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ABSTRACT

In the past, enterprises used to judge their performance based on a single indicator. But in the information age, big data is essential for measuring enterprise performance. This paper takes the listed pharmaceutical industry as the research object, and measures and compares the performance of China's pharmaceutical industry from both dynamic and static aspects through big data analysis. The study found that between 2013 and 2022, the average performance of China's pharmaceutical industry showed a U-shaped trend. The main reason is that the innovation ability of the pharmaceutical industry is declining, while the scale efficiency is continuously improving.At the same time, the performance of the pharmaceutical industry varies in terms of enterprise scale, nature of property rights, region, product categories.Therefore, this paper suggests that China's pharmaceutical industry should increase R&D investment, and expanding production scale while enhancing resource allocation to achieve high-quality development in China's pharmaceutical industry.

Keywords: Big data analysis, super-SBM model, pharmaceutical industry, performance measurement.

INTRODUCTION

With the rapid development of big data technology, its important role in enterprise performance evaluation is becoming increasingly significant. Big data can not only provide enterprises with rich data information, but also reveal the business rules and potential risks through in-depth analysis. In the enterprise performance evaluation, the big data is gradually changing the traditional evaluation method, making the evaluation more accurate and comprehensive. Through big data analysis, enterprises can adjust strategies and optimize resource allocation to excel in a competitive market. Unlike past evaluations based on single indicators like profit margin or ROE, big data analysis offers comprehensive performance indicators, overcoming the limitations and contradictions of single-index evaluations.

In China, the pharmaceutical industry serves as a crucial pillar of the national economy, significantly contributing to economic development and the protection of public health. However, the industry currently faces challenges such as slowing market expansion, weak innovation capabilities, and low environmental protection standards, which hinder its healthy development. By scientifically analyzing the performance level of the pharmaceutical industry, these issues can be identified, and corresponding countermeasures can be formulated, which provides a foundation for the industry's future growth. A correct understanding of the performance level is essential for promoting high-quality development of the industry.

Choosing the scientific method is crucial for analyzing the performance of the pharmaceutical industry using big data. Some effective references can be found in relevant literature. For example, Hothur and Reddy (2022) used the DuPont analysis to measure the financial performance of three Maharatna central public sector enterprises from 2010 to 2020. Awalia et al. (2023) measured the performance of Bank Muamalat Indonesia using the Economic Value Added method. Kaplan and Norton (1992) first introduced the Balanced Scorecard to comprehensively measure corporate performance. Tayles et al.(2007) explored the role of intellectual capital in modern corporate performance, suggesting that companies should focus on management, customer retention, R&D, and innovation. Some researchers also used principal component analysis or the topsis method to measure corporate performance(Li et al.,2018; Yu et al.,2020).The above methods measure the performance of enterprises from different angles and have their own advantages and characteristics.

In addition to these methods, there is a technique known as Data Envelopment Analysis (DEA), which is widely used to measure various efficiency values. Charnes et al. (1978) proposed the basic model of DEA—the CCR model, which is used to measure the comprehensive technical efficiency of decision-making units. Over time, the DEA method has been continuously improved and expanded, resulting in various derivative models, such as the BCC model, to accommodate different situations and needs. The DEA method has been widely applied in various fields, such as evaluating corporate efficiency, healthcare institution performance, and educational resource utilization efficiency.For example, Lahouel et al. (2021) used DEA to measure the social responsibility performance of 25 international airlines from 2010 to 2016. Wu et al. (2022) applied a dynamic DEA method to measure the cultural tourism performance of several Asian countries or regions from 2015 to 2019. Carlos et al. (2005) used DEA to measure the performance of 40 listed internet companies before the internet crisis broke out in 2000. Huang et al. (2021) combined DEA, factor analysis, and grey theory to address efficiency evaluation and ranking issues in uncertain systems.From the above, we can see that DEA is widely used in multiple fields. The reason is that DEA can handle multiple indexes without pre-setting index weights, which has the advantage of objectivity. Therefore, on the basis of the existing research, this paper will use DEA to analyze the big data related to the performance of the pharmaceutical industry, aiming at more accurately understand the performance status and development trends of China's pharmaceutical industry.

