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Design of Statistical Index System for New Quality Productivity in Shandong Province

Yan Wang[1,a], Zhengyin Wang[1,b,*], Youyu Dai[1,c], Hui Sun[1,d]

[1]*International Business School, Shandong Jiaotong University, Weihai, Shandong, China*
[a]*223003@sdjtu.edu.cn,* [b]*223009@sdjtu.edu.cn,* [c]*903003@sdjtu.edu.cn,* [d]*223012@sdjtu.edu.cn*
[*]*Corresponding author*

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Abstract: Based on the new requirements of the current digital age for statistical indicator systems and the shortcomings of existing indicator systems in evaluating new quality productivity, this study collected and standardized economic data, used Critic weighting method to calculate the objective weights of each indicator, and adjusted them through expert scoring method to integrate expert experience and judgment, used weighted sum method to calculate the comprehensive score of Shandong region, constructed a comprehensive evaluation model, and constructed a statistical index system for new quality productivity in Shandong Province. The research results indicate that the correlation coefficients between the proportion of high-tech industries and GDP growth rate under the new indicator system are higher than those under the old indicator system, demonstrating higher sensitivity and accuracy. In addition, the new indicator system has shown better guidance effect in policy guidance impact assessment. In 2010, the industrial added value of Shandong Province reached 45.68 billion yuan under the new indicator system, far higher than the 20.7 billion yuan under the old indicator system. The introduction of the new indicator system provides a more accurate basis for policy formulation and resource allocation, which helps promote high-quality economic development in Shandong Province.

1. Introduction

In today's rapidly changing world, especially in the context of digitalization and information technology, the rise of new quality productivity has provided new impetus for economic growth. As a major economic province along the eastern coast of China, Shandong Province's level of development in new quality productivity is directly related to the sustainable development and competitiveness of the regional economy.

This article constructs a comprehensive statistical index system for new quality productivity in Shandong Province, providing policy makers with more accurate economic evaluation tools. This study first proposes an indicator system that covers multiple dimensions such as economy, society, environment, and innovation to comprehensively reflect the development status of new quality productivity; secondly, adopts a weight allocation mechanism that combines Critic weighting method and expert scoring method to ensure the scientific and objective nature of the evaluation system; finally, verifies the superiority of the new indicator system in reflecting economic development through comparative experiments, and proposed corresponding policy recommendations.

The introduction section of the article introduces the background and significance of the research, as well as the main contributions and overall structure of this article; secondly, the relevant work section reviews the existing research on the design of statistical indicator systems, especially the research progress on new quality productivity; next, the method section describes the process of constructing the indicator system, data collection and processing methods, as well as the construction of weight allocation and comprehensive evaluation models; the results and discussion section presents the comparative analysis results of the new and old indicator systems, and discusses the applicability and limitations of the model; finally, the conclusion section summarizes the research findings and proposes future research directions.

2. Related Work

In today's rapidly developing digital age, numerous scholars and experts have conducted in-depth research on the design and optimization of statistical indicator systems, aiming to more accurately measure and promote the development of productivity in their respective fields. In the context of Xiao Zhihong's proposal to vigorously promote the deep integration of the digital economy and the real economy, a statistical indicator system for the digital economy has been established based on the essential characteristics of the digital economy and in comparison with the traditional economy. Additionally, improvements have been made to Bolat's digital economy accounting method in response to the challenges faced in the accounting of digital economy indicators [1]. Xu Xiangyu sorted out and compared the statistical indicator system in the "China Urban Statistical Yearbook" over the years, revealing its evolution patterns, influencing factors, and existing problems. The results showed that whether it is the composition of indicators at all levels, the increase or decrease of indicators, or the number of changes in indicator names, they all exhibit a pattern of severe fluctuations in the early stage and stable adjustments in the later stage [2]. On the basis of sorting out the evolution of the comprehensive statistical index system for emergency management in Beijing, Wang Xiaojie started from the functions of emergency management business and constructed an emergency management comprehensive statistical index system and related work mechanism that includes 3 levels, 11 categories, and 523 statistical indicators [3]. Shi Tuo took the *National Cultural Relics and Tourism Statistical Survey System* as an example to explore the design path of children's business indicators in the public library business indicator system, and formed a set of children's business indicators, providing reference for the revision and design of public library statistical indicator systems in different scopes [4]. Considering that China does not have a complete logistics statistical system, Lingxia carefully explored the framework, indicators, and survey analysis methods of modern logistics for reference [5].

