Proceedings of the 3rd International Conference on Financial Technology and Business Analysis
DOI: 10.54254/2754-1169/154/2024.20087

Research on the Operational Efficiency Evaluation of Listed Logistics Enterprises in China Based on the DEA-Malmquist Index

Yating Luo[1,a,*]

[1]*Institute of Logistics Science and Engineering, Shanghai Maritime University, Shanghai, 201306, China*
a. shilrily@163.com
**corresponding author*

Abstract: With the continuous development of the economy, the logistics industry has become increasingly important in the national economy. Logistics efficiency is the key to the operational development of logistics enterprises, and the operational efficiency level of listed logistics enterprises better reflects the overall efficiency of the logistics industry. Therefore, this paper evaluates the operational efficiency of listed logistics enterprises from the perspective of input and output. The BCC model and Malmquist index model, both from the data envelopment analysis (DEA) method, are applied. Data from 62 listed logistics enterprises in the transportation, warehousing, and postal sectors, categorized in the 2012 edition by the China Securities Regulatory Commission, covering the years 2019 to 2023, are selected for analysis. Operational cost, number of employees, total assets, and management expenses are used as input indicators, while net profit and operating revenue are used as output indicators. A comprehensive analysis from both static and dynamic perspectives leads to the conclusion that, over the past five years, the technical efficiency level of listed logistics enterprises is not high, scale efficiency has not reached the optimal level, and there is insufficient technological innovation capacity. Finally, based on the above analysis, specific suggestions are made regarding resource allocation, production scale, and technological innovation for enterprises.

Keywords: logistics enterprises, operational efficiency, DEA model, Malmquist index.

1. Introduction

With the continuous trend of increasing specialization and division of labor, the logistics industry's share in the national economy has been rising, and the tax revenue it generates has become an important component of local tax income, playing a key role in promoting economic growth and increasing national income. As the third largest source of profit, the logistics industry is of great significance in enhancing the competitiveness of the national economy. In 2023, China's total social logistics amounted to 352.4 trillion yuan, a year-on-year growth of 5.2%. However, the development of China's logistics industry has been relatively short, and it is still in a transitional period. While the number of logistics enterprises is growing rapidly, logistics efficiency remains low. According to data released by the National Bureau of Statistics, during the five years from 2019 to 2023, China's social

DOI: 10.54254/2754-1169/154/2024.20087

logistics total cost as a proportion of GDP remained stable at around 14.5%. In contrast, this ratio in the United States typically hovers around 8%, while in European countries, it ranges from 5% to 7%. This shows that there is still a significant gap between China's logistics development level and that of developed countries. As the primary representatives of the logistics industry, the operational efficiency of listed logistics enterprises most accurately reflects the development status of the logistics industry. Therefore, scientifically and accurately evaluating the operational efficiency of listed logistics enterprises is beneficial for these companies to understand their operational conditions, adopt targeted improvement measures, and promote the overall efficiency improvement of the logistics industry.

Existing literature abounds with studies on the evaluation of corporate operational efficiency. Wang Hongliang summarized the research literature on evaluating logistics enterprise performance, concluding that methods such as the Analytic Hierarchy Process (AHP), Fuzzy Comprehensive Evaluation, and Data Envelopment Analysis (DEA) are frequently used in the study of logistics enterprise performance [1]. Nguyen N.T. et al. used the Malmquist index to evaluate the operational efficiency of national logistics enterprises in Vietnam, concluding that the proportion of companies with improving efficiency was equal to those with declining efficiency, with innovation being the key factor promoting efficiency improvement [2]; Pan J.L. et al. used super-efficiency DEA and LMBP neural networks to fit the enterprise efficiency of companies, creating a quantitative model for performance evaluation and conducting simulation research, which showed that the indicator system well reflects the characteristics of reverse logistics [3]; Yu Y. used the DEA-Malmquist index model to analyze the development efficiency of China's logistics industry, concluding that the regional development imbalance of the logistics industry in China is becoming more prominent [4]. Xu Jinwen et al. studied the service innovation efficiency of listed logistics enterprises in China from 2017 to 2021, concluding that while service innovation efficiency is generally high, the pace of innovation is slow [5]; Kong Huiwei selected the panel data of 60 listed logistics enterprises from 2016 to 2018 as the research object, using the DEA-Tobit two-stage model to analyze enterprise operational performance. The study found that more than half of the logistics enterprises' inputs in both stages were largely ineffective and empirically verified the impact of regional economic development levels, regional logistics turnover efficiency, high-education employees, and debt ratios on logistics enterprise operational performance [6].