MODEL DESIGN AND CONSTRUCTION OF THE EVALUATION SYSTEM

Model Design

The DEA model mentioned above is a traditional data envelope analysis method. It considers radial changes in the input and output variables of decision-making units, ignoring the influence of the relaxation variables on the output results. When the actual values of multiple decision-making units are equal to the potential values, the efficiency value of these decision-making units may be 1. Using the DEA model, we are unable to re-rank decision-making units with efficiency values equal to 1. To address this, the researchers optimized the DEA model and developed the super-SBM model. Super-SBM model is a special form of the DEA model. The super-SBM model incorporates relaxation variables into the objective function, thereby enhancing a more accurate and efficient evaluation from the decision-making unit. It also includes undesired outputs, a feature absent in the traditional DEA model. Thus, the super-SBM model will be used to measure the performance value of the pharmaceutical industry, as shown in Equation 1 and 2.

$$TE^{*} = \min TE = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{a_i}{x_{i0}}}{\frac{1}{n+k}\left(\sum_{r=1}^{n}\frac{b_r}{y_{r0}}+\sum_{j=1}^{k}\frac{c_j}{p_{j0}}\right)} \tag{1}$$

$$s.t.=\begin{cases} a \geq \sum_{d=1}^{D}\lambda_d x_d \\ b \leq \sum_{d=1}^{D}\lambda_d y_d \\ c \geq \sum_{d}^{D}\lambda_d b_d \\ a \geq x_0, b \leq y_0, c \geq p_0, \lambda_d \geq 0 \end{cases} \tag{2}$$

In Equation 1 and 2, m, n, k represent the number of input indicators, expected output indicators, and undesired output indicators; x_{i0} represents the input value; y_{r0} represents the expected output value; p_{j0} represents unexpected output value; D represents the decision-making unit; a. b and c represent relaxation variables; λ represents the weight vector; TE * represents the efficiency value of the decision-making unit.A larger TE* indicates a higher decision-making unit.The super-SBM model can only measure the static financial performance of the decision-making unit. However, this paper uses panel data, which allows for the analysis of dynamic changes in performance of decision-making unit. Consequently, the Malmquist index can be calculated to describe these dynamic changes, as shown in Equation 3.

$$\begin{aligned} Malmquist &= \frac{D_{t+1}(x_{t+1}, y_{t+1})}{D_t(x_t, y_t)}\sqrt{\left[\frac{D_t(x_{t+1}, y_{t+1})}{D_{t+1}(x_{t+1}, y_{t+1})}\times\frac{D_t(x_t, y_t)}{D_{t+1}(x_t, y_t)}\right]} \\ &= EFFCH \times TECHCH \end{aligned} \tag{3}$$

In Equation 3, D is the distance function of the decision-making unit relative to the technical frontier; x is the input value; y is the output value; EFFCH is the rate of change of the comprehensive technical efficiency; TECHCH is the technical progress rate. Since the comprehensive technical efficiency ignores the impact of changes in the production scale of the decision-making unit when the scale return is variable, the M index can be further decomposed to eliminate the influence of the scale return changes on the technical efficiency, thus obtaining the change rate of pure technical efficiency, as shown in Equation 4.

$$\begin{aligned} Malmquist &= \frac{D_{t+1}^{V}(x_{t+1}, y_{t+1})}{D_t^{V}(x_t, y_t)}\times\left[\frac{D_t^{V}(x_t, y_t)}{D_{t+1}^{V}(x_{t+1}, y_{t+1})}\times\frac{D_{t+1}^{C}(x_{t+1}, y_{t+1})}{D_t^{C}(x_t, y_t)}\right]\times\sqrt{\frac{D_t^{C}(x_{t+1}, y_{t+1})}{D_{t+1}^{C}(x_{t+1}, y_{t+1})}\times\frac{D_t^{C}(x_t, y_t)}{D_{t+1}^{C}(x_t, y_t)}} \\ &= PECH \times SECH \times TECHCH \end{aligned} \tag{4}$$

In Equation 4, the D^V is the distance function when the scale reward is variable; D^C is the distance function when the scale reward is unchanged; PECH is the change rate of pure technical efficiency; SECH is the change rate of scale efficiency; TECHCH is the technical progress rate. Malmquist index, PECH, SECH, TECHCH is greater than 1 means that the efficiency value is increasing; equal to 1 means that the efficiency value is unchanged before and after; less than 1 means that the efficiency value is decreasing.