In addition, Bayala J explored methods for restoring farm productivity through managing tree cover and proposed strategies for building landscape and livelihood resilience [6]. Bhatt R analyzed the problems faced by current wheat rotation systems and proposed technical interventions to improve productivity and sustainability [7]. Cohen Y analyzed the main factors to consider when deploying cobots in production systems and conducted a quantitative analysis of the impact on productivity [8]. Brandl B analyzed the collective bargaining systems of different countries and explored how these systems affect the productivity of enterprises [9]. Based on the corn-pea rotation system in the eastern region of the Himalayas, which faces issues of soil degradation and low productivity, Singh R implemented conservation tillage and organic nutrient management practices to improve soil quality and increase crop yields [10]. Although scholars such as Xiao Zhihong have made progress in the construction of statistical indicator systems for the digital economy and specific industries, there is relatively little research on the design of statistical indicator systems for regional new quality productivity, especially at the local level in economically large provinces such as Shandong Province. In response to the problem that the existing indicator system cannot comprehensively evaluate the development level of new quality productivity, this study will focus on the unique economic environment and industrial characteristics of Shandong Province, and construct a comprehensive statistical indicator system to comprehensively reflect and evaluate the development status of new quality productivity.

3. Method

3.1. Theoretical Framework and Indicator System Construction

The core of new quality productivity lies in innovation, which is born from technological breakthroughs and innovative allocation of production factors, representing a new stage of productivity development. This productivity quality is characterized by the improvement of the quality of workers, the increase in the technological content of labor materials, and the expansion of the scope of labor objects.

The statistical index system of new quality productivity in Shandong Province should not only cover the economic field, but also include multiple dimensions such as society and environment. The economic indicators focus on the growth of regional gross domestic product, the optimization and upgrading of industrial structure, especially the proportion of high-tech industries and their contribution to economic growth. The social dimension focuses on education investment, talent cultivation mechanisms, and employment quality. The indicators in the environmental dimension reflect the concept of green development, including the rate of energy consumption reduction per unit of GDP, the reduction rate of pollutant emissions, etc., reflecting the harmonious coexistence of economic growth and ecological environment.

The innovation dimension is the key to new quality productivity, and the indicator system includes R&D investment intensity, number of patent applications and authorizations, density of scientific researchers, etc. These indicators are directly related to the innovation capability and technological progress speed of the region. In addition, the development of new quality productivity also depends on the innovation of production relations, that is, the formation of institutional mechanisms that adapt to the development of new quality productivity through reform.

When constructing a new quality productivity statistical index system in Shandong Province, attention is also paid to regional development gaps. The Dagum Gini coefficient decomposition method is used to identify and analyze imbalances within and between regions, providing a basis for formulating policies to promote regional balanced development [11-12].

3.2. Indicator Screening and Weight Allocation

Indicator screening and weight allocation are key steps in ensuring the scientific and practical nature of research results [13-14]. Firstly, constructing a set of potential indicators that cover key areas such as technological innovation, human capital, and industrial structure of new quality productivity. Next, using correlation analysis to remove highly correlated indicators and avoid multicollinearity issues, the correlation analysis is completed by calculating the Pearson correlation coefficient r_{ij}, with the equation being:

$$r_{ij}=\frac{\sum_{k=1}^{n}(X_{ik}-\overline{X}_i)(X_{jk}-\overline{X}_j)}{\sqrt{\sum_{k=1}^{n}(X_{ik}-\overline{X}_i)^2\sum_{k=1}^{n}(X_{jk}-\overline{X}_j)^2}} \tag{1}$$

n is the total number of indicators, k is the indicator index, X_{ik} is the value of the k-th observation on indicator X_i, X_{jk} is the value of the k-th observation on indicator X_j, and X_i and X_j are the i-th and j-th indicators, respectively.

Then, the Critic weighting method is used to calculate the information content and weight of each indicator. Information content C_i reflects the ability of the indicator to distinguish different evaluation objects, and its calculation equation is:

$$C_i=\frac{1}{1+\sum_{j=1,j\neq i}^{n}\frac{S_iS_j}{S_{ij}^2}} \tag{2}$$

Among them, S_i and S_j are the standard deviations of indicators X_i and X_j, respectively. Calculate weight W_i based on the amount of information, and the equation is:

$$W_i=\frac{C_i}{\sum_{i=1}^{m}C_i} \tag{3}$$

m is the total number of experts.