2. Research Methodology

In 1978, scholars Charnes A., Cooper W.W., and Rhodes E. first created the Data Envelopment Analysis (DEA) method [7]. DEA is a performance evaluation method that fits multi-dimensional data into a comprehensive indicator and then proposes directions for system improvement. It is a tool for measuring and analyzing the relative efficiency between similar organizations. By using mathematical programming models, DEA can evaluate the relative effectiveness between evaluated units with multiple inputs and outputs. This paper selects the BCC model with variable returns to scale and the DEA-Malmquist index model.

2.1. BCC Model

Among traditional DEA methods, the most commonly used are the CCR model and the BCC model. The CCR model was first created by scholars and assumes that the Decision Making Unit (DMU) operates under constant returns to scale to measure overall efficiency. Six years later, Banker, Charnes, and Cooper proposed the BCC model [8], which measures pure technical efficiency and scale efficiency under the assumption that the DMU operates under variable returns to scale. This paper adopts the BCC model, and its principle is as follows:

Assume there are n comparable research objects, i.e., n decision-making units, each with $m(x_1, x_2, x_3, \dots, x_m)$ types of inputs and $s(y_1, y_2, y_3, \dots, y_s)$ types of outputs. Let x_{ij} and y_{rj} represent the input amount of the i-th input and the output amount of the r-th output for a specific decision-making unit, respectively. The efficiency evaluation index for a specific decision-making unit $DMU_j(1 \le j \le n)$ is shown in formula (1).

$$h_j = \frac{\sum_{r=1}^{s} \mu_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} (v \ge 0; \mu \ge 0) \tag{1}$$

The efficiency evaluation index h_j refers to the input-output ratio under the weight coefficients v and μ. For convenience in calculation, constraints are added to ensure that the decision-making unit has an effective value $\theta = [0,1]$, and weight restrictions are imposed. Combining this with formula (2), it is transformed into a linear programming problem:

$$\max \sum_{r=1}^{s} \mu_r y_0$$
$$s.t. \begin{cases} \sum_{i=1}^{m} v_i x_{ij} - \sum_{i=1}^{s} \mu_r y_{rj} \ge 0, j = 1,2,\cdots,n \\ \sum_{i=1}^{m} v_i x_0 = 1 \\ v \ge 0; \mu \ge 0 \end{cases} \tag{2}$$

The dual model of the above equation is:

$$\min \theta$$
$$s.t. \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_0 \\ \sum_{j=1}^{n} \lambda_j y_j \ge y_0 \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda_j \ge 0, j = 1,2,\cdots,n \end{cases} \tag{3}$$

When $\theta = 1$, the DMU is fully efficient; when $\theta < 1$, the DMU is inefficient under DEA, indicating that resource waste exists.

DOI: 10.54254/2754-1169/154/2024.20087

2.2. Malmquist Index Model

The efficiency status calculated by the BCC model is static, whereas the DEA-based Malmquist index model can measure the efficiency change trends over different periods. This index consists of two elements: one measures the change in pure technical efficiency, and the other measures the change in scale efficiency. For a specific unit DMU_0, the Malmquist index from period *t* to *t=1* can be expressed as:

$$M_0 = \frac{D_{t+1}(x_0^{t+1}, y_0^{t+1})}{D_t(x_0^t, y_0^t)} \times \left[\frac{D_t(x_0^{t+1}, y_0^{t+1})}{D_{t+1}(x_0^{t+1}, y_0^{t+1})} \times \frac{D_t(x_0^t, y_0^t)}{D_{t+1}(x_0^t, y_0^t)}\right]^{\frac{1}{2}} \tag{4}$$

In formula (4), the first term on the right side represents the technical efficiency index. If its value is greater than 1, it indicates an improvement in technical efficiency. The second term on the right side represents the technological progress index, with a value greater than 1 indicating technological advancement, and less than 1 indicating technological regression. Multiplying the technical efficiency index by the technological change index yields the distance function of the productivity index (M_0), which can assess the stability of the evaluated unit's efficiency and the trend of changes in its efficiency value.

