Operational Efficiency Analysis of Listed Biomedical Companies in China: Three-Stage DEA and Malmquist Index

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Abstract. This study selects 74 Chinese listed biomedical companies as samples and utilizes a three-stage DEA and Malmquist index to calculate the input-output panel data of sample companies from 2018 to 2022 over a period of five years, conducting analysis from both static and dynamic perspectives. From the static analysis perspective, the overall efficiency of Chinese listed biomedical companies during the calculation period is relatively low, with pure technical efficiency being the main limiting factor, and there is significant variation in the overall operational levels of these companies. From the dynamic analysis perspective, 56.76% of companies have a total factor productivity exceeding 1, with technological progress being the main contributing factor, while scale efficiency index needs improvement. It is suggested that listed biomedical companies strengthen their emphasis on technology and enhance scale efficiency.

Keywords: Biomedical company; Operational efficiency; Three-stage DEA; Malmquist index.

1. Introduction

Currently, with the accelerated evolution of the world's new round of industrial revolution and technological revolution, technological innovation has become a "key variable" for the socioeconomic development of countries. Biomedical technology is an important field that will lead and support China's technological innovation development in the future, and it is also at the core of the new round of industrial revolution and technological revolution. Biomedical industry is a typical "high-input, high-risk, high-output, long-cycle"industry[1]. China's original research in biomedical and its capital market lag far behind those overseas. These characteristics drive Chinese biomedical companies to increasingly seek pharmaceutical outsourcing cooperation. This also indicates that international situations can significantly impact China's biomedical industry chain and system. For example, since early March 2024, Chinese biomedical stocks have been heavily impacted due to uncertainties related to US legislation. This study selects 74 listed biomedical companies and uses the three-stage DEA model and Malmquist index model to analyze their operational efficiency. The aim is to identify the bottleneck factors restricting the efficiency of listed pharmaceutical companies and provide suggestions for improving the operational efficiency of Chinese biomedical listed companies.

2. Literature Review

In terms of studying the operational efficiency of biomedical companies, it mainly involves two aspects. On one hand, various models are used to analyze and evaluate the efficiency of enterprises. On the other hand, enterprise efficiency is evaluated based on the construction of different evaluation indicator systems.

2.1 The Perspectives of Efficiency Evaluation in Listed Biomedical Companies

Regarding the current research on the efficiency of Chinese biomedical companies, some scholars have conducted studies from several perspectives such as pharmaceutical manufacturing, research and development and profitability. Wan[2] conducted a static and dynamic evaluation of the R&D efficiency of the Chinese pharmaceutical manufacturing industry across different sectors and regions. Wang et al.[3] conducted a calculation study on listed biomedical companies from the perspective of innovation efficiency, based on a three-stage DEA model. From the perspective of operational efficiency, Wang[4] conducted an empirical study on the panel data of biomedical companies listed on the Shanghai and Shenzhen stock exchanges from 2000 to 2017. Zhao[5] conducted an efficiency analysis of antibody-based biomedical companies from the perspectives of R&D and operations. Liu[6] explored the commonalities and differences in financing efficiency between Junshi Biosciences and sample companies from the perspective of financing efficiency using Composite DEA Model.

2.2 The Methods of Efficiency Evaluation in Listed Biomedical Companies

Currently, one of the main methods for evaluating enterprise operational efficiency is Data Envelopment Analysis (DEA). Chen et al.[7] evaluated the operational efficiency of 134 listed pharmaceutical companies in China using the DEA model, and the research found that the overall efficiency of listed pharmaceutical companies showed a declining trend. Liu et al.[8] calculated the operational efficiency of 46 listed biomedical companies in China using the DEA-BCC model and DEA-Malmquist model, and the study found that the overall efficiency of Chinese listed biomedical companies was relatively good. Xu et al.[9] compared the efficiency issues of companies listed on the Growth Enterprise Market and the Small and Medium Enterprise Board using the DEA method, and found that environmental factors have a significant impact on company efficiency. Sabouhi et al.[10] proposed an integrated hybrid method for designing flexible supply chains based on DEA and mathematical programming methods, and used a fuzzy DEA model to evaluate the efficiency of potential suppliers. Lin et al.[11] applied the three-stage DEA model and Malmquist productivity model to analyze the operational efficiency of pharmaceutical companies, concluding that the main cause of technical efficiency loss is pure technical inefficiency, and external environmental factors have a significant impact on the operational efficiency of the pharmaceutical industry.