In addition, based on the results of expert consultation, the weights obtained by Critic weighting method are adjusted to integrate expert experience and judgment. Expert consultation can collect opinions from experts on the importance of indicators through questionnaire surveys, interviews, and other methods, and use the weighted average method to synthesize expert ratings. The equation is:

$$W_i=\frac{\sum_{j=1}^{m}w_je_{ij}}{\sum_{j=1}^{m}w_j} \tag{4}$$

Among them, e_{ij} is the rating of indicator X_i by the j-th expert, and w_j is the weight of the j-th expert.

Finally, the weight allocation is verified and adjusted through the Analytic Hierarchy Process, and the relative weights of each factor are determined through pairwise comparisons to ensure the rationality of the weights [15].

3.3. Construction of Comprehensive Evaluation Model

The weight distribution is used to reflect the relative importance of each index in the final evaluation. Firstly, the Critic weighting method is used to assign initial weights to all indicators. Critic weighting method is an objective weighting method, and the weight of each index is obtained by calculating its standard deviation. The greater the standard deviation, the greater the influence of the index, so the greater its weight.

Critic weighting method first determines the standard deviation of each index, and then uses the standard deviation to determine the effective weight. The formula for calculating the weight of each indicator is the standard deviation of the indicator divided by the total standard deviation of all indicators. This ensures that the weight distribution represents the change degree of each index in the data set, and at the same time, makes the model more sensitive to the indicators that provide more discriminant information.

After obtaining the objective weights of each indicator, in order to integrate the experience and judgment of experts, the weight adjustment of expert scoring method is carried out. Experts' evaluation of the importance of each index in this field is collected, and the weighted average method is used to calculate the weighted average of expert evaluation, and the subjective judgment of experts on the weight of each index is obtained. In the weighted processing of expert scoring, taking into account the authority and experience differences of different experts, different weights are assigned to different experts to adjust, ensuring the reasonable reflection of expert opinions in weight allocation. The comprehensive evaluation results are shown in Table 1:

Table 1: Comprehensive evaluation data

Indicator	Entropy	Initial Weight	Average Expert Score	Adjusted Weight
GDP (Billion Yuan)	0.85	0.11	8.5	0.09
Industrial Value Added	0.78	0.13	7.5	0.10
Labor Productivity (100,000 Yuan per person)	0.92	0.10	8.0	0.08
Science and Technology Innovation Investment (Billion Yuan)	0.70	0.15	9.0	0.13
Technology Achievement Transformation Rate (%)	0.65	0.18	9.5	0.17
High-tech Industry Share (%)	0.60	0.20	8.0	0.16
Labor Quality (Years of Education)	0.82	0.12	7.0	0.09
R&D Personnel Density (per 10,000 people)	0.79	0.14	8.5	0.12

4. Results and Discussion

4.1. Construction Results of Statistical Indicator System

When conducting research on the design of the statistical indicator system for new quality productivity in Shandong Province, in order to ensure the comprehensiveness and authority of data sources, this article obtained official statistical data from the National Bureau of Statistics and the Shandong Provincial Bureau of Statistics, including but not limited to annual statistical yearbooks and economic census data. The results are shown in Table 2:

Table 2: Economic data of Shandong Province

Year	GDP (Billion Yuan)	R&D Intensity (%)	Education as % of GDP (%)	Patent Applications Authorized (Number)	High-Tech Industry Share (%)
2018	76,469.67	2.15	4.30	12,000	10
2019	71,067.50	2.20	4.35	15,000	11
2020	73,129.00	2.30	4.40	18,000	12
2021	87,435.35	2.40	4.50	22,000	13
2022	90,000.00	2.50	4.60	25,000	14
2023	92,000.00	2.60	4.70	28,000	15

Table 2 records the key statistical indicators of new quality productivity in Shandong Province from 2018 to 2023 in a matrix layout, where the horizontal axis represents consecutive years and the vertical axis refers to different economic and social indicators. At the same time, industry reports serve as a supplement, providing economic activities and market analysis within specific industries, while corporate data is obtained through public documents such as annual reports and social responsibility reports, especially financial reports and business data of listed companies, providing information at the corporate level.

