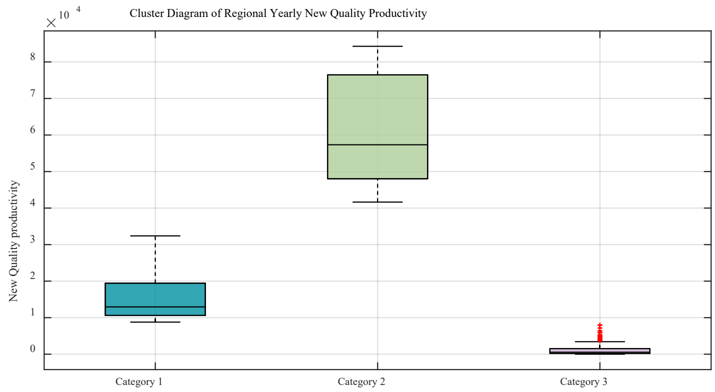

Figure 2. Clustering Diagram of New Quality Productivity for Regions Across Different Years

(2) Visual Analysis of New Quality Productivity for Various Regions in 2022

The specific clustering is shown in the following figure 3-4:

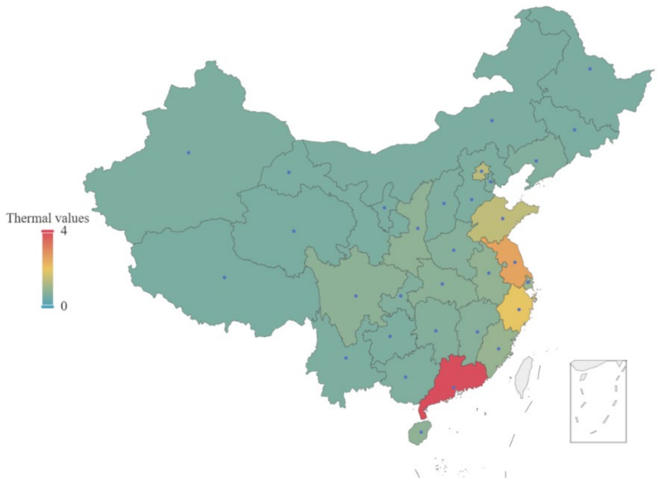

Figure 3. Cluster Overview Map of New Quality Productivity for Various Provinces in 2022

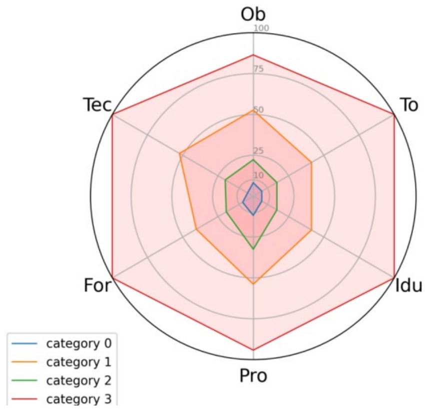

Figure 4. Four-Class Six-Dimensional Primary Indicator Radar Chart

As can be seen from the above, there are differences in new-quality productive forces across regions in China. Guangdong and the Yangtze River Delta region, being among the most dynamic and innovative areas in China's economy, show notably good performance [9]. The new-quality productive forces in central and western regions are weaker, possibly due to traditional industrial structures, a lower proportion of high-tech industries, and insufficient scientific and educational resources, which affect the quality level of the economy. Investment in and activities related to scientific and technological innovation refer to the government's input into talents, funds, technologies, and other aspects needed for such innovation activities. These activities and investments can directly enhance the innovation capabilities of enterprises [10].

2.4 Determining the Feature Importance of Indicators Based on the Pearson Linear Correlation Coefficient Method

Suppose there are m objects and n indicators, which can form a data matrix $X=(X_{ij})m*n$. Now, we are studying the correlation between the a column X_a and the b column X_b in the data matrix. Let the correlation coefficient between these two columns be denoted as rho(a,b).

$$rho(a,b)=\frac{\sum_{i=1}^{m}\left(X_{a,i}-\overline{X_a}\right)\left(X_{b,i}-\overline{X_b}\right)}{\left\{\sum_{i=1}^{m}\left(X_{a,i}-\overline{X_a}\right)^2\sum_{j=1}^{m}\left(X_{b,i}-\overline{X_b}\right)^2\right\}^{1/2}} \tag{3}$$

Where m represents the length of each column. The range of values for the correlation coefficient is from –1 to +1. A value of –1 indicates a perfect negative correlation, while a value of +1 indicates a perfect positive correlation. A value of 0 indicates no correlation between the columns. We take the absolute value of the correlation coefficient as the measure of feature importance.