3. Construction of the Efficiency Evaluation Index System

3.1. Principles for Selecting Evaluation Indicators

3.1.1. Principle of Availability

The selection of indicators is the premise and foundation for conducting the evaluation. When selecting indicators to evaluate the efficiency of listed logistics enterprises, the principle of availability must first be followed. The selected indicators should be relatively easy to obtain, and the data should be easy to collect and process, with reliable and stable sources.

3.1.2. Principle of Comprehensiveness

The comprehensiveness of the selected indicators is crucial to whether an accurate evaluation of the enterprise's operational efficiency can be made. A comprehensive evaluation of the operational efficiency of logistics enterprises can provide accurate results. If the selected indicators are overly narrow, the results of empirical analysis will be biased. Therefore, a relatively complete efficiency evaluation index system should be constructed.

3.1.3. Principle of Objectivity

The selected indicators should be objective, capable of representing the characteristics of the evaluated unit, and should effectively reflect the operational conditions of the listed logistics enterprises. These indicators should objectively reflect the features of the business efficiency research field, ensuring that the evaluation results are credible.

3.2. Selection of Indicators

Through reviewing the work of domestic and international scholars in this field, it has been found that in recent years, many scholars, when selecting indicators to evaluate the operational efficiency of listed logistics enterprises, have primarily considered three aspects: human resources, financial resources, and physical assets. Based on the principles of indicator selection and the operational

DOI: 10.54254/2754-1169/154/2024.20087

characteristics of logistics enterprises, this paper ultimately selects four input indicators and two output indicators, as shown in Table 1.

Table 1: Efficiency Evaluation Indicators for Listed Logistics Enterprises

Input Indicators	Output Indicators
Operating Costs	Total Operating Income
Total Assets	Net Profit
Management Expenses	
Number of Employees	

Among the selected input indicators, “Operating Costs” includes the costs and expenses related to the main business activities and other operational costs, reflecting the various costs incurred by listed logistics enterprises during their operations. “Total Assets” refers to the total sum of all economic resources owned or available for use by the enterprise. “Management Expenses” refer to the costs incurred by the enterprise due to organizational and management activities. The achievement of high-quality service goals for logistics enterprises depends on efficient management services in the departments, making management expenses a scientifically appropriate input indicator. “Number of Employees” represents the human capital investment of the enterprise.

Among the output indicators, “Total Operating Income” includes the income earned by the enterprise from its main business or other operations, representing the revenue generated by the logistics enterprise from providing services. “Net Profit” refers to the enterprise’s profit after taxes, also known as post-tax profit, and is the most effective indicator for reflecting the enterprise’s profitability.

3.3. Sample Selection

To ensure comparability between the decision-making units (DMUs) and to comprehensively reflect the current development status of the logistics industry, the sample enterprises were selected from A-share listed logistics companies in Shanghai and Shenzhen. According to the 2012 version of the China Securities Regulatory Commission (CSRC) classification, the industry classification is logistics, with a secondary classification as “Transportation, Storage, and Postal Services.” A total of 118 A-share listed logistics companies were selected. To account for data completeness, companies with data missing for the first two years after their initial public offering (IPO), or those with abnormal operations such as ST (special treatment) or missing indicator data, were excluded. Finally, 62 listed logistics companies were selected as the sample (Table 2), meeting the requirement that the number of DMUs is at least three times the sum of input and output indicators. The data for the indicators were sourced from the Guotai An database.

Table 2: Sample Listed Logistics Companies and Their Sub-Sectors

Industry Name	Sample Companies and Codes
Warehousing Industry (G59)	002492 Hengji Daxin, 002930 Great River Smarter, 300240 Feiliks, 600787 Zhongchu Stocks, 600794 Freetrade Science & technology, 603066 Inform Storage, 603535 Jiacheng Inc.

Table 2: (continued).

