Available online at http://ijdea.srbiau.ac.ir

Int. J. Data Envelopment Analysis (ISSN 2345-458X)

Vol. 12, No. 1, Year 2024 Article ID IJDEA-00422, Pages 10-22
Research Article

International Journal of Data Envelopment Analysis   Science and Research Branch (IAU)

A Decision-Making Model for Supplier Selection Based on Data Envelopment Analysis

H. Moradi*, Mehdi abbaszadeh

Received 3 July 2023, Accepted 13 January 2024

Abstract
This study aims to provide a comprehensive evaluation of the technical efficiency and scale of 15 suppliers of a production unit from 2020 to 2022. The research utilizes Data Envelopment Analysis (DEA) to analyze two scale assumptions that are generally employed: constant returns to scale (CRS), and variable returns to scale (VRS). The variables for the study were selected based on indicator availability, representation principles, and expert opinions. Investment, nonoperating expense cost and operating costs (including raw material costs, wages, and overhead costs) were considered as inputs, while net sales and return on investment were regarded as outputs. The results indicate that only two suppliers were operating at the optimal scale, and the scale efficiency of the supply chain displayed an increasing dispersion over the mentioned period. However, the net technical efficiency of the supply chain demonstrated an increasing concentration, suggesting an overall reduction in the gap between suppliers and an improvement in pure technical efficiency within the manufacturing unit's supply chain. This study provides valuable insights into the differences between suppliers from a macro perspective and offers guidance for manufacturing units looking to expand their supply chain.

Keywords: Data Envelopment Analysis, Supply Chain, return to scale, efficiency.

* Corresponding author: Email: hoda_mrd@gmail.com

1. Introduction

In today's rapidly evolving business landscape, organizations face increasingly complex decisions when selecting suppliers [1]. This directly affects the organization's ability to provide high-quality products and services effectively [2], and despite the multitude of suppliers in the market, finding the right supplier has become a challenging issue in organizations [3]. Thus, organizations have taken strict measures to select suppliers to ensure that they comply with the organization's supply chain considerations [4]. Choosing a suitable supplier affects cost management, quality control, timely delivery, supply chain responsiveness, and innovation capabilities [5]. However, choosing an inappropriate supplier can lead to increased costs, product defects, delays, and overall disruption in the chain [6]. Therefore, it is very important to evaluate the performance of suppliers to reduce such risks and ensure the smooth operation of the supply chain [7]. To overcome this challenge effectively, organizations have turned to data-driven approaches to help their decision-making processes [8]. These approaches allow decision-makers to make objective and informed choices based on quantitative data analysis rather than relying on subjective judgments or personal preferences. For this purpose, various methods have been introduced for such evaluation, including DEA. These methods enable organizations to analyze and compare the efficiency of suppliers by considering several inputs and outputs simultaneously and provide a comprehensive evaluation framework [9]. Classical models of the DEA method are divided into two categories: CCR and BCC [10]. Each of these cases can be examined from two viewpoints: input and output. In the CCR model, the assumption is on the CRS, and in the model, the assumption is on the VRS [11].

The current research aims to equip decision makers with tools to effectively simplify the supplier selection process and make informed choices based on quantitative data analysis. By adopting this decision-making model, organizations can increase their competitiveness, minimize supply chain risks, and build long-term partnerships with suppliers that align with their business goals and objectives. In this regard, by providing an appropriate model and using the available information, the technical efficiency of the suppliers is calculated in two scale assumptions, CRS and VRS, and Then, considering that managers are interested in obtaining scale effects, scale efficiency and the kinds of return to scale of suppliers are determined. In addition, this study provides solutions to reach the efficiency frontier for inefficient suppliers. In the next section, we provide a brief overview of the theoretical framework of the research, describe the data used, calculate the efficiency values, discuss the findings, and draw relevant conclusions.

2. The theoretical framework of research

In this section, we will briefly examine the methods used in this research from the perspective of the literature, and at the end, we will refer to the background of the research.