Construct the Evaluation Index System

The selection of appropriate input and output indicators is the premise of the establishing the super-SBM model, so the principle of index selection should be clarified to screen from many indicators. The principle of index selection can be summarized in the following four aspects:

(1)Briefness. It is not possible to include all indicators related to corporate performance in the super-SBM model, so it is necessary to screen the indicators, and the selected indicators should reflect the core characteristics of the research object. We need to take advantage of the information advantages of big data, while avoiding redundant indicators.
(2)Relevance. The premise of establishing the super-SBM model is that the input indicators and the output indicators are related. When selecting indicators, the connection between input indicators and output indicators should be taken into account, and indicators with weak correlation should not be selected.
(3)Integrity. Using the super-SBM model to calculate technical efficiency values requires complete data. So those indicators with many missing values need to be removed. As far as possible, ensure that the selected indicators have complete data, otherwise the model cannot output the results.
(4)Reliability. The index data selected by the model must be true and reliable. Therefore, as far as possible, the indicators should be audited by professional institutions and can be obtained from the annual reports of listed companies.

According to the above principles of selecting the four indicators, this article selects 5 input indicators and 5 output indicators from a large number of indicators related to enterprise performance. The indicators are shown as follows:

● Input indicators
(1) Total assets. Total assets reflect the cumulative input of the enterprise over a period of time.
(2) Total liabilities. The pharmaceutical industry is a capital-intensive industry, and relying on its own funds often cannot meet the development needs of enterprises. Total liabilities reflect the investment of enterprises with external funds.
(3) Total operating cost. The total operating cost is the total expenditure related to the business activities, and is the core input index.
(4) Period expenses. Period expenses include management expenses, R&D expenses, financial expenses and other expenses, which is the main component of the total operating cost, and is an important input index.
(5) Number of employees. The pharmaceutical industry is a labor-intensive industry. The production of pharmaceutical enterprises requires not only raw materials, but also a large amount of labor force. Therefore, the number of employees is also an important indicator to measure the scale of enterprise input.

● Output indicators
(1) Total operating revenue. Total operating revenue is the sum of an enterprise’s the total revenue, and it is the most core index reflecting an enterprise’s output.
(2) Main business revenue. Main business income is the most important part of the total operating revenue, reflecting the development of the main business of the enterprise, and reflecting the stable output capacity of the enterprise.
(3) Net profit. Revenue reflects the output scale of the enterprise, while the net profit reflects the output quality of the enterprise. Enterprises with high net profit margin have a higher output efficiency.
(4) Owner's equity. The purpose of the enterprise is to obtain a higher owner's equity, which is the long-term net output result of the enterprise, reflecting the cumulative net output value of the enterprise over a period of time.
(5) Net inventory. The pharmaceutical industry is a manufacturing industry, which needs to reserve a large number of materials and semi-finished products for production, as well as some products that have not been sold yet. The scale of inventory directly determines the capital backlog of enterprises. So inventory management is very important for pharmaceutical enterprises. Unlike the other four output indicators, the net inventory is an unexpected indicator. The larger the inventory, the lower the performance value.

Sample Selection and Data Description

In order to meet the data needs of the super-SBM model and analyze the changing trend of the performance of the pharmaceutical industry, this paper takes Chinese A-share listed pharmaceutical companies from 2013 to 2022. Before the establishment of the model, 115 A-share pharmaceutical manufacturing enterprises were selected, excluding enterprises with negative net assets, the words ST and ST * and many missing data.The data used in the text are all obtained from the Guotai'an Database.