Road Transportation Industry (G54)	000088 Yantian Port, 000429 Guangdong Expressway A, 000828 Dongguan Holdings, 002357 Fuling Transportation, 002627 Three Gorges Tourism, 600012 Anhui Expressway, 600023 Zhongyuan Expressway, 600033 Fujian Expressway, 600035 Chutian Expressway, 600269 Ganyu Expressway, 600350 Shandong Expressway, 600368 Wuzhou Transportation, 600377 Ninghu Expressway, 600548 Shenzhen Expressway, 600650 Jinjiang Online, 600834 Shanghai Metro, 601107 Sichuan Chengyu, 601188 Heilongjiang Transportation, 603223 Hengtong Shares
Air Transport Industry (G56)	000099 COHC, 600897 Xiamen Airport
Water Transport Industry (G55)	000507 Zhuhai Port, 000582 Beibu Gulf Port, 000905 Xiamen Port, 001872 China Merchants Ports, 002040 Nanjing Port, 002320 Haixia Shares, 600017 Rizhao Port, 600018 Shanghai Port Group, 600279 Chongqing Port, 600428 COSCO Shipping Special, 600575 Huaihe Energy, 600717 Tianjin Port, 600798 Ningbo Shipping, 601000 Tangshan Port, 601008 Lianyungang Port, 601018 Ningbo Port, 601228 Guangzhou Port, 601298 Qingdao Port, 601326 Qin Port Shares, 601866 COSCO Shipping Holdings, 601872 China Merchants Shipping, 601880 Liaogang Shares, 601919 COSCO Shipping Holdings, 603167 Bohai Ferry
Railway Transportation Industry (G53)	000557 Western Entrepreneurship, 600125 Tielong Logistics
Postal Industry (G60)	002120 Yunda Shares, 002352 SF Holding, 600233 Yuantong Express, 603056 Deppon Logistics
Cargo Handling and Freight Forwarding Industry (G58)	601598 China National Foreign Trade, 603128 Huamao Logistics, 603713 Milkway, 603967 Zhongchuang Logistics

3.4. Data Preprocessing

The DEA method requires that the input and output indicator data be non-negative. Since there are some negative values in the net profit data in the sample, the following normalization process was applied to the sample data [9] to ensure the accuracy of the calculation results:

$$\theta_{ij}^{*} = 0.1 + 0.9\frac{\theta_{ij} - \min(\theta_{ij})}{\max(\theta_{ij}) - \min(\theta_{ij})} \tag{5}$$

Where, $\min(\theta_{ij})$ and $\max(\theta_{ij})$ are the minimum and maximum values of the j-th indicator, respectively.

4. Empirical Results Analysis

4.1. Static Evaluation Based on DEA-BCC Model

This study uses the DEAP 2.1 software to conduct a static evaluation of the operational efficiency of 62 listed logistics companies from 2019 to 2023. Input and output data are calculated to obtain the composite efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) values for each company. These are categorized into two groups based on whether they are effective (efficiency value = 1) or ineffective (efficiency value < 1), as shown in Table 3. Generally, composite efficiency is calculated as the product of pure technical efficiency and scale efficiency, and it is used to measure the resource allocation capability of listed logistics companies as well as provide a comprehensive assessment of their resource usage efficiency. When the composite efficiency value is 1, it indicates that the input-output of the decision-making unit is fully effective. The number of companies with effective composite efficiency increased from 13 in 2019 to 18 in 2020, reaching the highest level during the five years. From 2021 to 2023, it showed a trend of first declining and then increasing, indicating that the operational situation of listed logistics companies fluctuated.

Pure technical efficiency indicates whether a company's industrial structure aligns with its overall operational requirements and whether it can achieve maximum benefits. When PTE equals 1, it means that the company's management is effective at the current technical level. If the PTE value is not 1, the company is in an ineffective state, meaning that it should improve its technical management level. In 2020, the number of companies with effective pure technical efficiency was the highest, reaching 27, accounting for 43.55%, indicating that these 27 companies had a high level of modern logistics technology.

Scale efficiency reflects the difference between a company's actual scale and the ideal optimal production scale. A value of 1 indicates that scale efficiency has reached the ideal state. The number of companies with effective scale efficiency is generally consistent with the composite efficiency. In 2020, the number of companies with effective scale efficiency reached its maximum of 19, accounting for 30.65%. In 2022, the number of companies with effective scale efficiency decreased to 9, the lowest value over the five years, accounting for only 14.52%. Overall, most companies have not achieved the optimal input-output balance and should adjust their scale in a timely manner to improve scale efficiency.

