sustainability

MDPI

Article

An Integrated Approach of Fuzzy Analytic Hierarchy Process and Super Slack-Based Measure for the Logistics Industry in Vietnam

Thi Kim Lien Nguyen *, Thi Lan Huong Nguyen, Tri Long Ngo, Bang An Hoang, Hong Huyen Le and Thi Thanh Hong Tran

Department of Economics-Business Administration, Thanh Dong University, Tu Minh, Hai Duong 171960, Vietnam; huongntl@thanhdong.edu.vn (T.L.H.N.); longnt@thanhdong.edu.vn (T.L.N.); anhb@thanhdong.edu.vn (B.A.H.); huyenlh@thanhdong.edu.vn (H.H.L.); hongttt@thanhdong.edu.vn (T.T.H.T.)
* Correspondence: liennntk@thanhdong.edu.vn; Tel.: +84-366-440-688

Abstract: In the context of economic development and international economic integration, Vietnam's logistics industry is developing to meet market demands for the transportation of goods; thus, many logistics enterprises have been formulated and expanded in recent years. This research aims to measure the efficiency of logistics enterprises and recommend a feasible solution to improve their future performance by integrating a super slack-based measure model (super-SBM) in data envelopment analysis and fuzzy analytic hierarchy processes (fuzzy AHP) in multi-criteria decision-making. The super-SBM model was utilized to conduct the efficiency scores of logistics enterprises from 2016 to 2022 based on calculating the ratio between input and output variables; the empirical result determined each enterprise's effectiveness and ineffectiveness. Next, the fuzzy AHP method evaluated and ranked criteria that directly impacted the operational process of logistics enterprises based on experts' opinions; the examined result suggested a feasible direction to improve future business efficiency. The proposed hybrid models are a helpful solution for efficiency determination and determining the development direction for logistics enterprises. An overall picture of the logistics enterprises was also drawn to describe their operational business process.

Keywords: super-SBM model; fuzzy AHP method; logistics industry

Citation: Nguyen, T.K.L.; Nguyen, T.L.H.; Ngo, T.L.; Hoang, B.A.; Le, H.H.; Tran, T.T.H. An Integrated Approach of Fuzzy Analytic Hierarchy Process and Super Slack-Based Measure for the Logistics Industry in Vietnam. *Sustainability* **2023**, *15*, 12654. https://doi.org/10.3390/su151612654

Academic Editor: Ripon Kumar Chakrabortty

Received: 8 July 2023
Revised: 2 August 2023
Accepted: 18 August 2023
Published: 21 August 2023

1. Introduction

Industrialization and modernization are the foundation for enhancing development of the logistics industry. The growth of smart technologies [1,2] has supported the processes of multimodal cargo delivery; as such, Industry 4.0 provides the need for transparency and integrity control in logistics [3,4]. Furthermore, the development of modern technologies in logistics centers has helped to improve quality levels of services [5]. Software tools can also help to optimize the whole process of city logistics [6], along with methods and techniques for improving the performance of the logistics industry. Lean manufacturing principles are used to develop measures for efficiency improvement via the use of sufficient warehouses, optimizing the research and inventory processes, and mechanizing internal logistics [7]. International leasing as a financial method that is implemented to improve the transport and logistics system [8]. These new technologies and methods help to make up practical approaches to increase efficiency in the logistics industry. According to statistics (2023) [9], the size of the global logistics industry in 2021 increased by EUR 2.7 trillion compared with the year 2020. Although the COVID-19 pandemic impacted most industries and led to economic crises, the global logistics sector has been pushed into a sharp recovery.

Vietnam's logistics services have been developed since the 2004 Commercial Law [10]: "Logistics was considered as commercial activities whereas traders organize the performance of one or many jobs including reception, transportation, warehousing, yard storage of cargoes, completion of customs procedures and other formalities and paperwork, provision of consultancy to customers, service of packaging, marking, delivery of goods, or other service related to goods according to agreements with customers to enjoy service charges." Since Vietnam became a member of the World Trade Organization in 2007, the logistics industry has had more opportunities to expand and develop. The e-commerce boom, growing supply of manufactured goods, and increasing consumption are significant elements in the elevation of Vietnam's logistics industry. As a result, the logistics sector has seen a sharp growth rate among the fastest expanding sectors, accounting for 4.5% of the country's GDP in 2021 [11]. Although Vietnam's logistics industry has experienced typical success, it still faces several challenges, such as high logistics costs, low technical quality, shortage of quality human resources, etc.; therefore, this study measured the business performance of Vietnam's logistics companies from 2016 to 2022 based on the super-SBM model in the DEA method; then, the relative criteria to increase logistics performance were formalized based on the fuzzy AHP method from experts' advice.

Previous research of the logistics industry has focused on analysis through a qualitative approach [12], calculation models of the environmental cost and environmental impact of logistics activities [13], interactive simulation modelling methods [14], fuzzy-set qualitative comparative analysis [15], and conditional logit models [16]. These studies, however, still lack research that integrates DEA and fuzzy AHP to measure efficiency and determine the value of certain factors; therefore, the purpose of this study is to integrate the super-SBM model in the DEA and fuzzy AHP methods, which are used to fill in the research gap of measuring the performance and analyzing the impact variables for the business efficiency of logistics companies in Vietnam. First, we used the super-SBM model in the DEA method to calculate the efficiency scores of each logistics company in Vietnam through the ratio between the output and input variables. Then, each efficient and inefficient case was identified to describe their operational business process and suggest a feasible solution to increase the efficiency score in ineffective cases by reducing the input excess and increasing an output shortage. The fuzzy AHP method was then implemented to identify the weights of the criteria, which could determine the impact level of the main and sub-criteria for improving a logistics company's performance in Vietnam. An overall picture of the operational process in historical times and the future development direction of Vietnam's logistics industry was illustrated as a valuable reference.

2. Literature Review

Previous research has used various methods to approach and analyze the logistics sector. The statistical learning method, for example, is applied to forecast prices and enhance a firm's competitiveness level [17]. The analytic hierarchy process method was used for the performance evaluation of green logistics [18]. A systematic literature review methodology analyzed documented barriers and benefits of Industry 4.0 technology adoption in warehouse management [19]. Applying the CCR model to the DEA method allowed for the measurement and determination of the efficient and inefficient cases and efficiency improvement of green supply chain management [20]. A qualitative research method was utilized to present the impacted variables of digital transformation regarding logistics enterprises in Vietnam [21]. In this study, the integration of the super-SBM model and fuzzy AHP was implemented to measure and improve the efficiency of Vietnam's logistics companies.

Decision-making will offer choices by determining a decision, collecting information, and assessing alternatives; thus, the DEA and fuzzy methods utilized in decision-making have expanded and been applied in various studies. The DEA method with efficiency calculation presents the performance of a decision-making unit (DMU) once the ratio of inputs and outputs are calculated. Wang et al. (2018) [22] implemented the measurement of efficiency scores of port logistics companies in Vietnam via the super-SBM model. Marto et al. (2022) [23] applied DEA optimization to present the performance of GDP per capital in EU regions. Goyal et al. (2008) [24] utilized fuzzy techniques to present decision-making concerning the outcome of auctions and the agent's bidding strategy in diverse criteria and market conditions. Dogan et al. (2023) [25] used the fuzzy theory to evaluate customer transactions.

The super-efficiency of a DMU presents increasing inputs and reducing outputs, in which a DMU's efficiency score has yet to become efficient [26]. The super-efficiency estimates separate scores for DMUs in the same period for efficient and inefficient cases. The super-SBM model integrates super-efficiency and has been applied in various aspects. For example, Zhou et al. (2018) [27] measured the eco-efficiency of 21 cities in Guangdong Province, China, based on multiple factors, such as capital, labor force, water supply, energy resources, etc. The empirical results identified the positive influence level and inhibiting factors. Wang et al. (2020) [28] estimated the efficiency of estate companies in Vietnam through the calculated values from 2012 to 2017 and determined the efficient and inefficient cases for every year. Huang and Liu (2020) [29] estimated the efficiency of a sustainable hydrogen product scheme when analyzing indicators such as scale, cost, energy consumption, etc. Du et al. (2021) [30] evaluated the ecological efficiency of marine ranching in Shandong, China, by evaluating the impacted criteria to explore the marine ranching ecological efficiency's leading causes of loss. Ma et al. (2022) [31] conducted the regional financial efficiency of 31 provinces in China when they calculated the efficiency score based on the ratio of inputs and outputs under the principle of the super-SBM model. The results indicate the different scores and positions for each province. These studies demonstrate that the super-SBM model is a suitable model for implementing the efficiency measurement of DMUs and can solve the drawback of scoring at the efficiency level.