The three-stage DEA evaluation model fully considers the comprehensive impact of various factors such as technology, scale, and environment on the efficiency level of enterprises, as well as other factors contained in redundant variables. Therefore, this paper will use a three-stage model combining DEA and Stochastic Frontier Analysis (SFA) to measure the operational efficiency of 74 Chinese biomedical companies from 2018 to 2022 and based on this, suggestions for promoting the improvement of operational efficiency of biomedical companies will be proposed.

3. Research Methods

3.1 Three-stage DEA

At present, the mainstream methods for efficiency evaluation in relevant industries are DEA and SFA. DEA is a systematic analytical method for evaluating the relative efficiency of decision-making units between multiple inputs and outputs. The concept was first proposed by Farrell[12] and later, Fare et al. modified the traditional DEA method to develop the Three-stage DEA model, which eliminates the influence of external environment and random errors.

1) **First Stage:** DEA-BCC Model

The original input and output data are utilized for the initial efficiency evaluation using an input-oriented model. The formula is as follows:

$$\min\ \theta - \varepsilon(\hat{e}^{T}S^{-} + \hat{e}^{T}S^{+})$$
$$\text{s.t.}\begin{cases}\sum_{i=1}^{n} X_i\lambda_i + S^{-} = \theta X_0 \\ \sum_{i=1}^{n} Y_i\lambda_i - S^{+} = Y_0 \\ \lambda_i \geq 0, S^{-}, S^{+} \geq 0\end{cases} \tag{1}$$

In Equation (1), $i = 1,2, \dots, n$ represents the decision-making unit, X,Y are the input and output vectors respectively. S^{+}, S^{-} represent slack variables for input and output indicators. θ denotes the technical efficiency value.

The decomposed comprehensive technical efficiency (TE) calculated by the model is as follows:

$$TE = SE * PTE \tag{2}$$

In Equation (2), scale efficiency (SE) reflects the impact of input scale changes on the comprehensive technical efficiency of listed biomedical companies, and pure technical efficiency (PTE) reflects the technological situation of listed biomedical companies.

2) Second Stage: SFA Regression Model

In the previous stage, the slack variables of each decision unit did not account for factors such as managerial inefficiency, environmental influences, and statistical noise. Therefore, in the second stage, the SFA model was employed. The following input-oriented SFA regression function was constructed:

$$S_{ni} = f(Z_i; \beta_n) + v_{ni} + \mu_{ni} \tag{3}$$

In Equation (3), $i = 1,2, \dots, n$ represents the decision units, S_{ni} represents the $n-th$ slack value of input data in the $i-th$ decision unit, where $n = 1,2, \dots, N$， $Z_i = (Z_{1i}, Z_{2i}, \dots, Z_{pi})$ is a p-dimensional vector of environmental variables, β_n is the parameter vector corresponding to the environmental variables, $v_{ni} + \mu_{ni}$ represents the environmental error term, where v_{ni} denotes the random error and μ_{ni} denotes the managerial inefficiency term.

Using SFA regression to adjust all decision units to the same external environment, the formula is as follows:

$$X_{ni}^{A} = X_{ni} + [max(f(Z_i, \hat{\beta}_n)) - f(Z_i, \hat{\beta}_n)] + [max(v_{ni}) - v_{ni}] \tag{4}$$

In Equation (4), X_{ni}^{A} represents the adjusted input, X_{ni} represents the original input, and the two brackets in the expression adjust the environmental factors and random disturbance terms to the same conditions, eliminating their impact on the efficiency value.

3) Third Stage: Adjusted DEA Model

The adjusted input variables obtained from the second stage are then combined with the original output variables and input into the DEA-BCC model again. Efficiency measurements are conducted using DEAP 2.1 software, resulting in efficiency values for each decision-making unit after removing the influence of environmental and random factors.

3.2 Malmquist Index

Since the three-stage DEA model can only measure the static efficiency of each decision-making unit in the same period, this paper constructs the Malmquist index, which further improves the evaluation system of the operational efficiency of the listed biomedical companies from the dynamic analysis. The index was first proposed by Sten Malmquist. This index is based on 1 and reflects the improvement or decrease of efficiency compared with the previous stage, greater than 1 indicates the improvement of efficiency; less than 1 indicates that the efficiency decreases. The expression is as follows:

$$M_0(x_{i+1}, y_{i+1}, x_i, y_i) = \left[\frac{D_0^{i}(x_{i+1}, y_{i+1})}{D_0^{i}(y_i, x_i)} \times \frac{D_0^{i+1}(x_{i+1}, y_{i+1})}{D_0^{i+1}(y_i, x_i)}\right]^{1/2} \tag{5}$$

Under the assumption of constant returns to scale (CRS), the Malmquist Productivity Index can be decomposed into two components: the change in technical efficiency (Effch) and the movement of the efficiency frontier (i.e., the technological progress index, Techch). Under the assumption of variable returns to scale (VRS), the Malmquist Productivity Index can be further decomposed into three parts: the technological progress index (Techch), the change in pure technical efficiency (Pech), and the change in scale efficiency (Sech).