2.1 Supply chain management

In general, supply chain management enables timely movement of goods from suppliers to manufacturers and from manufacturers to customers. Ultimately, this enables the organization to keep costs low [12]. Four decades have passed since the presentation of this concept by Oliver and Weber, and many advances have been made in the analysis, investigation, and development of concepts related to it [13]. Especially in today's turbulent environment, where competition from the level of organizations is focused on their supply chain because the supply chain has become one of the most important parts of the organization that can differentiate the organization from other competitors in the field of competition to improve its position in global markets [14]. In other words, supply chain management is no longer a cost center [15]; rather, it is one of the components of competitive strategies for the productivity and profitability of an organization [16]. In recent years, supply chain evaluation has been the subject of many researchers who have proposed and used different methods for this purpose. For example, Mzougui et al. used conventional multi-criteria decision-making (MCDM) methods to evaluate and select suppliers [17]. Some researchers, such as Moradi et al., use the DEA method alone [18], and others have used a combination of DEA with MCDM [19]. In this study, classic DEA models were used to evaluate supply chains.

2.2 Data envelopment analysis

Data envelopment analysis is a linear programming technique used in this study to evaluate the efficiency of suppliers in a production unit. This method has been utilized for many years in various fields [10]. Efficiency values resulting from the implementation of DEA are confined between zero and one. Suppliers are considered efficient if they obtain an efficiency score of one, implying that it is not possible to increase or decrease the outputs or inputs [20]. Suppliers with efficiency values less than one are deemed ineffective [21]. Each supplier is evaluated by comparing its efficiency with the efficiency limit [18]. The efficiency frontier is composed of the best-performing suppliers [22]. If a supplier lies on the efficiency frontier, it is considered fully efficient; otherwise, it is considered inefficient. The shape of the frontier is determined partially by assuming either CRS or VRS. The VRS model establishes a boundary by utilizing a convex body, restricting the efficiency of the CRS model [23]. In this study, CRS and VRS efficiency values were calculated to compare the efficiency of the scale. Considering that these two models are presented in two orientations, input-oriented and output-oriented, the nature of the model needs to be determined first. Input-oriented models aim to minimize inputs while keeping the output level constant, whereas output-oriented models strive to increase the output level while keeping inputs constant [10]. In this study, managers have more control over inputs than outputs. Therefore, an input-oriented nature was chosen, reflecting the primary goals of policymakers, such as cost reduction and resource limitation based on accountability. Equations 1 and 2 illustrate the input-oriented CCR and BCC models, respectively.

Input-oriented CCR model

$$
\begin{aligned}
&\text{Min } Z_0 = \theta \\
&\text{st:} \\
&\quad \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0} \quad (r = 1, 2, \ldots, s) \\
&\quad \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{i0} \quad (i = 1, 2, \ldots, m) \\
&\quad \lambda_j \geq 0
\end{aligned}
\tag{1}
$$

Input-oriented BCC model

$$
\begin{aligned}
&\text{Min } Z_0 = \theta \\
&\text{st:} \\
&\quad \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}, \quad (r = 1, 2, \ldots, s) \\
&\quad \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{i0}, \quad (i = 1, 2, \ldots, m) \\
&\quad \sum_{j=1}^{n} \lambda_j = 1, \quad (j = 1, 2, \ldots, n) \\
&\quad \lambda_j \geq 0 \ , \quad \theta \text{ is free}
\end{aligned}
\tag{2}
$$

This study considers determining the efficiency value of suppliers at their optimal scale, known as scale efficiency. The efficiency values obtained by assuming a constant returns to scale model (Relation 1) are not pure and are associated with scale efficiency. Therefore, to separate technical efficiency from scale efficiency, the VRS model was used to measure pure technical efficiency. As is clear from relations 1 and 2, the VRS pattern is obtained by adding an adverb to the CRS pattern. If there is a difference between the efficiency values resulting from the implementation of the VRS and CRS models, it indicates the concept of scale inefficiency, and the scale inefficiency value is the difference between the technical efficiency of the VRS and CRS models. Therefore, according to the said content, we have:

$$\text{CRS Score} = \text{puretechnical Eff}\left(\text{VRS Score}\right) \times \text{Scale Eff} \quad (3)$$

Therefore:

$$\text{Scale Eff} = \text{CRS Score} / \text{VRS Score} \quad (4)$$

The values of scale efficiency (Relation 4) help to understand the extent of the difference between suppliers since some suppliers do not operate under optimal conditions.