The fuzzy AHP method implements an assessment of the weights of criteria and priorities of alternatives [32] based on pairwise comparison. It is a combination of the AHP and fuzzy sets, and sets up the comparison matrix, aggregating multiple judgements, measuring the consistency, and defuzzifying the fuzzy weights [33] to evaluate the criteria and select alternatives; thus, it has been applied in various types of research. Rezaie et al. (2014) [34] measured the criteria weights that have an impact on the financial ratios on the efficiency evaluation of 27 Iranian cement firms in the Tehran Stock Exchange. Ali et al. (2014) [35] used the fuzzy AHP method to evaluate the weights of eight evidential layers in the Taherabad area of eastern Iran. Choosakun and Yeom (2021) [36] applied the fuzzy AHP method to assess the advanced public transport system in the Bangkok Metropolitan Region. The main characteristics were determined, including the reduction of traffic accidents related to public transportation, density of the smart public transport network, and waiting time for public transportation. Wang et al. (2022) [37] evaluated the flood risk related to 14 lines and 268 stations of the Guangzhou Metro in China via the fuzzy AHP method; the analyzed results determined that lines 3, 6, and 5 had the utmost overall risk level. Sahin and Kulakli (2023) [38] applied the fuzzy AHP method to define the weights of criteria during the evaluation of websites of four renowned universities in Türkiye that specialize in open education. The fuzzy AHP is a valuable tool to assess and rank criteria, and can evaluate the weights of criteria to recommend a feasible solution to improve and increase the operational performance of a particular object.

3. Methods

3.1. Research Framework

The performance and feasible solution for logistics companies in Vietnam has been estimated based on the super-SBM model and fuzzy AHP method, as shown in Figure 1.

Stage 1: Our objective is to investigate and explore the deep knowledge of Vietnam's logistics sector; thus, we collected the actual data and examined the criteria for improving the logistics companies' performance.

Stage 2: The theoretical research of logistics, super-SBM model, and fuzzy AHP were provided to clarify previous studies' backgrounds.

Stage 3: Data of Vietnam's logistics companies from 2016 to 2022 were gathered to measure their efficiency scores. All the collected data were tested by the Pearson correlation and were ensured to be "isotonic." The data must be removed and re-selected if any are unappreciated when their Pearson correlation value is not from −1 to +1 or is equal to "0". The appreciated data were used to determine efficient and inefficient logistics companies every year.

Stage 4: The efficiency scores presented their able business and exhibited the essential improvement of efficiency; thus, the fuzzy AHP method was used for identification of impacted criteria level. Initially, the criteria were discussed and presented; then, they were applied to compute the weights via the fuzzy AHP method's mathematics. Finally, the criteria's weights were determined, and the importance and improvement level for each criterion were determined and ranked.

Stage 5: The main results were reviewed and discussed with regard to the logistics industry's development.

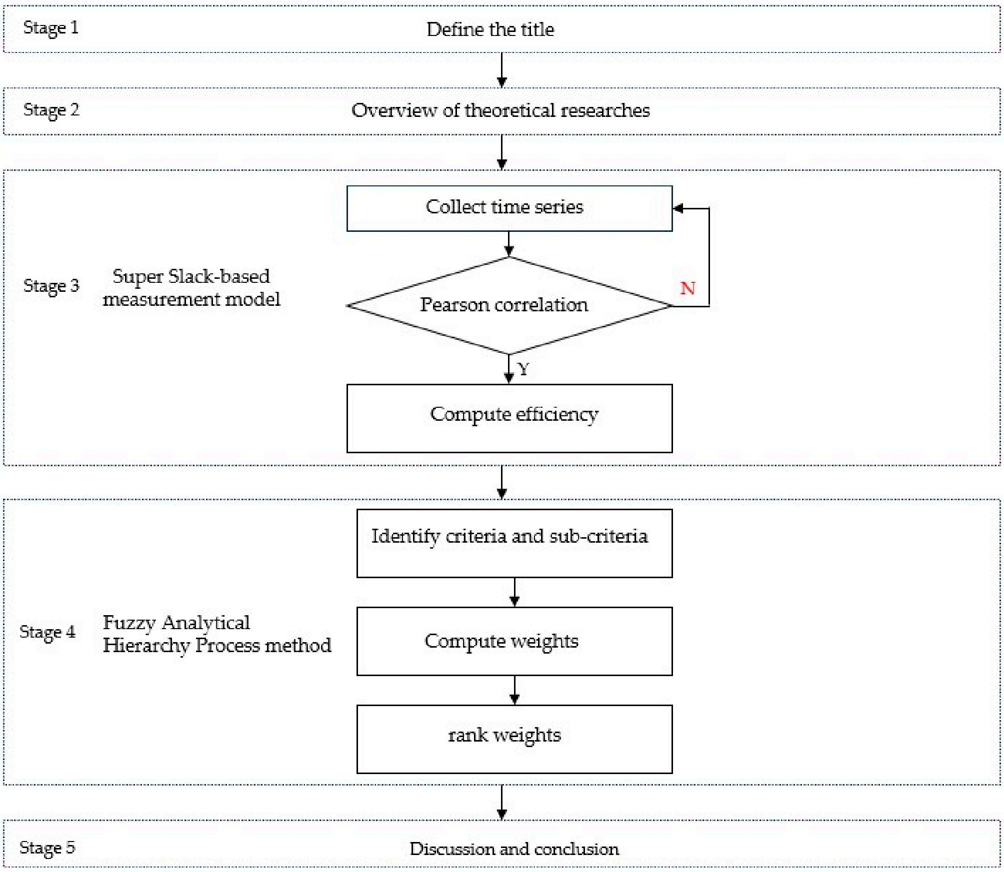

Figure 1. Research flowchart.

3.2. *Super-SBM Model*

Cooper et al. (2007) [39] indicated that data envelopment analysis is a linear programming methodology to determine the relative efficiency of multiple similar entities or decision-making units (DMUs). The observed data for DMUs are used for calculating the relative efficiency scores through a nonparametric procedure. Each DMU computes the efficiency scores according to a set of technical features, such as model orientation, model metrics, and a production possibility set. The model orientation presents three variants, including input-oriented, output-oriented, and non-oriented. Model metrics show two variants, namely, radial and non-radial models. Every model in the DEA method will have different access: the Charnes–Cooper–Rhodes (CCR) is a radial model with proportion changes [40]; a slack-based measure (SBM) is a non-radial model with specific slack for each input and output [41]; super efficiency shows the ranking efficient units and facilitates comparison based on parametric methods [42]; and super-SBM is a radial model that can measure the efficiency score and determine and identify the separate scores for both efficiency and inefficiency [43]. The super SBM model calculates the distance under variable return-to-scale conditions; therefore, this study used the super-SBM model to evaluate the performance of Vietnam' logistics companies. We set up logistics companies as nDMUs with the input $A = a_{ij}$ and output $B = b_{ij}(A, B > 0)$. The production possibility is determined as:

$$P = \{(a, b)\} \tag{1}$$

Subject to

$$a \geq X\lambda, b \leq B\lambda, \lambda \geq 0$$

where the non-negative vector is λ.

An expression utilized to describe a certain $DMU(a_0, b_0)$, the production possibility for a super-efficiency score, is employed as:

$$P(a_0, b_0) = \left\{ \left(\overline{a}, \overline{b} \right) \right\} \tag{2}$$

Subject to

$$\overline{a} \geq \sum_{j=1,\neq 0}^{n} \lambda_j a_j$$

$$\overline{b} \leq \sum_{j=1,\neq 0}^{n} \lambda_j b_j$$

$$\overline{b} \geq 0, \lambda \geq 0$$

With the weighted distance l_1 from (a_0, b_0) to $(\overline{a}, \overline{b}) \in P(a_0, b_0)$, the product of two indices (∂), including the distance in the input space and output space, which is defined as:

$$\partial = \frac{\frac{1}{m}\sum_{i=1}^{m} \overline{a_i}/a_{i0}}{\frac{1}{s}\sum_{r=1}^{s} \overline{b_r}/b_{r0}} \tag{3}$$

The input excess and output shortfall of this expression will be vectors s^- and s^+, respectively.