Table 3: Analysis of the Effectiveness Levels of Listed Logistics Companies under the DEA-BCC Model

		Composite Efficiency		Pure Technical Efficiency		Scale Efficiency	
		Number of Companies	Percentage	Number of Companies	Percentage	Number of Companies	Percentage
2019	Efficiency = 1	13	20.97%	23	37.10%	17	27.42%
	Efficiency < 1	49	79.03%	39	62.90%	45	72.58%
2020	Efficiency = 1	18	29.03%	27	43.55%	19	30.65%
	Efficiency < 1	44	70.97%	35	56.45%	43	69.35%
2021	Efficiency = 1	10	16.13%	20	32.26%	11	17.74%
	Efficiency < 1	52	83.87%	42	67.74%	51	82.26%
2022	Efficiency = 1	8	12.10%	16	25.81%	9	14.52%
	Efficiency < 1	54	87.10%	46	74.19%	53	85.48%
2023	Efficiency = 1	12	19.35%	23	37.10%	12	19.35%
	Efficiency < 1	50	80.65%	39	62.90%	50	80.65%

DOI: 10.54254/2754-1169/154/2024.20087

The trend in the operational efficiency of listed logistics companies from 2019 to 2023 is shown in Figure 1. Over the past five years, the number of companies with optimal composite efficiency exhibited an "N" shape, mainly due to fluctuations in scale efficiency, which had a major impact on composite efficiency. The average values of scale efficiency for the 62 listed companies each year fluctuated in line with those of composite technical efficiency. The average value of pure technical efficiency in each year remained around 0.95, indicating that the pure technical efficiency level of listed logistics companies in China is relatively high and that these companies have a strong level of modern logistics technology. Overall, despite fluctuations in pure technical efficiency, scale efficiency, and composite efficiency, more than half of the companies still did not achieve optimal efficiency over the past five years. The overall efficiency is relatively stable, with room for improvement.

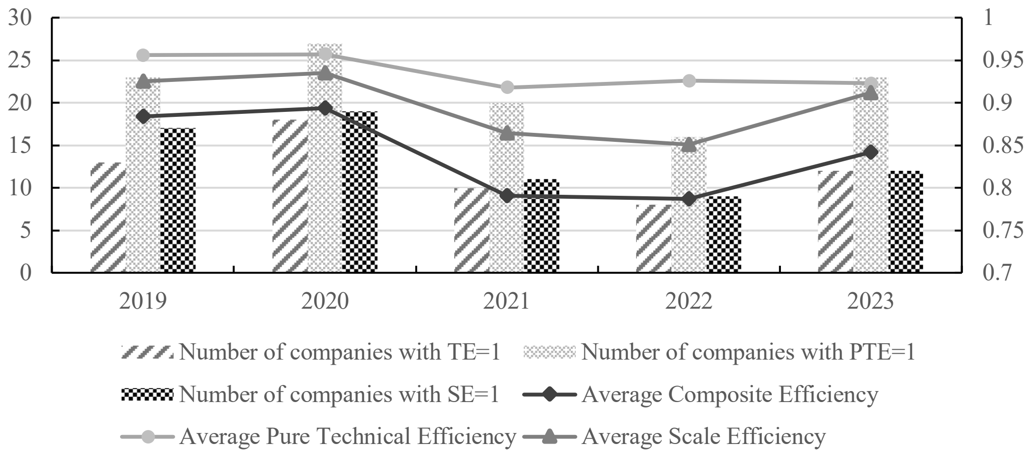

Figure 1: Trends in the Operational Efficiency of Listed Logistics Companies from 2019 to 2023

4.2. Dynamic Evaluation Based on the DEA-Malmquist Index Model

Based on panel data from 2019 to 2023, the total factor productivity change index for individual listed logistics companies is shown in Table 4. The average total factor productivity is 0.996, indicating a 0.4% decrease in total factor productivity for the listed logistics companies over the past five years. Further decomposition of the M index shows that the composite technical efficiency decreased by an average of 1.3% annually, while the technological progress index is 1.015, indicating an improvement in the companies' technological innovation capabilities in recent years. Further decomposition of composite technical efficiency into pure technical efficiency and scale efficiency reveals that pure technical efficiency first declined and then significantly increased, while scale efficiency fluctuated up and down over the past five years, with an average annual growth rate of -0.4%. This suggests that the changes in technical efficiency are primarily affected by scale efficiency, and most companies have not yet reached the optimal production scale.