2.3 Research Background

Thus far, much research has been conducted in the field of measuring technical efficiency and its scale, advantages, and benefits. Table 1 mentions a number of these that are somewhat close to the subject of the current research. However, measurement of supply chain efficiency has not been clearly discussed in the literature. In general, this research deals with estimating the technical efficiency and scale of the supply chain of a production unit in the time frame of 2020 to 2022. Because our study employs three-year-old data, the results are not meant to uncritically inform current decision-making processes, but rather to illustrate the potential value of such efficiency analyses. Simultaneously, the increase in production or decrease in input for inefficient suppliers is determined to achieve efficiency. Therefore, this study supports this research gap and offers suitable innovation. We hope that this study will lay the groundwork for future research.

Table 1. Research Background

Researcher	Title	Description	Result
Garcia Sanchez [24]	Technical and scale efficiency in Spanish urban transport: Estimating with data envelopment analysis	This study investigated the technical and scale efficiency of the Spanish transportation system using DEA	The results showed that the average technical efficiency and the scale of the Spanish public transportation system are 94.91 and 52.02%, respectively, and increasing service access is very important as a quality parameter in its performance
Sharma & Sharma [25]	Analyzing the technical and scale efficiency Of small industries in India: state-wise cluster study	This study examined the technical and scale efficiencies of 23 Indian states. To do this, he used the DEA model, specifically the BCC.	The results showed that seven states were technically efficient, whereas only two states were efficient in terms of scale efficiency. Most states operate with diminishing returns to scale, indicating more investment and employment creation spaces.

Kirigia & Asbu	[26]	Technical and scale efficiency of public community hospitals in Eritrea: an exploratory study	This study investigated the efficiency of Eritrean hospitals using a two-stage DEA to estimate the relative technical efficiency and scale of public hospitals.	This study showed that hospital data collected routinely in Eritrea can be used to identify relatively inefficient hospitals, as well as the sources of their inefficiency.
Wanke & Barros	[27	Public-Private Partnerships and Scale Efficiency in Brazilian Ports: Evidence from Two-Stage DEA Analysis	This study evaluates the impact of public and private partnerships of public ports in Brazil using the DEA method. This study aimed to achieve higher levels of scale efficiency.	The results indicated a strong positive impact of public-private partnerships on port-scale efficiency, corroborating their impacts on the most productive scale size.
Havidz et al	[28]	Technical and Scale Efficiency Employing Data Envelopment Analysis: Empirical Evidence from	This research investigated the technical efficiency and scale of 10 public Islamic banks in Indonesia with the intermediation approach and through the DEA method	The results showed that the average technical efficiency in the whole quarter for all Islamic state banks is 72.9% and the technical inefficiency is caused by pure technical inefficiency, compared to scale inefficiency
Yousef et al	[29]	Measuring the Relative Efficiency and Scale Efficiency of Health Organization in Thi Qar Province Using BCC Model	This study measured the relative and scale efficiencies of the health centers of Thi Qar province, Iraq, using the BCC model.	The results indicated that out of the eight treatment centers under investigation, six centers were efficient. In addition, the analysis of scale efficiency values showed that most hospitals achieved high efficiency in 2020 and improved their performance by 2021.

3. Research methodology

The statistical population of this study includes 15 suppliers of a production unit who were active from 2020 to 2022. Before measuring the efficiency of suppliers, it is necessary to determine the input and output variables. For this purpose, following the principles of representation and availability of indicators and considering the opinions of experts in the field and similar research, the input and output variables of the model were determined. Investment, nonoperating expense cost and operating costs (including raw material costs, wages, and overhead costs) were considered as inputs, while net sales and return on investment (ROI) were considered as outputs. Then, according to the nature of the investigated system and based on the mentioned materials, an appropriate DEA model was chosen to calculate efficiency. The data were analyzed using GAMS, EXCEL, and SPSS software. According to the stated content, the model used in the present study is a single-stage BCC and CCR input-oriented model (Relations 1 to 2). Then, scale efficiency (Relation 4) is used to increase the understanding of the fact that the difference in supplier performance is caused by the fact that some suppliers do not operate under optimal conditions. Investment and operating costs (including raw material costs, wages, and overhead costs) were considered as inputs, while net sales and return on investment were considered as outputs.

4. Findings

First, descriptive statistics was used to organize and describe the data used in this study. The indicators used for the descriptive analysis included the mean, maximum, minimum, and standard deviation. Table 2 lists the data.