If $Effch > 1$ indicates that the decision unit is closer to the production front and the technical efficiency increases, < 1 means that the utilization effect of the existing technology is not ideal; If $Techch > 1$ indicates that the scientific and technological level is significantly improved; If $Pech >$

1 indicates that the company can significantly improve production efficiency by optimizing management; and ≤ 1 indicates that these measures do not produce substantial improvement; If Sech > 1 indicates that the decision unit tends towards the optimal scale.

4. Data Source and Indicator Acquisition

4.1 Data Source

This study focuses on Chinese listed biomedical companies. Cross-sectional data from 2018 to 2022 are selected, including the proportion of research and development personnel, main business costs, R&D investment as a percentage of operating income, total operating income, operating profit, and other indicators. Samples with missing data and ST companies are excluded. Ultimately, 74 representative biomedical listed companies are selected as the research sample. The main sources of data include Guotai An database and China Economic and Financial Research Database .

4.2 Indicator Acquisition

4.2.1 Selection of Input-Output Variables

This study selects input and output variables based on principles such as authenticity, comprehensiveness, feasibility, representativeness, and independence, while also considering the requirements of DEA model variable selection and summaries from existing literature. Ultimately, 3 input variables and 3 output variables are chosen to construct the evaluation system for operational efficiency of listed biomedical companies (see Table 1 for details).

4.2.2 Selection of Environmental Variables

Environmental variables refer to factors that affect the operational efficiency of companies but are not subjectively controlled by the sample and cannot be changed in the short term. Therefore, these factors need to be excluded from the measurement of operational efficiency. Referring to the research results of relevant scholars in other industries or fields on the operational efficiency of companies, and considering the characteristics of biomedical companies, three environmental variables are finally determined: government subsidy intensity, company operating years, and Gross regional product per capita.

1) **Government subsidy intensity:** Financial support from the government is an important way to increase the income of biomedical companies[13]]. Under this policy, if companies can effectively allocate resources, it will help improve their operational efficiency.
2) **Company operating years:** The research and management experience of companies will gradually become richer with the growth of the company's age[14]. Consequently, they can more efficiently organize a series of activities such as technology, business, and finance, thereby enhancing the technical operational efficiency of the enterprise.
3) **Gross regional product per capita:** Gross regional product per capita refers to the per capita economic total of the region where the company is located. Regions with good economic development can provide abundant talent reserves and complete facility construction, which can reduce the comprehensive operating costs of biomedical companies.

Table 1 Evaluation Index System for Operational Efficiency

Indicator Type	Indicator Name	Indicator Meaning
Input	Research and Development(R&D) Staff Proportion	Reflect the human resources situation of listed companies
	Main Operating Costs	Reflects the company's production scale and equipment level
	R&D Investment to Revenue Ratio	Reflects the R&D expenses of listed companies.

Output	Total Operating Revenue	Reflects the profitability of listed companies.
	Operating Profit	Reflects the overall profitability of listed companies.
	Asset Turnover Ratio	Reflects the risk resistance ability of listed companies.
Environmental Variables	Government Subsidy Intensity	Detailed amount of government subsidies received by a company.
	Company Operating Years	Number of years a company has been in operation.
	Gross regional product per capita	Translation of the per capita GDP of the province/city where a company is located.

5. Empirical Results Analysis

5.1 First Stage: Analysis of Traditional DEA Model Results

5.1.1 Comprehensive Efficiency Analysis

According to the traditional DEA model, the operational efficiency of 74 biomedical companies from 2018 to 2022 was calculated using standardized data with DEAP 2.1. The results are ranked by comprehensive technical efficiency, as shown in Table 2.