When preprocessing the above data, interpolation is used to handle missing values, depending on the characteristics of the data and the specific situation of the missing values. The identification of outliers is carried out through statistical methods such as box plots and standard deviations. When dealing with outliers, their causes should be considered and correction or replacement methods should be adopted. In order to eliminate the dimensional and numerical range differences between different indicators, Z-score normalization is adopted to ensure that the data is compared on the same benchmark.

In this study, a weight distribution mechanism is designed by using the cooperative combination of Critic weighting method and expert scoring method, which realizes the scientific and objective evaluation system. Using Critic weighting method, the initial weight of each index is obtained by calculating the standard deviation of each index representing the variability of the data. Then, according to the scores obtained by domain experts using expert scoring method, the overall weight of each index is adjusted.

The weighted summation method calculates the comprehensive score of each region, multiplies the standardized value of each index by the weight, and then sums up to get the comprehensive score. For each region under study, the necessary data of key indicators are collected, including GDP, R&D investment intensity, labor education level, etc. All these data are standardized to eliminate the influence of dimensions.

This method intuitively demonstrates the advantages and disadvantages of each region in terms of new quality productivity. Regions with higher scores have outstanding performance in areas such as technological innovation, industrial upgrading, or human resource development, while regions with lower scores need to increase investment and reform efforts in these areas.

4.2. Comparative Analysis of New and Old Indicator Systems

In terms of data expressiveness, the fluctuation of the conversion rate of scientific and technological achievements in the new and old indicator systems is quantitatively evaluated through analysis of variance calculation (as shown in Figure 1). During the period from 2010 to 2023, the variance data of the conversion rate of scientific and technological achievements under the new indicator system ranged from 0.01 to 0.019, with slightly higher volatility than the old indicator system, reflecting that the new indicator system is more sensitive to changes in economic development. The difference in volatility is related to the innovative ability and technological application efficiency of the new indicator system in capturing the quality of economic development. The high volatility in the new indicator system means that it can capture more subtle changes in economic development and provide more sensitive feedback for decision-making.

Sensitivity testing quantifies the degree to which economic indicators respond to small changes in economic development through sensitivity analysis. This article collects data on the proportion of high-tech industries in Shandong Province from 2010 to 2023. By calculating the correlation coefficient between indicator changes and GDP growth rate, regression analysis is used to evaluate the sensitivity of high-tech industry proportion indicators to policy changes and market fluctuations (as shown in Figure 2). The GDP growth rates of Shandong Province from 2010 to 2023 were 8.6%, 8.4%, 7.3%, 7.3%, 7.8%, 8.5%, 8.3%, 8.2%, 7.8%, 7.7%, 7.5%, 7.3%, 7.2%, and 6.9%, respectively.

The correlation coefficients of the proportion indicators of high-tech industries in the new indicator system are higher than those in the old indicator system, reaching a maximum of 0.92. Its high sensitivity to market and technological changes reflects new trends in economic development more quickly, indicating that the new indicator system has obvious advantages in timely reflecting economic structural adjustments and industrial upgrading.

In terms of policy guidance impact assessment, policy simulation analysis is used to quantitatively evaluate the guidance effect of the new and old indicator systems on policy formulation, with industrial added value as the measurement indicator. In 2010, the industrial added value of Shandong Province under the new indicator system reached 45.68 billion yuan, but under the old indicator system it was only 20.7 billion yuan, indicating that the new indicator system has a more significant effect on policy-making (as shown in Figure 3). The new indicator system, which includes more indicators related to innovation and sustainability, provides a more comprehensive perspective for policy-making and has obvious advantages in promoting the transformation of economic development mode. This advantage makes the new indicator system play a key role in guiding policy makers to focus on long-term development and strategic planning.