The super-efficiency (∂^*) of the super-SBM model is calculated as:

$$\partial^* = \min\partial = \frac{\frac{1}{m}\sum_{i=1}^{m} \overline{a_i}/a_{i0}}{\frac{1}{s}\sum_{r=1}^{s} \overline{b_r}/b_{r0}} \tag{4}$$

Subject to

$$\overline{a} \geq \sum_{j=1,\neq 0}^{n} \lambda_j a_j$$

$$\overline{b} \leq \sum_{j=1,\neq 0}^{n} \lambda_j b_j$$

$$\overline{a} \geq a_0, \overline{b} \leq b_0, b \geq 0, \lambda \geq 0$$

The super-efficiency scores present efficient scores with $\partial^* \geq 1$ and inefficient scores with $\partial^* < 1$. The inefficient case needs to find a feasible solution to improve its efficiency score by increasing the value of the output factors and decreasing the value of the input factors.

3.3. Fuzzy Analytic Hierarchy Process

The fuzzy analytic hierarchy process integrates qualitative and quantitative methods to define the eigenvalues and eigenvectors based on the determining the fuzzy numbers and the triangular fuzzy judgment matrix [44]. The eigenvector presents the priorities of the alternatives for a positive reciprocal pairwise comparison judgment matrix. The fuzzy AHP method is used to determine the priority vectors and rank alternatives.

3.3.1. Triangular Fuzzy Number

A fuzzy number is a fuzzy set with real numbers. A triangular fuzzy number is a fuzzy number with three points [45]. We set up x_1, x_2, and x_3 to be real numbers; the triangular fuzzy number $X = (x_1, x_2, x_3)$ is shown in Figure 2.

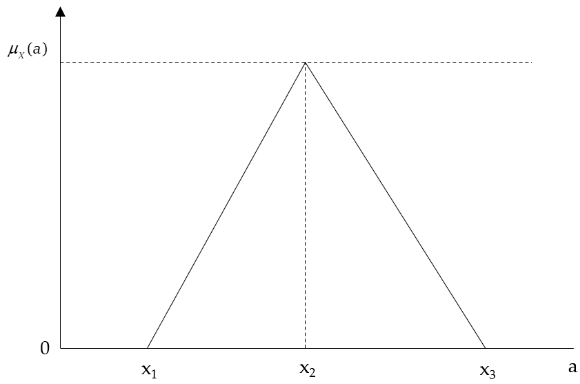

Figure 2. Triangular fuzzy number.

The parameters including x_1, x_2, and x_3 present the smallest possible value, most promising value, and largest possible value, respectively [46]. The triangular fuzzy number is determined as:

$$t(x_1, \alpha, x_2, x_3) = \begin{cases} 1 - \dfrac{x_2 - x_1}{x_2 - \alpha}(\alpha \leq x_1 \leq x_2) \\ 1 - \dfrac{x_1 - x_2}{x_3 - x_2}(x_2 < x_1 \leq x_3) \\ 0, (x_1 < \alpha, x_1 > x_3) \end{cases} \tag{5}$$

The triangular fuzzy number ranges from $\widetilde{1}$ to $\widetilde{9}$.

3.3.2. Fuzzy Linguistic Scale

A fuzzy linguistic scale indicates the quality of information retrieval and formulates a method of choosing the optimum set of values of qualitative attributes [47]. Ryjov (1987) [48] and Ryjov (1992) [49] measured the fuzzy linguistic scale by calculating the actual object's properties. The performance of candidates for each criterion is utilized to identify the evaluation criteria weights when formulating pair-wise comparison metrics among the criteria. The linguistics scale is used for measuring the performance of candidates [50], as shown in Table 1.

Table 1. Linguistic scale.

Fuzzy Number	Linguistic Scale	Scale of Fuzzy Number	Positive Reciprocal Fuzzy Scale
$\widetilde{1}$	Equal importance	(1, 1, 1)	(1, 1, 1)
$\widetilde{2}$	Intermediate values between $\widetilde{1}$ and $\widetilde{3}$	(1, 2, 3)	(1, 1/2, 1/3)
$\widetilde{3}$	Moderate importance	(2, 3, 4)	(1/2, 1/3, 1/4)
$\widetilde{4}$	Intermediate values between $\widetilde{3}$ and $\widetilde{5}$	(3, 4, 5)	(1/3, 1/4, 1/5)
$\widetilde{5}$	Essential importance	(4, 5, 6)	(1/4, 1/5, 1/6)
$\widetilde{6}$	Intermediate values between $\widetilde{5}$ and $\widetilde{7}$	(5, 6, 7)	(1/5, 1/6, 1/7)
$\widetilde{7}$	Very vital importance	(6, 7, 8)	(1/6, 1/7, 1/8)
$\widetilde{8}$	Intermediate values between $\widetilde{7}$ and $\widetilde{9}$	(7, 8, 9)	(1/7, 1/8, 1/9)
$\widetilde{9}$	Extremely vital importance	(9, 9, 9)	(1/9, 1/9, 1/9)

Source: Buckley (1985) [51].

3.3.3. Fuzzy AHP Algorithm

The fuzzy AHP method is formulated with fuzzy logic theory and sets the AHP scale into a fuzzy triangle scale [52]; it is developed via the following steps:

Step 1: Determine the problem, then establish a hierarchical analysis framework from the triangle number.

Step 2: Generate a comparison matrix; the matrix has a strong position for the consistency framework and is used for analyzing the overall priority sensitivity for change. We set the number of criteria as n, the weight for criterion as w_i, and the ratio of the weight and criterion as x_{ij}; therefore, the pair-wise comparison is computed by:

$$x_{ij} = \frac{w_i}{w_j}, i, j = 1, 2, 3, \ldots n \tag{6}$$

The fuzzy pairwise comparison matrix will be:

$$\widetilde{X} = \begin{bmatrix} 1 & x_{12} & x_{13} & x_{14} \\ x_{21} & 1 & x_{23} & x_{24} \\ x_{31} & x_{32} & 1 & x_{34} \\ x_{41} & x_{42} & x_{43} & 1 \end{bmatrix} \tag{7}$$

Then, invert the fuzzy number:

$$\overline{X}^{-1} = (x_1, x_2, x_3)^{-1} \tag{8}$$

The inversion for the fuzzy pairwise comparison matrix will be:

$$\widetilde{X}^{-1} = \begin{bmatrix} 1 & x_{12} & x_{13} & x_{14} \\ 1/x_{21} & 1 & x_{23} & x_{24} \\ 1/x_{31} & 1/x_{32} & 1 & x_{34} \\ 1/x_{41} & 1/x_{42} & 1/x_{43} & 1 \end{bmatrix} \tag{9}$$

Step 3: The fuzzy geometric mean value will be calculated by:

$$\begin{gathered} \widetilde{g}_{ij} = \widetilde{X}_1 \otimes \widetilde{X}_2 \otimes \widetilde{X}_3 \otimes \widetilde{X}_4 = (x_{11}, x_{21}, x_{31}) \otimes (x_{12}, x_{22}, x_{32}) \otimes (x_{13}, x_{23}, x_{33}) \\ \otimes (x_{14}, x_{24}, x_{34}) = (x_{11} * x_{12} * x_{13} * x_{14}, x_{21} * x_{22} * x_{23} * x_{24}, x_{31} * x_{32} * x_{33} * x_{34}) \end{gathered} \tag{10}$$

Step 4: The weight value of the fuzzy vector is conducted:

$$w_i = \left(\frac{x_1 + x_2 + x_3}{3} \right) \tag{11}$$

Step 5: After the vector weight value is calculated, the alternative value is estimated to rank the criteria and give a selection of decisions. The result provides a comparison of the criteria and the importance of alternative comparisons to each criterion.

In decision making problems, the fuzzy AHP method indicates various selection problems [33], distinctions between ranking factors [53], and the treatment of imprecise and vague estimates in uncertain environments [54]. This study was utilized to analyze and evaluate the measurement values of criteria to determine their impact level for the logistics company's performance.

4. Results

4.1. Efficiency Measurement

In recent years, Vietnam's logistics industry has transformed due to economic impacts. In this study, the super-SBM model in the DEA method was used for measuring the business efficiency of Vietnam' logistics companies from 2016 to 2022, which could present an overall observation of the operational process and provide a better understanding of how to improve it.