In order to avoid the influence of index dimension on index analysis, this paper adopts the max-min standardization method to standardize the initial index, as shown in Equation 5.

$$x^{*}=\frac{x-\min(x)}{\max(x)-\min(x)} \tag{5}$$

RESULTS OBSERVATION

Static Efficiency Measure and Comparison

For the selected indicators, this paper uses DEA-Solver5.0 to calculate the TE of each sample enterprise from 2013 to 2022, which reflects the comprehensive performance level of the enterprise. Because this value reflects the performance of the decision-making unit for the current year, which is also called the static performance value. The primary objective of this paper is to determine the overall performance level of the pharmaceutical industry by calculating the average performance of the sample enterprises each year, thereby reflecting the industry's overall performance. Additionally, the model decomposes TE into PTE and SE. PTE reflects the production efficiency of the decision-making unit under the influence of management and technical factors. The SE represents the economies of scale of the decision-making unit. The performance values of the pharmaceutical industry from 2013 to 2022 are shown in Table 1.

Table 1: TE and its decomposition from 2013 to 2022.

Year	TE	PTE	SE
2013	0.6050	0.8551	0.7192
2014	0.6030	0.8373	0.7325
2015	0.6003	0.8166	0.7475
2016	0.5938	0.7953	0.7618
2017	0.5898	0.7772	0.7741
2018	0.5906	0.7709	0.7809
2019	0.5882	0.7637	0.7853
2020	0.5999	0.7665	0.7963
2021	0.6080	0.7704	0.8024
2022	0.6103	0.7710	0.8044

Source: This study.

As shown in Table 1, from 2013 to 2022, TE of China's pharmaceutical industry initially declined and then rose. PTE remained stable after an initial decline, while Se increased year by year. This trend shows that the development quality of China's pharmaceutical industry began to decline in 2013 but improved after 2018. The similarity in trends between TE and PTE suggests that changes in TE are primarily driven by PTE. Meanwhile, the consistent improvement in SE indicates that China's pharmaceutical industry has not yet reached optimal production scale, leaving significant room for further development.

Dynamic Efficiency Measure and Comparison

The values in Table 1 reflect the static value of the pharmaceutical industry performance and represent the absolute performance for each year. To understand the changes in performance over time, we can measure the Malmquist index and its decomposition indices. As proposed in Equation 4, the Malmquist index can be decomposed into PECH, SECH, and TECHCH. PECH reflects the ability of enterprises to improve production efficiency by optimizing resource allocation and improving management methods. SECH reflects whether the company's production scale is close to its optimal size. TECHCH reflects t the enterprise's ability to innovate and apply new technologies, knowledge, and organizational structures. Malmquist index and its decomposition indices greater than 1 indicate that the performance of the pharmaceutical industry is improving. The model results are shown in Table 2.

Table 2: Malmquist and its decomposition from 2013 to 2022.

Year	Malmquist	TECHCH	PECH	SECH
2013-2014	0.9968	0.9972	0.9843	1.0193
2014-2015	0.9963	0.9806	1.0002	1.0215
2015-2016	0.9937	0.9617	1.0160	1.0205
2016-2017	0.9927	0.9751	1.0041	1.0166
2017-2018	1.0013	0.9946	1.0012	1.0096
2018-2019	1.0054	1.0238	0.9770	1.0070
2019-2020	1.0214	1.0523	0.9613	1.0141
2020-2021	1.0146	1.0330	0.9785	1.0077
2021-2022	1.0062	1.0536	0.9561	1.0036

Source: This study.

As shown in Table 2, the dynamic change index of the performance of China's pharmaceutical industry, represented by the Malmquist index, was less than 1 from 2013 to 2017. This indicates that there were significant challenges and a general backward trend in the industry's development during these five years. However, from 2018 to 2022, the Malmquist index was greater than 1, indicating that the performance of the pharmaceutical industry is improving and the overall development of the industry is improving. TECHCH shows the same trend as the Malmquist index, indicating that the technological innovation of the pharmaceutical industry has also experienced an initial decline followed by a rise. PECH contrary to the Malmquist index and TECHCH. It shows that the efficiency of technology use and management of the pharmaceutical industry has increased initially and then decreased, and the current resource allocation capacity of the pharmaceutical industry has declined. From 2018 to 2022, the SECH was greater than 1, indicating that the scale efficiency of the pharmaceutical industry is constantly improving, and the expansion of production scale has improved the performance of the pharmaceutical industry.