Table 2 Operating Efficiency of the biomedical Companies in the First Phase from 2018 to 2022

Listed Companies	Overall Technical Efficiency	Pure Technical Efficiency	Scale Efficiency
XueRong Pharmaceutical Co., Ltd.	1.00	1.00	1.00
Tibet Rhodiola Pharmaceutical Holding Co., Ltd.	1.00	1.00	1.00
Baiyunshan Pharmaceutical Holdings Co., Ltd.	1.00	1.00	1.00
Shanghai Pharmaceuticals Holding Co., Ltd.	1.00	1.00	1.00
Jiangsu Hengrui Medicine Co., Ltd.	0.98	1.00	0.98
Jilin Jiqing Pharmaceutical Co., Ltd.	0.97	0.99	0.99
Fosun Pharma	0.97	1.00	0.97
RunTec Medical Co., Ltd.	0.95	0.98	0.97
CR Double-Crane Pharmaceutical Co., Ltd.	0.94	1.00	0.94
Changchun High & New Technology Industries (Group) Inc.	0.93	0.96	0.97
Zai Lab	0.92	0.93	0.99
Nanjing Pharmaceuti-cal Co., Ltd.	0.92	1.00	0.92

*Due to space constraints, only partial results are displayed.

Without considering the influence of environmental factors and random errors, the average values of the three types of efficiency for biomedical companies in different regions from 2018 to 2022 are 0.60, 0.69, and 0.85 respectively. Their comprehensive technical efficiency is relatively low, while their scale efficiency is relatively high. It can be inferred that the low operational efficiency of biomedical companies is largely due to low management and technological levels. Regarding comprehensive efficiency, four listed companies have achieved the highest value of 1 in terms of comprehensive efficiency indicators. This result indicates that these companies have achieved significant achievements in operational performance and have strong competitive advantages.

However, among the 74 listed companies, 41 companies have comprehensive efficiency values lower than the mean, indicating that the overall operational level of Chinese listed biomedical companies is relatively average. Additionally, the lowest value of comprehensive efficiency is 0.22, which differs by 0.78 from the highest comprehensive technical efficiency value. This suggests that there is significant variation in comprehensive efficiency among Chinese listed biomedical companies.

5.2 Second Stage: Stochastic Frontier Analysis (SFA)

The efficiency values calculated in the first stage include the interference factors of external environment and random variables, resulting in certain biases in the actual efficiency calculation results, which cannot accurately reflect the internal management level of the sampled biomedical companies. In this stage, the Stochastic Frontier Analysis (SFA) regression model will be used with the slack variables obtained from the first stage's input indicators as the dependent variables. The external environmental variables, including government subsidy intensity, operating years, and per capita regional GDP, will be used as explanatory variables. The Frontier4.1 software will be employed for SFA regression analysis of cross-sectional data from 2018 to 2022. The regression results are shown in Table 3 (presenting the regression results for the year 2022 in this study).

Table 3 Summary of SFA Model Regression Results

Variable	The Slack Variable of the R&D Staff Proportion	The Slack Variable of the Main Operating Costs	The Slack Variable of the R&D Investment to Revenue Ratio
Constant Term	0.048	0.004	-0.003
Government Subsidy Intensity	0.009	-0.001	0.023
Company Operating Years	-0.094	-0.006	-0.005
Gross Regional Product Per Capita	0.013	-0.001	0.009
σ^2	0.037	0.000	0.018
γ	1.000	0.950	1.000

5.2.1 Government Subsidy Intensity

The regression coefficients of government subsidy intensity on the slack variables of the proportion of R&D personnel and R&D investment as a percentage of operating income are both positive. This suggests that an increase in government subsidies may lead companies to overly rely on government funding support, neglecting their own operational efficiency and profitability. This could be because companies might blindly expand production and recruitment scale with the increase in government subsidies, leading to waste of R&D resources and redundant R&D personnel. Government subsidy intensity is negatively correlated with the slack variable of main business costs. An increase in government subsidies may reduce the waste of main business costs for companies. Government subsidies may be used for equipment upgrades and other purposes, intensifying competition within the industry. Companies may pursue more rational planning of their operations, which could help reduce the waste of main business costs.

5.2.2 Company Operating Years

The regression coefficients of company operating years on the slack variables of the three input indicators are all negative. This suggests that the longer the company's operating years, the lower the redundancy in inputs. From the perspective of R&D resource supply, an increase in company operating years strengthens its brand effect and provides it with more R&D projects and the need for more R&D personnel. This also helps to avoid waste of R&D personnel resources to some extent. With the increase in company maturity and the accumulation of management experience, the company's organizational structure becomes more complete, enabling it to more effectively and targetedly manage various resources, thereby improving the utilization rate of main business costs.

Moreover, more mature companies have more sophisticated R&D management chains, such as research teams that include not only researchers but also project managers and other management staff closely integrated with research tasks. This refinement and perfection of the team also help avoid waste of significant R&D investment.