4.1.1. Data Analysis

Based on the research objective of evaluating the performance of logistics companies in Vietnam and the principle of the super-SBM model, the input and output variables of nine logistics companies in Vietnam from 2016 to 2022, i.e., Petrovietnam Transportation Corporation (PVT); Vietnam National Shipping Lines (MVN); Pacific Petroleum Transportation Joint Stock Company (PVP); International Gas Product Shipping Joint Stock Company (GSP); Airports Corporation Of VietNam (ACV); Port of Hai Phong Joint Stock Company (PHP); Dinh Vu Port Investment and Development Joint Stock Company (DVP); Transimex Corporation (TMS); and South Logistics Joint Stock Company (STG), were selected when their data were posted on Vietstock [55]. Three input variables, including the current assets (CA), non-current assets (NCA), and owner's equity (OE), and two output variables, including the net revenue (NR) and net profit after tax (NPFT), as shown in Figure 3, are the main points in the financial statement to determine each company's business performance; thus, they were selected to measure business efficiency.

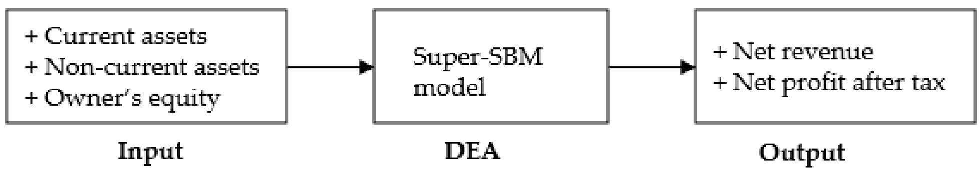

Figure 3. Data flowchart.

Input variables:

Current assets: All short assets alternate in the operational process, including cash, bank deposits, short-term receivables, and inventory. The current assets' validity term is often short and can return the capital within one year or a business cycle.

Non-current assets: The assets have high capital and long use, and include tangible fixed assets, intangible fixed assets, and other long-term assets.

Owner's equity: The investment funds are owned by the sole proprietor, partner, or shareholders.

Output variables:

Net revenue: The business profit of an enterprise is achieved from the business activities during managing and delivering the products.

Net profit after tax: The business result of an enterprise after deducting fees, including core operations and the net of taxes.

The historical values of logistics companies in Vietnam from 2016 to 2022 were collected and are summarized in Table A1. The maximum values of CA, NCA, OE, NR, and NPFT were 40,221, 25,185, 43,806, 18,329, and 8214, respectively; the minimum values of CA, NCA, OE, NR, and NPFT were 320, 54, 377, 518, and 33, respectively. All the collected data were positive and appreciated to apply in the super-SBM model.

4.1.2. Pearson Correlation Coefficient

The super-SBM model in the DEA method was used for measuring the business efficiency of Vietnam's logistics companies from 2016 to 2022. The data were applied to calculate the score of efficiency needed to test the correlation coefficient to ensure the isotonic relationship between the variables. The relationship between the variables of the DEA method identified three types of correlation, including that between the input and output, among the inputs only, and among the outputs only [56]. Their values range from −1 to 1, whereaswherein those close to zero indicate a low association, and those close to −1 and +1 indicate a robust linear association. Positive values of the correlation coefficient showed a tendency of one variable to increase or decrease together with another variable. Negative values of the correlation coefficient have a tendency to rise in value of one variable and decrease in value of the other variable [57]. The values of the correlation coefficient of the logistics companies in Table A2 ranged from 0.28232 to +1; thus, they were positive values and had a linear relationship between the variables. This demonstrates that these nine logistics companies' data were suitable for use in the super-SBM model for calculating their business efficiency scores.

4.1.3. Business Efficiency

The DEA method was utilized to measure the performance of DMUs, and the super-SBM model was utilized for conducting separate efficiency scores for DMUs over each year. Table 2 presents the efficiency change of logistics companies from 2016 to 2022. Their scores had a large fluctuation; the distances between the minimum and maximum values of PVN, MVN, PVP, GPS, ACV, PHP, DVP, TMS, and STG were, respectively, 2.36093, 2.03102, 0.8139, 6.2013, 0.87678, 0.80248, 1.22739, 0.62347, and 1.15685. Four companies, i.e., MVN, GPS, DVP, and TMS, always achieved an efficiency score in the whole-term when their scores were above one number in the whole-term, whereas GSP held the highest efficiency before the COVID-19 pandemic appeared in 2020. The remaining logistics companies had both inefficient and efficient scores. PVT and ACV attained efficiency, excluding 2021, when the PVT score reduced sharply to 0.71634, and the ACV score decreased sharply to 0.12322. STG revealed efficiency in 2017, 2021, and 2022; its lowest score was 0.5051 in 2016. PHP was efficient in 2016 and 2020; its lowest score was 0.57517 in 2017. PVP was a unique company that only attained an efficiency score in one year, i.e., a score of 1.09951 in 2020; additionally, it had the lowest efficiency in four periods, including three continual years from 2016 to 2018, with 0.28561, 0.30384, and 0.54837, respectively, and 0.75669 in 2022. The operations of each company were directly impacted by the COVID-19 pandemic, which resulted in lower efficiency scores in 2020 and further resulted in postponing manufacturing and discontinuity in the global supply chain.

Table 2. Business efficiency scores from 2016 to 2022 of logistics companies in Vietnam.

DMUs	2016	2017	2018	2019	2020	2021	2022
PVT	1.47896	1.21982	1.55269	1.62353	3.07727	0.71634	1.10850
MVN	2.53397	2.53341	2.16434	2.14556	3.03102	1.00000	2.58562
PVP	0.28561	0.30384	0.54837	0.71986	1.09951	0.72758	0.75669
GSP	5.62939	8.09925	3.39223	2.59714	2.65493	1.89795	1.95881
ACV	1.00000	1.00000	1.00000	1.00000	1.00000	0.12322	1.00000
PHP	1.37765	0.57517	0.68637	0.63470	1.21104	0.74996	0.81636
DVP	2.32096	1.29849	1.99321	1.67440	2.09580	2.35935	2.52588
TMS	1.67996	1.16393	1.23256	1.09705	1.15367	1.72052	1.26460
STG	0.50510	1.66195	0.58248	0.66432	0.66694	1.10816	1.09653

The results of nine logistics companies in Vietnam during the period of 2016–2022 from the super-SBM model in the DEA method escalated their efficiency scores to determine the ineffectiveness and effectiveness. Per the analyzed results, five logistics companies obtained inefficient scores; they should focus on improving their business results through an effective operating process. In this study, we investigated, analyzed, and suggested feasible solutions to increase the business values of Vietnam's logistics companies via the fuzzy AHP method.

4.2. Performance Improvement Direction

4.2.1. Strategic Structure in Business

Daniel et al. (2000) [58] revealed that cost, quality, and technologies were important factors for increasing the performance of a logistics company. David et al. (2017) [59] presented the critical factors, including industrial policy priorities, strategic infrastructure development, public–private logistics market growth, communication network configuration, and logistics performance. Pham and Nguyen (2020) [60] pointed out that marketing strategy quality, competitors in the logistics market innovation technology, etc., impact the performance of a logistics business. Based on these previous studies and the principle of the fuzzy AHP method, as well as the purpose of increasing the business efficiency of a logistics company, this study modified and established the FAHP structure of the increase of logistics performance, as shown in Figure 4.