ANALYSIS OF THE HETEROGENEITY IN PHARMACEUTICAL INDUSTRY PERFORMANCE

From the above analysis, it can be seen that the performance level of China's pharmaceutical industry experienced a U-shaped trend from 2013 to 2022, while the utilization of technology and management efficiency first rose and then fell. This development trend reflects the overall changes in the pharmaceutical industry. To further analyze the heterogeneity of performance under different characteristic conditions in China's pharmaceutical industry, we can distinguish from various perspectives and explore the performance heterogeneity of different types of enterprises. Below, we analyze the TE and Malmquist index of the pharmaceutical industry from the aspects of asset scale, geographical region, enterprise ownership, and main business.

Scale Heterogeneity

We categorized the sample enterprises based on their asset scale. Enterprises with assets greater than the average total assets were classified as large enterprises, while those with assets smaller than the average total assets were classified as small enterprises. The performance levels of large and small enterprises were calculated separately, as shown in Table 3.

Table 3: Scale Heterogeneity of Performance from 2013 to 2022.

	TE		Malmquist	
Year	Large Enterprises	Small Enterprises	Large Enterprises	Small Enterprises
2013	0.5934	0.6094	-	-
2014	0.5983	0.6048	1.0004	0.9953
2015	0.5929	0.6032	0.9888	0.9994
2016	0.5661	0.6060	0.9727	1.0029
2017	0.5596	0.6014	0.9880	0.9944
2018	0.5600	0.6029	0.9996	1.0020
2019	0.5722	0.5944	1.0459	0.9898
2020	0.6058	0.5974	1.0277	1.0188
2021	0.6242	0.6003	1.0259	1.0092
2022	0.6449	0.5939	1.0194	0.9999

Source:This study.

From Table 3, it can be observed that there are distinctive differences in the TE and Malmquist index between large and small enterprises. From 2013 to 2020, the TE of large enterprises was smaller than that of small enterprises. After 2020, the TE of large enterprises surpassed that of small enterprises. This could be because, before 2020, the scale efficiency of large enterprises was lower than that of small enterprises. Large enterprises commonly faced issues such as "big enterprise disease," where management efficiency and resource allocation efficiency were inferior to those of small enterprises. Small enterprises had advantages in resource utilization. The outbreak of the COVID-19 pandemic in 2020 highlighted the technological advantages of large enterprises. Large enterprises were able to secure more orders, leading to higher operational efficiency.From the perspective of the Malmquist index, the efficiency of large enterprises showed a distinct U-shaped trend. From 2015 to 2018, the Malmquist index of large enterprises was consistently below 1, whereas after 2019, it was consistently above 1. In contrast, the Malmquist index of small enterprises did not exhibit a regular pattern of change.

Regional Heterogeneity

We categorized the sample enterprises based on their registered location, dividing China's 31 provincial regions into three parts: Eastern, Central, and Western regions. This classification allows for the analysis of efficiency differences in the pharmaceutical industry across different regions, as shown in Table 4.

Table 4:Regional Heterogeneity of Performance from 2013 to 2022.

	TE			Malmquist		
Year	Eastern	Central	Western	Eastern	Central	Western
2013	0.6055	0.5997	0.6115	-	-	-
2014	0.6038	0.6009	0.6034	0.9976	1.0019	0.9856
2015	0.5965	0.6099	0.5983	0.9897	1.0142	0.9910
2016	0.5904	0.6065	0.5857	0.9919	0.9976	0.9937
2017	0.5888	0.6027	0.5728	0.9979	0.9920	0.9755
2018	0.5946	0.5927	0.5735	1.0087	0.9844	1.0024
2019	0.5888	0.5905	0.5825	1.0027	1.0042	1.0167
2020	0.6058	0.5970	0.5838	1.0288	1.0189	0.9997
2021	0.6089	0.6099	0.6017	1.0066	1.0250	1.0260
2022	0.6124	0.6129	0.5989	1.0069	1.0082	1.0007

Source:This study.