Table 2: Descriptive analysis of research data

	Mean	Std. Deviation	Minimum	Maximum
ROI	10. 18	1. 600	7	14
net sales	792391. 84	371308. 610	108738	2079720
nonoperating expense	105014. 40	79416. 550	50876	375786
overhead costs	240407. 64	97666. 632	80874	528158
wages Cost	43210. 20	8374. 129	30387	60434
raw material costs	212. 87	284. 512	52	984
Investment	406688. 89	198919. 790	87000	1020000

Table 3: supplier efficiency values during the period 2020-2021

DMU's	Year	CRS	VRS	Scale Eff	kinds of returns to scale
DMU_1	1399	0. 5726	0. 7376	0. 7763	**DRS**
	1400	0. 6243	0. 6484	0. 9629	**DRS**
	1401	0. 518	0. 6511	0. 7955	**IRS**
DMU_2	1399	0. 7615	1. 0000	0. 7615	**DRS**
	1400	0. 9240	1. 0000	0. 924	**DRS**
	1401	0. 8403	0. 9259	0. 9075	**DRS**
DMU_3	1399	0. 8154	0. 8247	0. 9887	**DRS**
	1400	0. 6592	0. 8464	0. 7788	**DRS**
	1401	0. 6658	0. 7839	0. 8493	**DRS**
DMU_4	1399	0. 9210	0. 9300	0. 9904	**DRS**
	1400	1. 0000	1. 0000	1. 0000	**CRS**
	1401	0. 9145	0. 9456	0. 9671	**IRS**
DMU_5	1399	0. 8809	0. 9202	0. 9573	**IRS**
	1400	0. 9493	0. 9498	0. 9994	**DRS**
	1401	0. 8837	0. 9107	0. 9707	**IRS**
DMU_6	1399	1. 0000	1. 0000	1. 0000	**IRS**
	1400	0. 9111	1. 0000	0. 9111	**CRS**
	1401	0. 9631	1. 0000	0. 9631	**IRS**
DMU_7	1399	0. 8615	0. 9859	0. 8738	**IRS**
	1400	0. 7871	0. 8601	0. 9151	**DRS**

	1401	0. 9285	1. 0000	0. 9285	**IRS**
DMU_8	1399	1. 0000	1. 0000	1. 0000	**CRS**
	1400	1. 0000	1. 0000	1. 0000	**CRS**
	1401	1. 0000	1. 0000	1. 0000	**CRS**
DMU_9	1399	0. 888	1. 0000	0. 888	**IRS**
	1400	0. 9306	1. 0000	0. 9306	**IRS**
	1401	1. 0000	1. 0000	1. 0000	**CRS**
DMU_{10}	1399	0. 8488	0. 8563	0. 9912	**DRS**
	1400	0. 8612	1. 0000	0. 8612	**IRS**
	1401	0. 9507	1. 0000	0. 9507	**IRS**
DMU_{11}	1399	0. 7763	0. 7765	0. 9998	**IRS**
	1400	0. 6866	0. 7244	0. 9479	**IRS**
	1401	0. 6750	0. 6783	0. 9952	**DRS**
DMU_{12}	1399	0. 8321	0. 8402	0. 9904	**DRS**
	1400	0. 7298	0. 7985	0. 9139	**DRS**
	1401	0. 7183	0. 7771	0. 9243	**DRS**
DMU_{13}	1399	0. 9126	0. 9183	0. 9938	**DRS**
	1400	0. 8862	0. 9429	0. 9399	**DRS**
	1401	0. 9935	1. 0000	0. 9935	**IRS**
DMU_{14}	1399	0. 8916	0. 8987	0. 9921	**IRS**
	1400	0. 7881	1. 0000	1. 0000	**IRS**
	1401	0. 8163	1. 0000	0. 8163	**IRS**
DMU_{15}	1399	1. 0000	1. 0000	1. 0000	**CRS**
	1400	1. 0000	1. 0000	1. 0000	**CRS**
	1401	1. 0000	1. 0000	1. 0000	**CRS**

As mentioned, after collecting information on the suppliers of the system under review from 2020 to 2022, the efficiency of the suppliers was calculated using the GAMS software. The efficiency results for the suppliers during the period under review are shown in Table 3. Equation 4 was used to calculate the efficiency of the scale, and the efficiency values of the scale were calculated using Equation 4. Subsequently, the efficiency values obtained from the implementation of BCC and CC are compared. If these two values are equal, the type of return to scale is constant (CRS), and otherwise, it is variable.