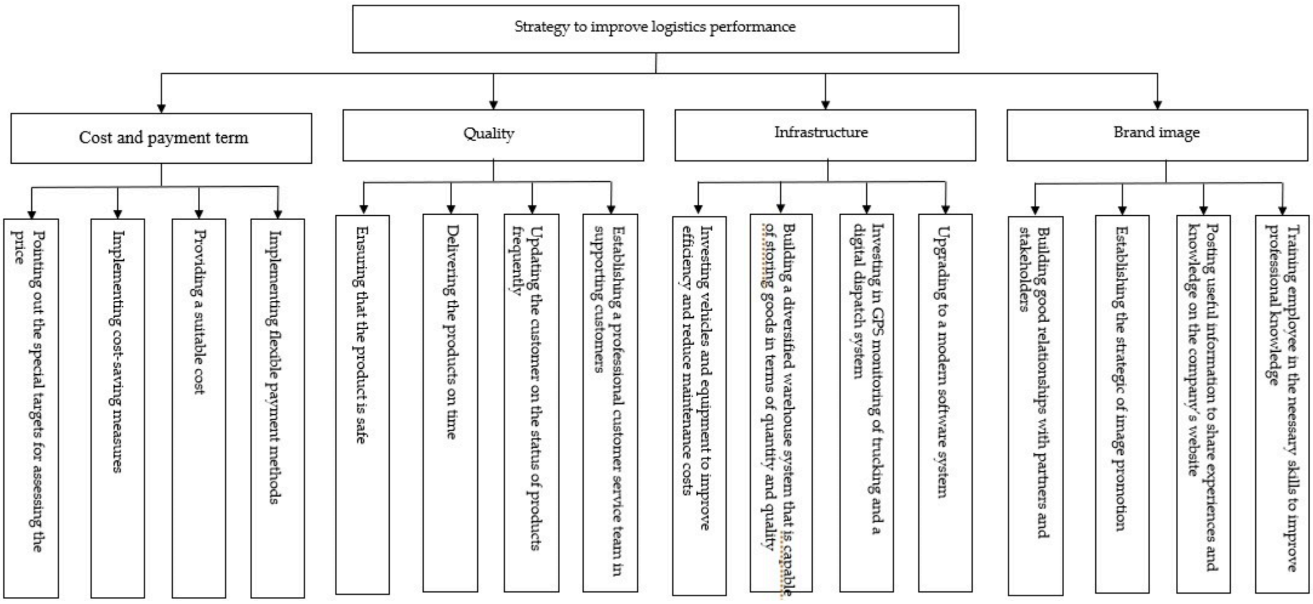

Figure 4. Improvement structure of logistics company's efficiency.

Figure 4 indicates that the strategy's goal to improve logistics performance in the first step. The four main criteria under the goal are the second level of the hierarchical structure. Sixteen sub-criteria under four main criteria are the third level of the hierarchical structure. Four main and sixteen sub-criteria were established to determine the impact factors to increase business efficiency; the main meaning of these criteria was clarified as shown in Table 3.

Table 3. Criteria for strategy implementation improves logistics performance.

Main Criteria	Sub-Criteria	Description
M_1—Cost and payment term	S_{11}—Pointing out the special targets for assessing the price S_{12}—Implementing cost-saving measures S_{13}—Providing a suitable cost S_{14}—Implementing flexible payment methods	The cost of each transportation type and the suitable payment term should be determined with detailed information.
M_2—Quality	S_{21}—Ensuring that the product is safe S_{22}—Delivering the products on time S_{23}—Updating the customer on the status of products frequently S_{24}—Establishing a professional customer service team in supporting customers	The goods are not damaged in transit are delivered in a timely manner. Additionally, the logistics company should follow-up closely and inform the consumer of the status of shipments frequently.
M_3—Infrastructure	S_{31}—Investing vehicles and equipment to improve efficiency and reduce maintenance costs S_{32}—Building a diversified warehouse system that is capable of storing goods in terms of quantity and quality S_{33}—Investing in GPS monitoring of trucking and a digital dispatch system S_{34}—Upgrading to a modern software system	
M_4—Brand image	S_{41}—Building good relationships with partners and stakeholders S_{42}—Establishing the strategic of image promotion S_{43}—Posting useful information to share experiences and knowledge on the company's website S_{44}—Training employees in the necessary skills to improve professional knowledge	

4.2.2. Analysis Results of Criteria

The factors above were designed based on the fuzzy AHP method. This questionnaire was delivered and evaluated by logistics and supply chain management experts with more than ten years of related work experience and a post-undergraduate degree.

The result of the pairwise comparison matrix of the main criteria was set up based on the triangular fuzzy number.

$$X = \begin{bmatrix} (1,1,1) & (1/8,1/7,1/6) & (9,9,9) & (9,9,9) \\ (6,7,8) & (1,1,1) & (6,7,8) & (1/7,1/6,1/5) \\ (1/9,1/9,1/9) & (1/8,1/7,1/6) & (1,1,1) & (1/8,1/7,1/6) \\ (1/9,1/9,1/9) & (5,6,7) & (6,7,8) & (1,1,1) \end{bmatrix} \tag{12}$$

The fuzzy geometric value

$$\widehat{G} = \begin{bmatrix} (1X0.125X9X9), (1X0.143X9X9), (1X0.167X9X9) \\ (6X1X6X0.143), (6X1X1X0.143), (8X1X8X0.2) \\ (0.111X0.125X1X0.125), (0.111X0.143X1X0.125), (0.111X0.167X1X0.167) \\ (0.111X5X6X1), (0.111X6X7X1), (0.111X7X8X1) \end{bmatrix}^{1/4} = \begin{bmatrix} (1.7838, 1.8444, 1.9168) \\ (1.5059, 1.6905, 1.8915) \\ (0.2042, 0.2183, 0.2358) \\ (1.3512, 1.4698, 1.5794) \end{bmatrix} \tag{13}$$

The fuzzy weights and weights

$$w_f = \begin{bmatrix} (0.3172, 0.3531, 0.3956) \\ (0.2678, 0.3237, 0.3904) \\ (0.0363, 0.0418, 0.0487) \\ (0.2403, 0.2814, 0.326 \end{bmatrix} = \begin{bmatrix} 0.3527 \\ 0.3249 \\ 0.0419 \\ 0.2805 \end{bmatrix} \tag{14}$$

The findings of the factors were conducted based on the process above, as shown in Table 4.

Table 4. The weights of criteria.

Main Criteria	Weights	Sub Criteria	Weights	Integrated Weight	Rank
M_1	**0.25905**	S_{11}	0.29363	0.07022	6
		S_{12}	0.24089	0.05761	8
		S_{13}	0.41784	0.09993	4
		S_{14}	0.04764	0.01139	16
M_2	**0.57556**	S_{21}	0.41792	0.14414	1
		S_{22}	0.33007	0.07894	5
		S_{23}	0.09161	0.02460	12
		S_{24}	0.16040	0.04056	11
M_3	**0.05868**	S_{31}	0.30444	0.06789	7
		S_{32}	0.44953	0.10751	3
		S_{33}	0.07213	0.01645	15
		S_{34}	0.17390	0.04159	10
M_4	**0.10671**	S_{41}	0.57983	0.13867	2
		S_{42}	0.15936	0.03811	12
		S_{43}	0.07718	0.01846	14
		S_{44}	0.18363	0.04392	9

Table 4 presents the weight of each criterion to describe their importance level. For the main criteria, M_2 has the highest weight at 0.57556; the second weight belongs to M_1 at 0.25905; the third weight is M_4 at 0.10671; and M_3 has the lowest weight at 0.05868. As a result, the range of the main criteria for the improvement of logistic performance is as follows: $M_2 > M_1 > M_4 > M_3$. The logistics company's quality is essential to identify, enhance, and increase development.

Each main criterion is explained particularly by the sub-criterion when an expert reviewed and evaluated the detailed sub-criterion. The weight of the cost and payment term is ranked $S_{13} > S_{11} > S_{12} > S_{14}$; this result indicates that S_{13} has an important and high effect. The weight of quality is organized as $S_{21} > S_{22} > S_{24} > S_{23}$; thus, S_{21} has the highest value and, most importantly, an increase in the quality processes. The weights of the sub-criteria for infrastructure are arranged as $S_{32} > S_{31} > S_{34} > S_{33}$; S_{32} has the most important meaning in building the infrastructures. The range of weight for a brand image's sub-criteria is organized as $S_{41} > S_{44} > S_{42} > S_{43}$, which means that S_{41} has an important and high impact in building the brand image of a logistics company.

The integrated valuation for each sub-criterion was conducted by the integration and calculation of the sub-criteria; the findings present the overall importance level of each criterion in a range: $S_{22} > S_{23} > S_{34} > S_{32} > S_{11} > S_{21} > S_{44} > S_{41} > S_{14} > S_{42} > S_{12} > S_{43} > S_{31} > S_{33} > S_{24} > S_{13}$. Furthermore, delivering products on time with an integrated weight of 0.14414 demonstrates the highest value, which indicates that it is the most important and meaningful element in improving and increasing the business performance of logistics companies in Vietnam.

The empirical results exhibit the classification and importance level of sub- and main criteria in improving the performance of Vietnam's logistics companies. The findings reveal that each logistics company should improve their quality of service by ensuring product safety, delivering the products on time, updating customers on the status of products frequently, and having professional customer service. Consequently, quality is an essential element that the customer uses for identifying and selecting the logistics service.