Table 4: 2019-2023 Malmquist Index and Its Decomposition for Listed Logistics Companies

Year	Composite Technical Efficiency	Technological Progress	Pure Technical Efficiency	Scale Efficiency	Total Factor Productivity
2019-2020	1.012	0.927	1.012	1.000	0.939
2020-2021	0.878	1.184	0.918	0.956	1.083
2021-2022	0.995	0.968	0.984	1.010	0.963

DOI: 10.54254/2754-1169/154/2024.20087

Table 4: (continued).

2022-2023	1.074	0.986	1.078	0.996	1.006
Average	0.987	1.009	1.002	0.991	0.996

Figure 2 provides a more intuitive view of the changes in total factor productivity for logistics companies from 2019 to 2023. Among all the influencing factors, the change in the technological progress index aligns with the fluctuations in total factor productivity, indicating that technological progress is a major factor in measuring the development of listed logistics companies. Companies should further enhance their technological levels and innovation capabilities to promote transformation and upgrading. The scale efficiency fluctuates around 1, suggesting that while the companies' management levels are relatively stable, there is still significant room for improvement in achieving economies of scale.

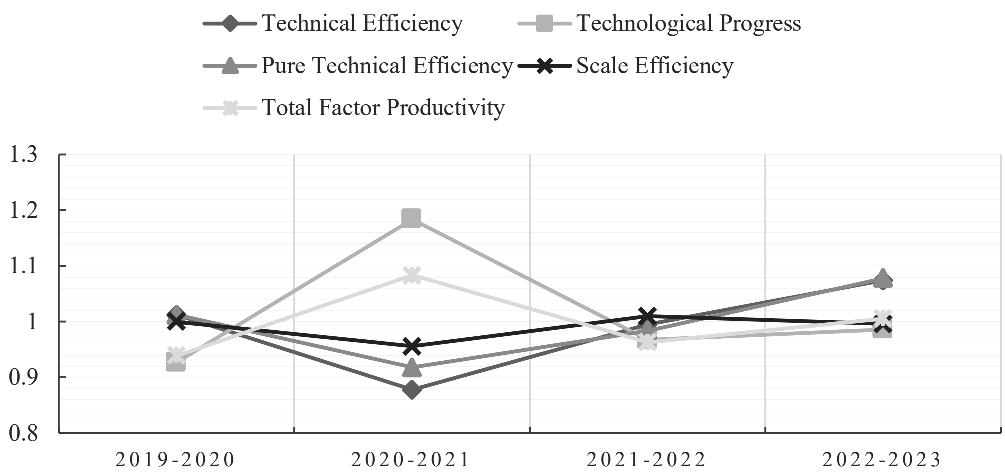

Figure 2: Total Factor Productivity Change Trend for Listed Logistics Companies from 2019 to 2023

5. Conclusion and Countermeasures

5.1. Research Conclusions

This study primarily uses the DEA-BCC model and the DEA-Malmquist dynamic index model to analyze the technical efficiency and total factor productivity of 62 listed logistics companies on the main board. The main conclusions are as follows:

Firstly, in terms of static evaluation, the current technical level of listed logistics companies is acceptable. However, the overall composite efficiency value is not ideal, with more than half of the companies failing to achieve effective efficiency. Scale efficiency has a significant impact on the overall efficiency level.

Secondly, in terms of dynamic evaluation, changes in technical efficiency are mainly influenced by scale efficiency and the technological progress index. The technological progress index and the fluctuation trend of total factor productivity are generally consistent, indicating that technological innovation has become the main driver of the development of listed logistics companies. Therefore, the reasons for the relatively low operational efficiency of some listed logistics companies are primarily due to insufficient resource allocation capacity, failure to achieve optimal scale, and a lack of innovation capabilities.

5.2. Countermeasures to Improve the Operational Efficiency of Listed Logistics Companies

5.2.1. Optimize Resource Allocation and Achieve Economies of Scale

Firstly, listed logistics companies need to adjust their organizational structure. Through asset restructuring and other measures, companies should streamline their industrial structure and make full use of limited resources such as transportation resources, network resources, and external resources, thereby improving the efficiency of resource use. Secondly, listed logistics companies should improve their management levels and standardize management systems in line with the industrial structure. Specialization in division of labor and collaboration should be achieved to make full use of resources and talent. Thirdly, logistics companies should adapt to market changes in a timely manner and adjust their industrial scale according to market conditions. Given the current favorable logistics market situation, logistics companies may, when necessary, expand their operational scale by merging small enterprises. This will help achieve optimal resource allocation and mutually beneficial outcomes, ultimately reaching the ideal optimal scale and realizing economies of scale.