The feature importance of the indicators is as follows figure 5:

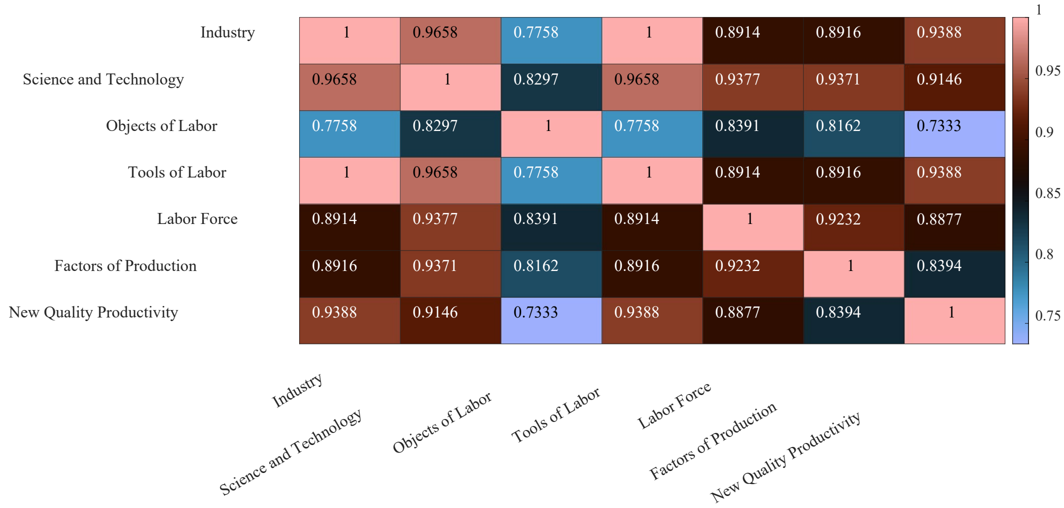

Figure 5. Heatmap of Primary Indicator Feature Importance

The comprehensive analysis of the primary and secondary indicators indicates that science and technology, Estate, and labor tools play a crucial role in influencing the new quality productivity of a region.

2.5 Reliability Test, Pearson Linear Regression Test

To fully validate the reliability of the model, we conducted P-value tests, Chi-square tests, and reliability tests.The test results are presented as follows in Table .10.

Table.10. Tests of CR Values, CA Coefficients, Correlation, and P-values for Each Indicator

Primary Indicators	CR	CA	MSE	R^2	P-value
Estate	0.834242	0.792344	1.0817	0.9548	3.999e-11
Science and Technology	0.934242	0.924354			
Factors of Production	0.843653	0.868327			
Labor Force	0.851237	0.813274			
Labor Tool	0.913743	0.884623			
Labor Object	0.763425	0.823413			

From the above table, we can see that the model has a high level of confidence and strong significance.

3. Results

The significance of the characteristic values for the six Primary indicators regarding the new quality productivity is shown in the Table.11.below:

Table.11. Primary Indicator Characteristic Importance

Primary Indicator	Characteristic Importance	Primary Indicator	Characteristic Importance
Estate	0.9388	Labor Force	0.8877
Science and Technology	0.9146	Labor Tool	0.9388
Factors of Production	0.8394	Labor Object	0.7333

The results of the comprehensive analysis of indicators show that science and technology, industry, and labor tools play a critical role in influencing regional new quality productivity. These factors not only determine the competitiveness of the regional economy but also significantly impact the enhancement of productivity and the capability for sustainable development.

4. Conclusion

Research has found that coastal provinces such as Guangdong and Jiangsu stand out in terms of new high-quality productivity. In 2022, their scores for new quality productivity were 84,282.92148 and 2,682.267442 respectively, significantly higher than those of other provinces. This is attributed to factors such as industrial foundations, technological innovation, and regional policies. By contrast, central and western provinces are constrained by industrial structures and infrastructure, with the maximum difference in new quality productivity scores from leading provinces being up to 84,278.56008. Excluding Guangdong, which is exceptionally developed, the gap in new quality productivity scores among other provinces shows a relatively gradual increase in an east-to-west direction, indicating the imbalanced nature of China's development.This study provides a basis for economic policy formulation and resource allocation, highlighting critical factors such as technological innovation. Future research could explore regional cooperation and policy coordination to enhance national new high-quality productivity, driving high-quality development across the country.

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