5. Discussion

The COVID-19 pandemic in 2020 had an impact on the worldwide transportation and logistics industry as a result of travel restrictions, border closures, flight cancellations, and lockdown restrictions; therefore, the logistics industry faced a unique challenge once the supply chain was disturbed. Figure 5 shows that the global logistics market in 2020 was worth USD 8.6 trillion [61], then it was reduced to USD 8.4 trillion in 2021 [62]. In

2022, once the COVID-19 pandemic had come under control, the logistics industry softly recovered and developed, and the global logistics market increased by approximately USD 10.41 trillion [9], thus reducing the global logistics market by USD 0.2 trillion in 2021.

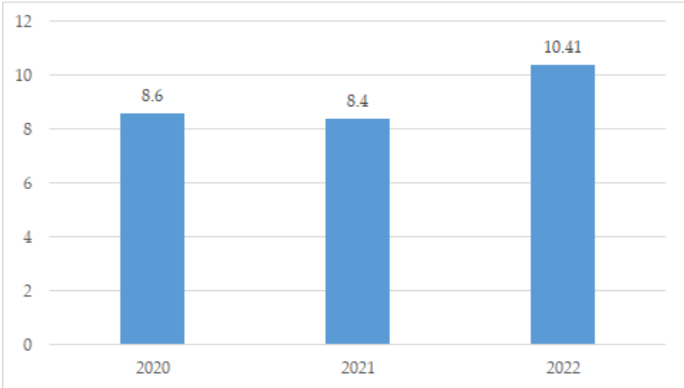

Figure 5. Global logistics market.

Vietnam had begun to achieve sustainable economic development when the COVID-19 pandemic directly impacted the logistics industry, resulting in the decline in the performance of its many logistics companies. Based on the super-SBM model, Table 2 reveals the shortfall performance levels of logistics companies as follows: PVT (2.36093); MVN (2.03102); ACV (0.87678); GSP (0.75698); PHP (0.46108); and PVP (0.37193). Since 2022, as the COVID-19 pandemic came under control, the performance recovered and increased as follows: PVT (0.39216); MVN (1.58562); ACV (0.87678); GSP (0.06086); PHP (0.06640); PVP (0.02911); and DVP (0.16653). In contrast, two companies, namely, TMS and STG, reduced their efficiency scores to 0.45992 and 0.01163, respectively, in 2022. As a result, the development of logistics enterprises depends on economic growth; furthermore, logistics companies must develop strategies to attract customers and increase their business performance.

This study suggests the improvement of logistics enterprises' performance when establishing and implementing strategies via consulting with experts when evaluating the impacted elements through the fuzzy AHP method. The criteria weights were estimated and analyzed to determine their importance in attracting customers to increase business performance. The results in Section 4.2.2 denote that a logistics company must have reasonable cost and payment term, high quality, modern and sufficient infrastructure and must build up a reputable brand image. Additionally, the final detailed result shows that companies must ensure their products are in the delivery process without damage or loss and will be delivered on time, and companies should update the milestones frequently. Each logistics company has a private business strategy; however, they establish strategies and plans based on customers' demand, applying Industry 4.0 technologies, such as the Internet of Things, automated guided vehicles, autonomous vehicles, artificial intelligence, big data, data mining, blockchain, cloud computing, electronic and mobile marketplaces, and realistic applications [63]. Companies must also construct modern warehouse systems with enough space to handle shipments. Consequently, logistics companies require suitable policies to persuade customers and ensure customer reliability.

The proposed approach, the super-SBM model, examined the collected data through the Pearson correlation, and then calculated the efficiency score to determine the effectiveness and ineffectiveness. The empirical result indicates that MVN, GSP, ACV, DVP, TMS, and STG always attained efficiency in the whole-term, although the COVID-19 pandemic from 2020 to 2022 impacted and postponed the global supply chain; moreover, PVT, PVP, and PHP were significantly influenced by the COVID-19 pandemic, which is reflected in their efficiency score, which was sharply reduced, and their inefficiency score. Next, the fuzzy AHP method analyzed the main and sub-criteria based on the experts' opinion. The finding reveals that logistics companies should have a suitable strategy for establishing and managing their delivery processes to improve service quality, increase customer service, innovate technology, and set up a diversified warehouse.

6. Conclusions

The logistics industry is the backbone of economic development, i.e., it is a bridge to connect and deliver products from the manufacturer to customers through different transportation modes, such as air, ocean, truck, and train; hence, researchers have studied and presented different approaches to logistics to evaluate operational processes, estimate future performance, and suggest recommendations to improve efficiency. It should be noted, however, that previous research on logistics has exhibited performance and impact criteria that have not been combined to measure the efficiency and evaluate the requirements to draw an overall picture of the operational process and its influencing elements. This study integrated the super-SBM model in the DEA method to estimate the efficiency scores, and the fuzzy AHP method to determine the weights and identify the importance of each criterion in establishing a strategy for improving efficiency for logistics companies in Vietnam.

Significant results were discovered as follows: the business performance of nine logistics companies was evaluated to identify efficient and inefficient periods based on the super-SBM model. These detailed efficiency scores revealed the operational status so that the estimated calculation was implemented by the fuzzy AHP method to determine the impact level of the criteria.

The empirical results help logistics companies to identify their abilities, positions, and challenges in supply chain management and find a feasible solution to improve future performance. Furthermore, customers can learn about logistics companies' professional competence to select a suitable service. Readers typically process deep knowledge of Vietnam's logistics industry and understand their operational processes.

Although this study presents the performance and recommends a solution to improve logistics companies' efficiency scores in Vietnam, it still has drawbacks. First, all of the logistics companies' data were not collected; future research could gather more decision-making units to offer a broader picture. Second, the input and output variable factors were not diverged; future research could consider more factors, such as labor force, net interest after tax, etc., to obtain a large and deep measurement. Third, excluding the experts' opinions, further study could implement an investigation for logistics companies to understand their status and difficulties in specific scenarios. This study only analyzed and indicated the current situations; further research could use more models, such as grey forecasting, tableau, and ARIMA models, to estimate the future value.

Author Contributions: T.K.L.N. designed the research framework, analyzed the data, and wrote the draft paper; T.L.H.N. and B.A.H. gathered the data; T.L.N. analyzed the data; H.H.L. created the visualization; T.T.H.T. reviewed and edited the paper. All authors have read and agreed to the published version of the manuscript.

Funding: This research received the support of Thanh Dong University (Project No. TDU.1792010).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: We would like to thank the anonymous reviewers for their valuable comments.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Description data (Million Dong).

Indication	Years	(I)CA	(I)NCA	(I)OE	(O)NR	(O)NPFT
Max	2016	22,151	25,185	25,054	14,633	2718
Min		320	73	377	616	33
Average		4403	6814	4921	4354	501
SD		6766	9040	7374	4864	806
Max	2017	26,343	22,820	27,384	13,830	4122
Min		458	54	388	627	53
Average		4966	6313	5491	4675	781
SD		7896	8238	8072	5057	1201
Max	2018	31,264	22,260	30,749	16,090	6148
Min		410	280	404	639	64
Average		5618	6135	6122	5088	963
SD		9379	7702	9085	5304	1844
Max	2019	37,291	20,885	36,757	18,329	8214
Min		367	421	452	560	52
Average		6368	5967	7056	5222	1195
SD		11252	7099	10883	5690	2492
Max	2020	37,974	18,928	37,565	9972	1642
Min		395	359	462	518	60
Average		6702	5432	7235	4031	468
SD		11421	6347	11066	3218	472
Max	2021	37,568	17,412	37,653	13,267	3189
Min		542	329	658	609	56
Average		7138	5456	7778	4502	767
SD		11286	5917	11046	3811	897
Max	2022	40,221	19,817	43,806	14,350	7127
Min		507	280	737	585	82
Average		7630	5911	9047	5531	1459
SD		12,040	6568	12,919	5115	2129

Note: SD—standard deviation.

Table A2. Pearson correlation.