If a variable return to scale was identified, efficiency values were calculated using the BCC model with decreasing returns to scale. Subsequently, the results of this approach and the BCC model were compared to determine the type of return to scale. If these two values are equal, it implies a decreasing return to scale (DRS). However, if the values are not equal, this suggests an increasing return to scale (IRS).

In Table 1, the efficiencies of the CCR and BCC represent the existing and optimal conditions, respectively, and the scale efficiency is obtained using Equation 4. These are long-term conceptual values that indicate the ratio of an increase in output to an increase in the number of inputs. In addition, the average net technical efficiency of the suppliers from 2020 to 2022 was calculated. As shown in Figure 1, the average net technical efficiency of the eight suppliers is 0. 95 to 1; among these three suppliers, 8, 9, and 15 obtain the maximum efficiency. The average net technical efficiency of the two suppliers was 1, followed by 11, with the lowest average technical efficiency among the 15 suppliers.

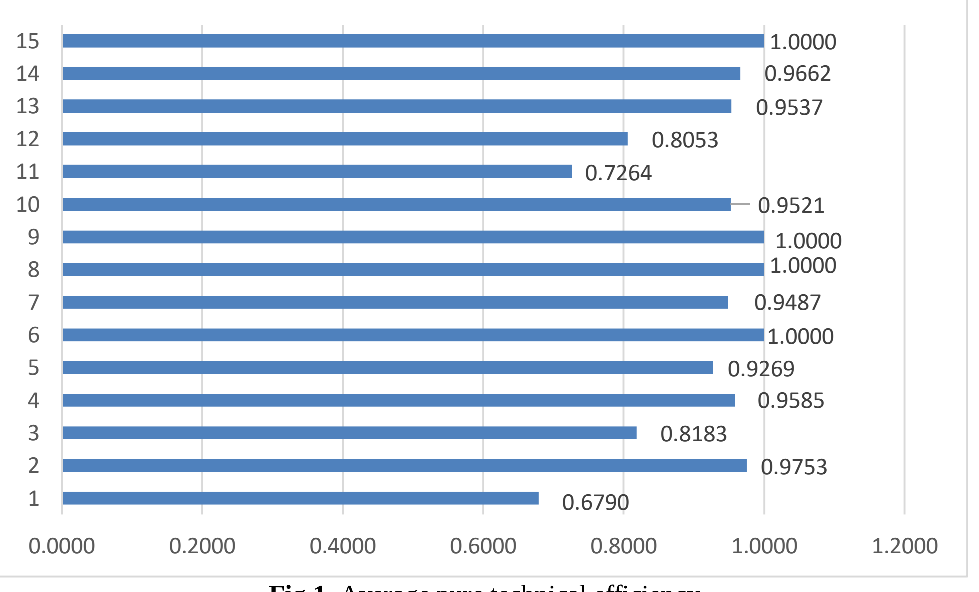


Fig.1. Average pure technical efficiency

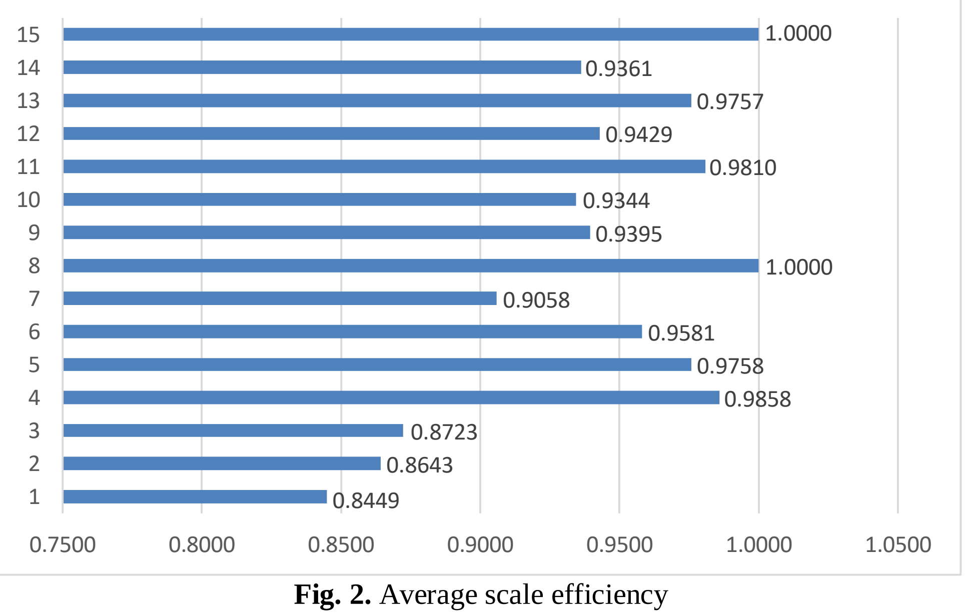


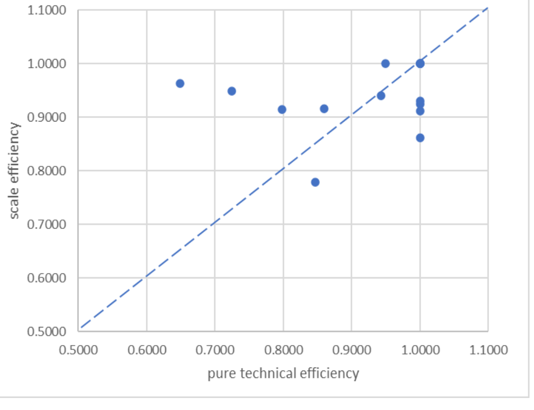
Fig. 2. Average scale efficiency