From Table 4, it can be observed that from 2013 to 2022, the TE of the pharmaceutical industry in the Eastern and Central regions were generally higher than those in the Western region in most years. The Malmquist index of the three regions exhibit the same trend, with the Eastern and Central regions having higher Malmquist index compared to the Western region. However, there is no significant difference in the TE and Malmquist index between the Eastern and Central regions.Looking at the changes in indicators across different years, the TE and Malmquist index of three regions generally followed a U-shaped trend over time.

Enterprise Ownership Heterogeneity

According to the nature of enterprise ownership, enterprises can be classified into state-owned enterprises and private enterprises, and their performance may exhibit significant differences. Therefore, we conducted an analysis of enterprises with different ownership structures, as shown in Table 5.

Table 5: Enterprise Ownership Heterogeneity of Performance from 2013 to 2022.

	TE		Malmquist	
Year	State-Owned Enterprises	Private Enterprises	State-Owned Enterprises	Private Enterprises
2013	0.6056	0.6046	-	-
2014	0.6046	0.6021	0.9984	0.9958
2015	0.6010	0.5999	0.9997	0.9944
2016	0.5807	0.6011	0.9761	1.0035
2017	0.5756	0.5976	0.9912	0.9935
2018	0.5769	0.5982	1.0020	1.0009
2019	0.5898	0.5873	1.0275	0.9932
2020	0.6001	0.5998	1.0172	1.0237
2021	0.6073	0.6083	1.0166	1.0135
2022	0.6158	0.6073	1.0169	1.0002

*Source:*This study.

From Table 5, it can be observed that from 2013 to 2022, the TE of state-owned enterprises were higher than private enterprises in most years. This indicates that China's pharmaceutical industry differs from typical competitive industries. The unique nature of ownership makes state-owned pharmaceutical enterprises to secure government orders more easily, leading to higher performance levels. In terms of the Malmquist index, state-owned pharmaceutical enterprises experienced a distinct "U" shaped trend, whereas private enterprises did not show a clear trend.

Product Category Heterogeneity

We categorized the sample into traditional Chinese medicine enterprises and Western medicine enterprises based on product nature to analyze the impact of product category on enterprise performance, as shown in Table 6.

Table 6: Product Category Heterogeneity of Performance from 2013 to 2022.

	TE		Malmquist	
Year	Chinese medicine	Western medicine	Chinese medicine	Western medicine
2013	0.6107	0.6020	-	-
2014	0.6110	0.5989	1.0010	0.9946
2015	0.5998	0.6005	0.9866	1.0013
2016	0.5808	0.6005	0.9779	1.0018
2017	0.5751	0.5973	0.9896	0.9943
2018	0.5746	0.5988	0.9987	1.0026
2019	0.5876	0.5885	1.0291	0.9933
2020	0.5893	0.6053	1.0042	1.0302
2021	0.5921	0.6161	1.0047	1.0197
2022	0.5819	0.6249	0.9896	1.0147

Source:This study.

From Table 6, it can be observed that from 2013 to 2022, the TE and Malmquist index of traditional Chinese medicine enterprises were lower than those of Western medicine enterprises in most years. Additionally, the Malmquist index for traditional Chinese medicine enterprises was below 1 in most years, while the Malmquist index for Western medicine enterprises was above 1 in most years. This indicates that the overall operating conditions of traditional Chinese medicine enterprises were inferior to those of Western medicine enterprises, and the performance growth rate of traditional Chinese medicine enterprises was lower than that of Western medicine enterprises.