Variables	Years	(I)CA	(I)NCA	(I)OE	(O)NR	(O)NPAT
(I)CA	2016	1.00000	0.92139	0.98540	0.75533	0.89535
(I)NCA		0.92139	1.00000	0.85088	0.92967	0.66602
(I)OE		0.98540	0.85088	1.00000	0.65281	0.95649
(O)NR		0.75533	0.92967	0.65281	1.00000	0.42586
(O)NPAT		0.89535	0.66602	0.95649	0.42586	1.00000
(I)CA	2017	1.00000	0.87790	0.99728	0.83220	0.98353
(I)NCA		0.87790	1.00000	0.86397	0.98383	0.78969
(I)OE		0.99728	0.86397	1.00000	0.81680	0.98705
(O)NR		0.83220	0.98383	0.81680	1.00000	0.73336
(O)NPAT		0.98353	0.78969	0.98705	0.73336	1.00000

Table A2. *Cont.*

Variables	Years	(I)CA	(I)NCA	(I)OE	(O)NR	(O)NPAT
(I)CA	2018	1.00000	0.88469	0.99832	0.87881	0.97220
(I)NCA		0.88469	1.00000	0.89262	0.98206	0.75441
(I)OE		0.99832	0.89262	1.00000	0.88583	0.96822
(O)NR		0.87881	0.98206	0.88583	1.00000	0.75862
(O)NPAT		0.97220	0.75441	0.96822	0.75862	1.00000
(I)CA	2019	1.00000	0.87773	0.99863	0.91968	0.97899
(I)NCA		0.87773	1.00000	0.88684	0.98120	0.77050
(I)OE		0.99863	0.88684	1.00000	0.92947	0.97642
(O)NR		0.91968	0.98120	0.92947	1.00000	0.84384
(O)NPAT		0.97899	0.77050	0.97642	0.84384	1.00000
(I)CA	2020	1.00000	0.89029	0.99843	0.60807	0.88362
(I)NCA		0.89029	1.00000	0.88254	0.88381	0.72344
(I)OE		0.99843	0.88254	1.00000	0.60578	0.90665
(O)NR		0.60807	0.88381	0.60578	1.00000	0.51587
(O)NPAT		0.88362	0.72344	0.90665	0.51587	1.00000
(I)CA	2021	1.00000	0.88665	0.99773	0.29993	0.30724
(I)NCA		0.88665	1.00000	0.88160	0.69276	0.67083
(I)OE		0.99773	0.88160	1.00000	0.29169	0.28232
(O)NR		0.29993	0.69276	0.29169	1.00000	0.90929
(O)NPAT		0.30724	0.67083	0.28232	0.90929	1.00000
(I)CA	2022	1.00000	0.90249	0.99870	0.77528	0.99705
(I)NCA		0.90249	1.00000	0.91209	0.96945	0.92440
(I)OE		0.99870	0.91209	1.00000	0.78834	0.99842
(O)NR		0.77528	0.96945	0.78834	1.00000	0.80503
(O)NPAT		0.99705	0.92440	0.99842	0.80503	1.00000

References

1. Chung, S.H. Applications of smart technologies in logistics and transport: A review. *Transp. Res. E Logist. Transp. Rev.* **2021**, *153*, 102455. [CrossRef]
2. Orozonova, A.; Gapurbaeva, S.; Kydykov, A.; Prokopenko, O.; Prause, P.; Lytvynenko, S. Application of smart logistics technologies in the organization of multimodal cargo delivery. *Transp. Res. Procedia* **2022**, *63*, 1192–1198. [CrossRef]
3. Barreto, L.; Amaral, A.; Pereira, T. Industry 4.0 implications in logistics: An overview. *Procedia Manuf.* **2017**, *13*, 1245–1252. [CrossRef]
4. Holubčík, M.; Koman, G.; Soviar, J. Industry 4.0 in Logistics Operations. *Transp. Res. Procedia* **2021**, *53*, 282–288. [CrossRef]
5. Mariusz, K.; Ludmiła, F.D.; Szymon, W. Modern technologies development in logistics centers: The case study of Poland. *Transp. Res. Procedia* **2021**, *55*, 268–275.
6. Šourek, D. Software Support of City Logistics' Processes. *Transp. Res. Procedia* **2021**, *55*, 172–179. [CrossRef]
7. Voronova, O. Improvement of warehouse logistics based on the introduction of lean manufacturing principles. *Transp. Res. Procedia* **2022**, *63*, 919–928. [CrossRef]
8. Nechaev, A.; Barykina, Y.; Tyapkina, M. Development of methodological approaches to improve the transport and logistics system using the international leasing. *Transp. Res. Procedia* **2022**, *63*, 441–448. [CrossRef]
9. Statistics. Size of the Logistics Industry Worldwide 2018–2022. 2023. Available online: https://www.statista.com/statistics/943517/logistics-industry-global-cagr/ (accessed on 1 May 2023).
10. The State President. Commercial law. No. 36/2005/QH11. 2005. Available online: https://thuvienphapluat.vn/van-ban/Thuong-mai/Luat-Thuong-mai-2005-36-2005-QH11-2633.aspx (accessed on 1 May 2023).