In addition, the average efficiency of the scale of suppliers from 2020 to 2022 was calculated. As shown in Figure 2, the average scale efficiency of seven suppliers is in the range of 0.95 to 1, among which two suppliers, 8 and 15, have obtained the maximum efficiency. The average net technical efficiency of two suppliers 1 and then 11 has the lowest average technical efficiency among 15 suppliers.

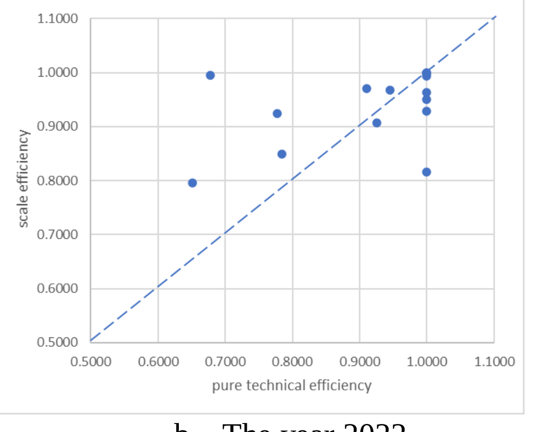
Figure 3 (a, b) shows the relationship between net technical efficiency and scale efficiency in 2020 and 2022, respectively. In these graphs, the x-axis shows pure technical efficiency, and the y-axis shows scale efficiency. Scattered points below the 45-degree line show that are the contribution of net technical efficiency in the calculation of efficiency greater than the scale efficiency. Specifically, the scattered points above the 45°line show that the contribution of scale efficiency to the calculation of efficiency is greater than that of pure technical efficiency.

In general, the efficiency distribution of the scale of the supply chain of the production unit under investigation from 2020 to 2022 is increasingly scattered, while the distribution of pure technical efficiency is increasingly concentrated in the same period. The increasingly concentrated distribution of net technical efficiency shows that the gap between suppliers is decreasing and reflects, to some extent, the progress of net technical efficiency in the supply chain of the manufacturing unit under consideration.