5.2.3 Gross Regional Product Per Capita

The regression coefficients of Gross Regional Product Per Capita on the slack variables of the proportion of R&D personnel and R&D investment as a percentage of operating income are both positive. A higher per capita regional GDP indicates a stronger regional effect, leading to a greater attraction of R&D talent and possibly lower acquisition costs for talent, which may result in biomedical companies hoarding more human resources and causing waste of human resources. There are differences in economic development among different regions, and regions with higher economic development levels tend to have greater demand for biomedicals. This may lead to the emergence of multiple R&D lines within companies in these regions to shorten the R&D time, resulting in waste of R&D investment. The regression coefficient of Gross Regional Product Per Capita on the slack variable of main business costs is negative. When the Gross Regional Product Per Capita of the biomedical company's location increases, it usually indicates an improvement in the economic level of that region, which often leads to fiercer competition among companies in that region. This forces companies to have more reasonable organizational structures and business strategies, thereby reducing the redundancy of main business costs.

5.3 Analysis of DEA Model Results after Removing Environmental Variables

Based on the inputs adjusted in the second stage for the pharmaceutical companies, the input-output average results excluding environmental factors were recalculated using the DEAP 2.1 software. After removing environmental factors, the mean values of comprehensive technical efficiency, pure technical efficiency, and scale efficiency of 74 Chinese pharmaceutical companies from 2018 to 2022 showed varying degrees of change. Specifically, the comprehensive technical efficiency decreased by 5.1%, pure technical efficiency increased by 10.7%, and scale efficiency decreased by 14.6%. This indicates a significant positive impact of environmental factors on the operational efficiency of pharmaceutical companies.

Regarding comprehensive technical efficiency, after excluding environmental factors, three companies, Xuesai Kang, Hengrui Medicine, and Shanghai Pharmaceuticals, achieved a comprehensive technical efficiency of 1, essentially at the production frontier and could be considered industry benchmarks. Conversely, 11 companies such as Nanjing High-Tech, Fuerda, and Xuerong Biotechnology experienced significant declines, with decreases ranging from over 20% to as high as 54.4%. This suggests that these companies were significantly overestimated before adjustment, with environmental factors contributing to this overestimation. Additionally, 60.8% of the companies had a comprehensive technical efficiency of less than 0.6, indicating that the operational efficiency level of the majority of pharmaceutical companies is relatively low, with significant room for improvement.

Regarding pure technical efficiency, after removing environmental factors, five companies - Qizheng Tibetan Medicine, Kuihua Pharmaceutical, Xuesai Kang, Hengrui Medicine, and Shanghai Pharmaceuticals - exhibited outstanding performance during the calculation period, achieving an optimal pure technical efficiency of 1. This indicates that they possess relatively advanced technologies within the pharmaceutical industry, representing enterprises with distinct local characteristics, reflecting their commitment to developing advanced technologies and enhancing their core competitiveness amid intense competition.

Regarding scale efficiency, compared to the first stage, seven companies including Guoen Shares and Aoxiang Pharmaceuticals showed an increase in scale efficiency after considering the disturbances of environmental factors and random errors. This suggests that environmental factors and random errors have a partial inhibitory effect on the scale efficiency of these seven listed pharmaceutical companies. Furthermore, the scale efficiency of the remaining 67 companies was lower than before adjustment, indicating that they have not effectively utilized their scale effects.

Hence, they should promptly adjust their organizational management methods to enhance operational efficiency.

As for the scale return coefficient, on average, only seven companies per year were in the decreasing returns to scale (DRS) stage, while 11 companies were in the scale efficiency valid (-) stage, and the remaining 56 companies were all in the increasing returns to scale (IRS) stage. This implies that the Chinese pharmaceutical industry has enormous development potential, which can be realized by continuously increasing investment and expanding scale to achieve higher development goals.

5.4 Efficiency Analysis Based on Malmquist Index

Due to the different production frontiers selected in the three-stage DEA analysis, the results obtained are static, making it impossible to observe efficiency change trends by comparing the changes in each year. Therefore, this study computed the Malmquist index and its decomposition indicators for the years 2018-2022 to overcome this limitation. Using the DEA 2.1 software, we accurately calculated the Malmquist index and decomposed it into comprehensive technical efficiency change (EFFCH), technological progress change (TECHCH), pure technical efficiency change (PECH), scale efficiency change (SECH), and total factor productivity (TFPCH), as shown in Table 4.