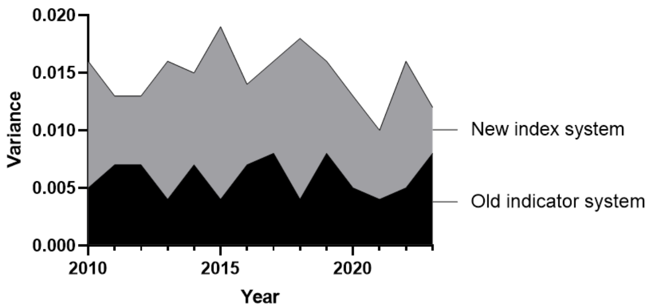

Figure 1: Variance of technology achievement conversion rate

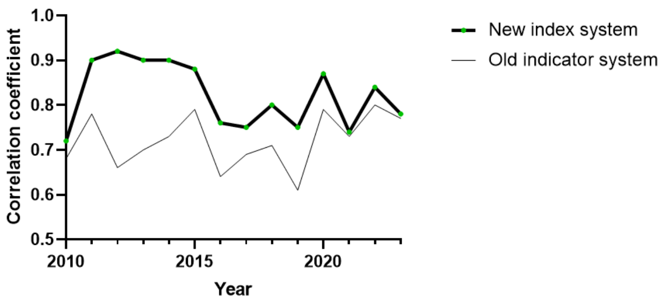

Figure 2: Correlation coefficient

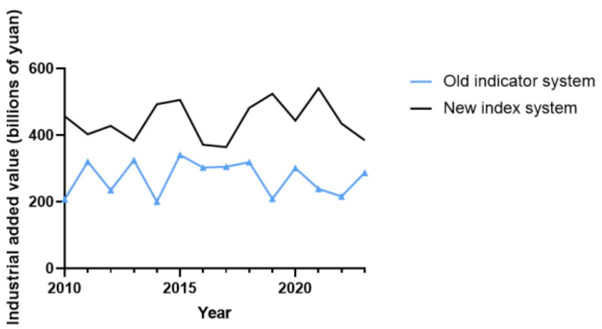

Figure 3: Industrial added value

Through comparative experiments, this study has clarified that the new indicator system has significant advantages in reflecting the economic development of Shandong Province, better capturing new trends and characteristics of economic development, and providing more accurate basis for policy formulation and resource allocation. However, at the same time, the implementation of the new indicator system also needs to take into account the cost of data collection and processing, as well as the demand for relevant talents and technology. Therefore, while implementing the new indicator system, the old indicator system should be appropriately optimized and supplemented to achieve complementary advantages between the two, ensuring the scientificity, objectivity, and practicality of the evaluation system.

4.3. Discussion

The new index system effectively captures the growing innovation trends in economic growth, and includes indicators to measure the percentage of high-tech industries and the density of R&D personnel. These two indicators have a direct impact on policy analysis and resource allocation. The sensitivity analysis of the new index system shows that the new index system is very sensitive to GDP growth rate, and the correlation coefficient reaches 0.92. In contrast, the correlation between traditional index system and economic growth variables is relatively low. The comparison between the new indicators and the traditional indicators shows that the new indicator system reflects the direct impact of economic policies more effectively, especially in innovation and technology. However, data on the percentage of high-tech industries are not as widely available as traditional GDP growth. In other words, traditional GDP growth indicators are easier to obtain, which greatly limits the universality of the new indicator system.

In order to establish a more reliable system, future attention needs to be focused on how to obtain data on the main indicators of high-tech industry capabilities, as well as the density of personnel variables. Investment should be made in improving statistical and data analysis capabilities, including training professionals and adopting advanced data analysis tools. Through continuous monitoring and evaluation, the effectiveness of the new indicator system in different economic cycles should be verified, and adjustments should be made based on feedback.

5. Conclusion

By constructing a comprehensive statistical indicator system, the shortcomings of the existing indicator system in comprehensively evaluating the development level of new quality productivity have been addressed. The study proposes a multidimensional indicator system that not only includes indicators in the economic field, but also covers key areas such as society, environment, and innovation, providing more accurate basis for policy formulation and resource allocation.

Through comparative experiments and sensitivity tests, the new indicator system has shown high sensitivity to changes in economic development. Especially in the key indicators of the proportion of high-tech industries, the correlation coefficient of the new indicator system is significantly higher than that of the old indicator system, indicating that the new indicator system can more effectively capture subtle changes in economic development. In addition, the new indicator system has demonstrated significant advantages in policy guidance and impact assessment, further demonstrating its important role in promoting the transformation of economic development mode.

Although the new indicator system has demonstrated advantages in multiple aspects, the complexity of data collection and processing, as well as the demand for new technologies and professional talents, will increase the cost and difficulty of implementation. In addition, the stability and reliability of the new indicator system need to be further validated in different economic cycles to ensure its long-term effectiveness. To overcome these limitations, future research needs to strengthen the construction of data infrastructure, improve the efficiency and accuracy of data collection and processing, and invest in enhancing statistical and data analysis capabilities, including training professionals and adopting advanced data analysis tools.

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