CONCLUSION

In the current increasingly fierce competition, using big data for enterprise performance evaluation is an important way for businesses to understand themselves and solve problems effectively. Based on big data related to the pharmaceutical industry, this paper scientifically measures the average performance of Chinese pharmaceutical enterprises from 2013 to 2022. The analysis reveals that during this ten-year period, the average performance of China's pharmaceutical industry showed a U-shaped trend. The primary reason for this trend is a decrease in innovation capacity from 2013 to 2017, which gradually improved thereafter. Technology usage and management efficiency of the pharmaceutical industry rises first and then decreases, indicating that the current resource allocation capacity of the pharmaceutical industry has decreased and the need for improved management capabilities. The continuous improvement of scale efficiency suggests that the pharmaceutical industry has not yet reached its optimal production scale, and can still expand further to enhance efficiency.In addition, there are differences in the performance of pharmaceutical enterprises in terms of enterprise scale, region, property right nature and product category.In most years, the performance of small enterprises is higher than that of large enterprises. The performance of enterprises in the eastern and central regions is higher than that of enterprises in the western region. The performance of state-owned enterprises is higher than that of private enterprises. he performance of enterprises producing western medicine is higher than that of enterprises producing traditional Chinese medicine

From the above conclusions, it can be seen that the future development of China's pharmaceutical industry should focus on increasing investment in innovation and improving resource allocation capabilities to achieve high-quality development. At the same time, enterprises should pay attention to the influence of scale, property right nature and other factors on the performance .

REFERENCES

Awalia, A. P., Marliyah, M., & Ilhamy, M. L. (2023). Analysis of financial performance assessment using the economic value added (EVA) method (study at Bank Muamalat Indonesia 2019-2021). *Indonesian Journal of Economics and Management*, 3(3), 618-629.doi:journal.unisnu.ac.id/NUIEJ/article/view/57

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, 2(6), 429-444.https://doi.org/10.1016/0377-2217(78)90138-8

Hothur, S. & Reddy, K.J. (2022). Financial performance evaluation of selected CPSEs of India through dupont analysis.doi:10.17010/ijf/2022/v16i5/169517

Huang, M. , Xia, T. , Chen, Z. , Pan, E. , & Xi, L. . (2021). A dea integrated grey factor analysis approach for efficiency evaluation and ranking in uncertain systems. *Computers & Industrial Engineering*(162-), 162.https://doi.org/10.1016/j.cie.2021.107681

Jiang, L., Li, Y., & Cai, L. P. (2018). Evaluation of enterprise economic performance based on principal component analysis. *Journal of Interdisciplinary Mathematics*, 21(5), 1309–1314. https://doi.org/10.1080/09720502.2018.1498004

Kaplan, R. S., & Norton, D. P. (1992). The balanced scorecard: Measures that drive performance. *Harvard Business Review*, 70(1), 71-79.

Lahouel, B. B., Zaied, Y. B., Song, Y., & Yang, G. L. (2021). Corporate social performance and financial performance relationship: A data envelopment analysis approach without explicit input. *Finance Research Letters*, 39, 101656.https://doi.org/10.1016/j.frl.2020.101656

Serrano-Cinca, C., Fuertes-Callén, Y., & Mar-Molinero, C. (2005). Measuring DEA efficiency in Internet companies. *Decision Support Systems*, 38(4), 557-573.https://doi.org/10.1016/j.dss.2003.08.004

Tayles, M. , Pike, R. H. , & Sofian, S. . (2007). Intellectual capital, management accounting practices and corporate performance. *Accounting, Auditing & Accountability Journal*, 20(4), 522-548.https://doi.org/10.1108/09513570710762575

Wu, Y. C., & Lin, S. W. (2022). Efficiency evaluation of Asia's cultural tourism using a dynamic DEA approach. *Socio-Economic Planning Sciences*, 84, 101426.https://doi.org/10.1016/j.seps.2022.101426

Yu, X., Suntrayuth, S., & Su, J. (2020). A comprehensive evaluation method for industrial sewage treatment projects based on the improved entropy-topsis. *Sustainability*, 12(17), 6734.https://doi.org/10.3390/su12176734

Awalia, A. P., Marliyah, M., & Ilhamy, M. L. (2023). Analysis of financial performance assessment using the economic value added (EVA) method (study at Bank Muamalat Indonesia 2019-2021). *Indonesian Journal of Economics and Management*, 3(3), 618-629.doi:journal.unisnu.ac.id/NUIEJ/article/view/57