11. Statistics. GDP Contribution of the Transportation and Storage Sector in Vietnam from 2015 to 2021. 2023. Available online: https://www.statista.com/statistics/1047729/vietnam-gdp-contribution-of-transportation-and-storage-sector/ (accessed on 1 May 2023).
12. Pham, H.C.; Nguyen, T.T.; Scott, M.; Tran, K.N.Q. Information Sharing in Logistics Firms: An Exploratory Study of the Vietnamese Logistics Sector. *Asian J. Shipp. Logist.* **2019**, *35*, 87–95. [CrossRef]
13. Liu, L.; Long, Z.; Kou, C.; Guo, H.; Li, X. Evaluation of the Environmental Cost of Integrated Inbound Logistics: A Case Study of a Gigafactory of a Chinese Logistics Firm. *Sustainability* **2023**, *15*, 11520. [CrossRef]
14. Wang, R.; Li, J.; Bai, R. Prediction and Analysis of Container Terminal Logistics Arrival Time Based on Simulation Interactive Modeling: A Case Study of Ningbo Port. *Mathematics* **2023**, *11*, 3271. [CrossRef]
15. Risberg, A.; Jafari, H.; Sandberg, E. A configurational approach to last mile logistics practices and omni-channel firm characteristics for competitive advantage: A fuzzy-set qualitative comparative analysis. *Int. J. Phys. Distrib. Logist. Manag.* **2023**, *53*, 53–70. [CrossRef]
16. Dalila, R. Tracking the Van: The role of forward linkages in logistics MNEs' location choices across European NUTS 3 regions. *Pap. Reg. Sci.* **2023**, *102*, 217–460.
17. Nataraj, S.; Alvarez, C.; Sada, L.; Juan, A.A.; Panadero, J.; Bayliss, C. Applying Statistical Learning Methods for Forecasting Prices and Enhancing the Probability of Success in Logistics Tenders. *Transp. Res. Procedia* **2020**, *47*, 529–536. [CrossRef]
18. De Souza, E.D.; Kerber, J.C.; Bouzon, M.; Rodriguez, C.M.T. Performance evaluation of green logistics: Paving the way towards circular economy. *Clean. Logist. Supply Chain* **2022**, *3*, 100019. [CrossRef]
19. Tikwayo, L.N.; Mathaba, T.N.D. Applications of Industry 4.0 Technologies in Warehouse Management: A Systematic Literature Review. *Logistics* **2023**, *7*, 24. [CrossRef]
20. Zaare, T.F.; Daneshvar, S. Benchmark Approach for Efficiency Improvement in Green Supply Chain Management with DEA Models. *Sustainability* **2023**, *15*, 4433. [CrossRef]
21. Le, V.H.; Dang, Q.H. The Factors Affecting Digital Transformation in Vietnam Logistics Enterprises. *Electronics* **2023**, *12*, 1825.
22. Wang, C.N.; Day, J.D.; Lien, N.T.K.; Chien, L.Q. Integrating the Additive Seasonal Model and Super-SBM Model to Compute the Efficiency of Port Logistics Companies in Vietnam. *Sustainability* **2018**, *10*, 2782. [CrossRef]
23. Marto, M.; Lourenço, M.J.; Madaleno, M. An Evaluation of the Efficiency of Tertiary Education in the Explanation of the Performance of GDP per Capita Applying Data Envelopment Analysis (DEA). *Sustainability* **2022**, *14*, 15524. [CrossRef]
24. Goyal, M.; Lu, J.; Zhang, G. Decision Making in Multi-Issue e-Market Auction Using Fuzzy Techniques and Negotiable Attitudes. *J. Theor. Appl. Electron. Commer. Res.* **2008**, *3*, 97–110. [CrossRef]
25. Dogan, O. A Recommendation System in E-Commerce with Profit-Support Fuzzy Association Rule Mining (P-FARM). *J. Theor. Appl. Electron. Commer. Res.* **2023**, *18*, 831–847. [CrossRef]
26. Chen, Y.; Du, J.; Hoa, J. Super-efficiency based on a modified directional distance function. *Omega* **2013**, *41*, 621–625. [CrossRef]
27. Zhou, C.S.; Shi, C.Y.; Wang, S.J.; Zhang, G.J. Estimation of eco-efficiency and its influencing factors in Guangdong province based on Super-SBM and panel regression models. *Ecol. Indic.* **2018**, *86*, 67–80. [CrossRef]
28. Wang, C.N.; Hsu, H.P.; Wang, J.W.; Kao, Y.C.; Nguyen, T.P. Strategic Alliance for Vietnam Domestic Real Estate Companies Using a Hybrid Approach Combining GM (1,1) with Super SBM DEA. *Sustainability* **2020**, *12*, 1891. [CrossRef]
29. Huang, Y.S.; Liu, S.J. Efficiency evaluation of a sustainable hydrogen production scheme based on super efficiency SBM model. *J. Clean. Prod.* **2020**, *256*, 120447. [CrossRef]
30. Du, Y.W.; Jiang, J.; Li, C.H. Ecological efficiency evaluation of marine ranching based on the Super-SBM model: A case study of Shandong. *J. Clean. Prod.* **2021**, *131*, 108174. [CrossRef]
31. Ma, F.N.; Li, J.Y.; Ma, H.W.; Sun, Y. Evaluation of the Regional Financial Efficiency Based on SBM-Shannon Entropy model. *Procedia Comput. Sci.* **2022**, *199*, 954–961. [CrossRef]
32. Emrouznejad, A.; Marra, M. The state of the art development of AHP (1979–2017): A literature review with a social network analysis. *Int. J. Prod. Res.* **2017**, *55*, 6653–6675. [CrossRef]
33. Liu, Y.; Eckert, C.M.; Earl, C. A review of fuzzy AHP methods for decision-making with subjective judgements. *Expert Syst. Appl.* **2020**, *161*, 113738. [CrossRef]
34. Rezaie, K.; Ramiyani, S.S.; Nazari-Shirkouhi, S.; Badizadeh, A. Evaluating performance of Iranian cement firms using an integrated fuzzy AHP–VIKOR method. *Appl. Math. Model.* **2014**, *38*, 5033–5046. [CrossRef]
35. Ali, N.; Mohammad, H.K.; Majid, G. Application of fuzzy AHP method to IOCG prospectivity mapping: A case study in Taherabad prospecting area, eastern Iran. *Int. J. Appl. Earth Obs. Geoinf.* **2014**, *33*, 142–154.
36. Choosakun, A.; Yeom, C. Developing Evaluation Framework for Intelligent Transport System on Public Transportation in Bangkok Metropolitan Regions Using Fuzzy AHP. *Infrastructures* **2021**, *6*, 182. [CrossRef]
37. Wang, G.; Liu, L.; Shi, P.; Zhang, G.; Liu, J. Flood Risk Assessment of Metro System Using Improved Trapezoidal Fuzzy AHP: A Case Study of Guangzhou. *Remote Sens.* **2021**, *13*, 5154. [CrossRef]
38. Şahin, Y.; Kulakli, A. Evaluation of Open and Distance Education Websites: A Hybrid Multi-Criteria Decision-Making Approach. *Systems* **2023**, *11*, 58. [CrossRef]
39. Cooper, J.O.; Heron, T.E.; Heward, W.L. *Applied Behavior Analysis*; Pearson: New York, NY, USA, 2007.
40. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the Efficiency of Decision-Making Units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]

41. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
42. Andersen, P.; Niels, C.P. A Procedure for Ranking Efficient Units in Data Envelopment Analysis. *Manag. Sci.* **1993**, *39*, 1261–1264. [CrossRef]
43. Tone, K. A slacks-based measure of super-efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2002**, *243*, 32–41. [CrossRef]
44. Saaty, T.L. Decision-making with the AHP: Why is the principal eigenvector necessary. *Eur. J. Oper. Res.* **2003**, *145*, 85–91. [CrossRef]
45. Cheng, C.H. Group opinion aggregation based on a grading process: A method for constructing triangular fuzzy numbers. *Comput. Math. Appl.* **2004**, *48*, 1619–1632. [CrossRef]
46. Ballı, S.; Korukoğlu, S. Operating System Selection Using Fuzzy AHP and TOPSIS Methods. *Math. Comput. Appl.* **2009**, *14*, 119–130. [CrossRef]
47. Ryjov, A. Fuzzy Linguistic Scales: Definition, Properties and Applications. In *Soft Computing in Measurement and Information Acquisition*; Reznik, L., Kreinovich, V., Eds.; Studies in Fuzziness and Soft Computing; Springer: Berlin/Heidelberg, Germany, 2003; Volume 127, pp. 23–38.
48. Ryjov, A. The Degree of Fuzziness of Fuzzy Descriptions. In *Mathematical Cybernetics and its Application to Biology*; Moscow University Publishing: Moscow, Russia, 1987; pp. 60–77.
49. Ryjov, A. *The Axiomatic Definition of a Linguistic Scale Fuzziness Degree, Its Major Properties and Applications*; Johnson Space Center, North American Fuzzy Logic Proceeding Society (NAFIPS'92); NASA: Houston, TX, USA, 1992; pp. 21–29.
50. Deliktas, D.; Ustun, O. Multiple criteria decision-making approach for industrial engineer selection using fuzzy AHP-Fuzzy TOPSIS. *Anadolu Univ. J. Sci. Technol. A—Appl. Sci. Eng.* **2018**, *19*, 58–82. [CrossRef]
51. Buckley, J.J. Fuzzy hierarchical analysis. *Fuzzy Sets Syst.* **1985**, *17*, 233–247. [CrossRef]
52. Dwi, P.; Mochammad, S. Fuzzy Analytical Hierarchy Process Method to Determine the Quality of Gemstones. *Adv. Fuzzy Syst.* **2018**, *2018*, 9094380.
53. Chen, S.J.; Hwang, C.L. *Fuzzy Multiple Attribute Decision Making*; Springer: New York, NY, USA, 1992.
54. Zadeh, L.A. Fuzzy sets. *Inf. Control.* **1965**, *8*, 338–353. [CrossRef]
55. Vietstock. 2023. Available online: https://finance.vietstock.vn/ (accessed on 19 January 2023).
56. López, F.J.; Ho, J.C.; Ruiz-Torres, A.J. A computational analysis of the impact of correlation and data translation on DEA efficiency score. *J. Ind. Prod. Eng.* **2016**, *33*, 192–204. [CrossRef]
57. Kirch, W. Pearson's Correlation Coefficient. In *Encyclopedia of Public Health*; Springer: Dordrecht, Germany, 2008; pp. 1090–1091.
58. Daniel, F.L.; Scott, B.K.; John, O. The effects of logistics capabilities and strategy on firm performance. *J. Bus. Logist.* **2000**, *21*, 47–67.
59. David, W.H.; Paul, C.H.; Daniel, Y.L. Critical factors that affect logistics performance: A comparison of China, Japan and Korea. *Int. J. Shipp. Transp. Logist.* **2017**, *9*, 107–129.
60. Pham, V.H.; Nguyen, T.T. Factors affecting marketing strategy of logistics business—Case of Vietnam. *Asian J. Shipp. Logist.* **2020**, *36*, 224–234.
61. Martin, P. Global Logistics Market Size by Region 2020. 2022. Available online: https://www.statista.com/statistics/1069868/total-global-logistics-market-size-region/ (accessed on 3 June 2023).
62. Martin, P. Logistics Industry Worldwide—Statistics & Facts. 2023. Available online: https://www.statista.com/topics/5691/logistics-industry-worldwide/#topicOverview (accessed on 3 June 2023).
63. Mladen, K.; Giulio, P.A.; Pier, P.M.; Snežana, T. Evaluation of the smart reverse logistics development scenarios using a novel MCDM model. *Clean. Environ. Syst.* **2022**, *7*, 100099.