5.2.2. Strengthen Technological Innovation and Develop Smart Logistics

Total factor productivity is significantly influenced by fluctuations in the technological progress index. Technological progress is an important aspect of improving the operational efficiency of listed logistics companies. Therefore, companies must improve their technological innovation capabilities to achieve growth. The development of smart logistics is accelerating, but most logistics companies are still relying primarily on manual operations, constrained by limitations in operating costs, quantity, and proficiency. As a result, logistics companies should actively upgrade their logistics equipment to automation, use automated equipment to improve the efficiency of logistics operations, deploy intelligent operational equipment, and develop smart logistics. Companies should also strive to provide high-efficiency, high-quality services, promoting a virtuous cycle between transportation volume and service quality. In addition, logistics companies should focus on strengthening logistics information technology innovation, building logistics information platforms, and advancing the informatization process of logistics management. Companies should actively promote the transformation and upgrading of the logistics industry toward digitalization and intelligence.

5.2.3. Increase Profitability and Enhance Profit Output

Another factor affecting the operational efficiency of listed logistics companies is insufficient output. During data collection, it was found that many companies are in a loss-making state. Given that the logistics industry has shifted from a high-profit era to a low-profit era, listed logistics companies should focus on reducing resource wastage and controlling costs. Efforts should be made to save on talent costs and operating costs, effectively controlling expenses to increase profit output. Additionally, listed logistics companies should promote personalized services and obtain additional profits by providing value-added services, thereby establishing their core competitiveness and improving profitability.

5.2.4. Introduce Technological Talent and Focus on Talent Development

On one hand, listed logistics companies should actively introduce compound logistics talent. The recruitment of talent should align with the needs of the logistics industry’s development. Forward-thinking technological talent should be recruited, especially in areas such as digital economy transformation and intelligent upgrading, where there are talent gaps. On the other hand, logistics

DOI: 10.54254/2754-1169/154/2024.20087

companies should accelerate talent development by regularly conducting vocational education and training, formulating reasonable talent management systems, and improving the overall quality of logistics professionals. This will, in turn, improve the service quality and professionalism of logistics companies. Additionally, listed logistics companies should make reasonable arrangements for their staffing structure, determining the optimal number of employees based on the company's characteristics. This will help avoid wastage of labor and achieve the optimal staffing scale, ultimately improving the company's operational management level.

References

[1] Wang, H. (2021). A review of the performance evaluation index system of logistics companies. Economic Research Guide, (10), 10-12.

[2] Nguyen, N. T., & Tran, T. T. (2019). Raising opportunities in strategic alliances by evaluating the efficiency of logistics companies in Vietnam: A case of Cat Lai Port. Neural Computing and Applications, 31(11), 7963-7964.

[3] Pan, J. L., Li, G. L., & Luo, H. Y. (2021). Reverse logistics enterprise performance research based on super-efficiency DEA and LMBP neural network. Journal of Physics: Conference Series, 2025(1), 012087.

[4] Yu, Y. (2021). Research on the efficiency of China's logistics industry in the context of high-quality economic development: Based on the DEA-Malmquist index model. International Journal of Social Science and Education Research, 4(1), 84-89.

[5] Xu, J. W., Zhang, Y. H., Zhou, T., et al. (2024). A study on the service innovation efficiency evaluation of listed logistics companies in China. China Business Review, (11), 130-133.

[6] Kong, H. W., Xie, J. P., Chen, Q. N., et al. (2024). A study on the operational performance of logistics companies in China based on the DEA-Tobit two-stage model. Shanghai Management Science, 46(2), 74-80.

[7] Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. European Journal of Operational Research, 2(6), 429-444.

[8] Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science, 30(9), 1078-1092.

[9] Huo, L., Cai, C. A., & Huang, J. (2021). The efficiency of China's OFDI to ASEAN from a dynamic perspective: An empirical analysis based on super-efficiency DEA-Tobit. Investment Research, 40(4), 17-28.