Table 4 Malmquist Index and its Decomposition Indicators

YEAR	EFFCH	TECHCH	PECH	SECH	TFPCH
2018-2019	1.076	0.920	1.117	0.957	0.991
2019-2020	1.082	0.948	1.021	1.060	1.022
2020-2021	1.100	0.906	1.100	1.007	0.985
2021-2022	0.824	1.553	0.868	0.960	1.213
mean	1.020	1.082	1.026	0.996	1.053

After eliminating the influence of environmental factors and random errors, it can be observed that the average TFPCH of the 74 biomedical companies is 1.053, indicating an annual increase of 5.3% in TFPCH over the 5-year period. Examining the components of TFPCH change, the average The change index of EFFCH of increased by 2%. Specifically, The change index of PECH was 1.026, representing a 2.6% increase, indicating a gradual improvement in the technological level of Chinese pharmaceutical companies. The change index of SECH had an average value of 0.996, indicating a decrease of 0.4%, suggesting that scale efficiency has not been fully realized. The average change index of TECHCH was 1.082, representing an increase of 8.2%. Therefore, the improvement in TFPCH of biomedical companies is attributed to both overall technological progress and the enhancement of comprehensive efficiency within the enterprises, with the latter mainly benefiting from the improvement in pure technical efficiency[15].

In a horizontal comparison of the 74 listed biomedical companies, their TFPCH change indices are compared to assess the industry's development equilibrium. The results show that 42 companies, accounting for 56.76% of the decision-making units, have a TFPCH exceeding 1, indicating that more than half of the companies prioritize and continuously strengthen their technological capabilities while exploring development scales and operational methods suitable for themselves. Among them, Wanze shares and Xinghu Technology have relatively high TFPCH indices, at 1.654 and 1.601 respectively, far exceeding the annual average TFPCH of the 74 companies. This also indicates that these two companies are in a stage of rapid and stable development.

6. Research Conclusion and Recommendations

Based on the panel data of 74 listed biomedical companies in China from 2018 to 2022, this study first established an evaluation system for the operational efficiency of biomedical companies from the perspective of "input-output-environment," considering the influence of environmental factors and random disturbances in the evaluation process. We constructed a three-stage DEA-Malmquist model to analyze the operational efficiency of biomedical listed companies from both static and dynamic perspectives. The main research conclusions of this study are as follows:

Static analysis indicates that after excluding environmental factors, the comprehensive technical efficiency, pure technical efficiency, and scale efficiency of biomedical companies have all undergone certain changes. During the period from 2018 to 2022, both comprehensive efficiency and scale efficiency were overestimated, while pure technical efficiency was underestimated, indicating that environmental factors have a significant impact on the technical efficiency of biomedical companies. Additionally, the majority of enterprises exhibit increasing returns to scale (IRS), indicating tremendous development potential that can be realized by expanding scale to improve scale efficiency.

Dynamic analysis reveals that over the five-year period, Chinese pharmaceutical companies face a contradiction between scale efficiency and technical efficiency. The average value of pure technical efficiency is greater than 1, indicating that the technological level of Chinese pharmaceutical enterprises is gradually improving. The average value of scale efficiency is less than 1, indicating that scale efficiency has not been fully realized. However, due to the improvement in pure technical efficiency and technological progress, the company's comprehensive technical efficiency continues to rise. Therefore, we can promote the simultaneous improvement of scale efficiency and pure technical efficiency by investing in scale.

Based on the above conclusions, this paper proposes the following recommendations:

1) **Strengthen Technological Drive and Talent Support:** biomedical companies should enhance employee learning and understanding of the frontier, improve professional levels, and translate research results into productivity to enhance the company's core competitiveness. Seizing the key support for technological innovation, achieving dual-drive of technological innovation and talent introduction, continuously promoting key technological innovation, focusing on tackling core key technologies, and driving company development through innovation.
2) **Optimize Resource Allocation to Improve Scale Efficiency:** Given that the majority of scale efficiencies are in an increasing state, companies should appropriately expand production scale to increase scale efficiency and reasonably allocate resources to improve resource utilization. Moreover, companies should seize the opportunity of government policy support to expand production scale by reducing operating costs.
3) **Enhance Management Level to Activate Operational Vitality:** Enterprises should improve their management level, optimize organizational structure and business strategies, and ensure the full utilization of various resources. Additionally, companies should achieve synergistic improvement of technological progress and scale expansion through streamlined management, finding the optimal investment combination and operation mode to enhance their comprehensive technical efficiency.

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