Figure 3. Scatter diagram of purely technical, and scale efficiencies



a. The year 2020



b. The year 2022

5. Discussion

In this study, the efficiency values of the suppliers of a production unit are calculated using input-oriented approaches. The results showed that the mentioned technique, considering the amount of investment, non-operating expense cost, and operating costs including raw material costs, wages, and overhead costs as inputs, and the number of net sales and return on investment as outputs, the ability to aggregate these items and translate them into it has a single measure of efficiency. In general, the findings of this study highlight the need to develop and adopt integrated strategies for supply chains. In addition, with some adjustments to the analysis intervals, this method for supply chain analysis can help

managers adjust their supply chain strategies more easily, especially when they feel that the chain is exposed to risks. Therefore, this method provides managers with a framework for conservative decision-making. According to Table 2, the technical efficiency values of variable scale efficiency are greater than the technical efficiency values of constant scale efficiency because the production function in the VRS mode is Always under the CRS function. In addition, the efficiency value of suppliers considering the constant return to scale is 0.8571, and in the case of the variable return to scale, it is 0.9140. This means that suppliers should systematically increase their output by 1.16 times to achieve efficiency and by 1.09 times to achieve optimal scale while achieving efficiency. Considering the average efficiency of the supplier's period, supplier 1 is known as the most inefficient supplier with a score of 0.5716, assuming constant returns to scale, and 0.6790, assuming variable returns to scale. Suppliers 8 and 15 are the most efficient suppliers and operate on an optimal scale.
Since this study quantified efficiency in the two scale assumptions of constant and variable efficiency, it is possible to identify efficient suppliers that can serve as a reference and model for other suppliers. Suppliers 1, 4, and 13 in the third period; suppliers 5, 6, and 7 in the first and third periods; suppliers 9 and 11 in the first and second periods; supply supplier 10 in periods two and three; supplier 13 in period three; and supplier 14 in all three periods have returned to the ascending scale. Thus, these suppliers had the necessary economic justification for their activities during the aforementioned periods. According to the principles of microeconomics, in this case, the curves of final and average production have an upward trend. As a result, the economic unit is not operating at an optimal level of production and is in the initial phase of production. This means that the curves of marginal and average costs have a downward trend, and the supplier is in the downward part of the LAC. This demonstrates the economies of scale, particularly for supplier 14. The highest efficiency method for the scale related to supplier 11 was 0.9858. The implication is that the efficiency of this supplier, in terms of both constant and variable returns to scale, is almost the same. Therefore, this supplier operates near the second production area and still has the economic justification to expand its activity. Supplier 2 also has a decreasing return to scale, which indicates a lack of economies of scale; in other words, this supplier is in the ascending part of the LAC. . Efficient suppliers with decreasing returns, such as supplier 2, will lose their efficiency compared to other suppliers if the use of inputs increases without changing other conditions. As a result of the development and expansion of production in this group of suppliers, the policy will not be efficient only with the expansion of inputs. However, this problem is different for efficient suppliers with increasing returns to scale.

By developing and expanding their production using other inputs, these suppliers can positively impact their technical efficiency if the conditions of the other suppliers are constant. This situation is especially true for supplier 6 in the third period. However, suppliers with constant returns to scale can increase production by using more inputs while maintaining existing technical efficiency. Future research can focus on new computational models and techniques to build DEA-based models in multistage production processes while calculating comprehensive efficiency values. It is also recommended to use the Malmquist index to examine the changes in total productivity during the study period and evaluate the trend of changes in suppliers' productivity.

References

[1] Hosseini Dolatabad A, Heidary Dahooie J, Antucheviciene J, Azari M, Razavi Hajiagha SH. Supplier selection in the industry 4.0 era by using a fuzzy cognitive map and hesitant fuzzy linguistic VIKOR methodology. Environ Sci Pollut Res. 2023;30(18):52923–42.

[2] Salhab H, Allahham M, Abu-AlSondos I, Frangieh R, Alkhwaldi A, Ali B. Inventory competition, artificial intelligence, and quality improvement decisions in supply chains with digital marketing. Uncertain Supply Chain Manag. 2023;11(4):1915–24.

[3] Echefaj K, Charkaoui A, Cherrafi A, Garza-Reyes JA, Khan SAR, Chaouni Benabdellah A. Sustainable and resilient supplier selection in the context of circular economy: an ontology-based model. Manag Environ Qual An Int J. 2023;34(5):1461–89.

[4] Moradi H, Rabbani M, babaei meybodi H, Honari M. Development of a Range-Adjusted Measure-Based Common Set of Weights for Dynamic Network Data Envelopment Analysis using a Multi-Objective Fractional Programming Approach. J Ind Eng Manag Stud. 2022;9(2):13–32.

[5] Sharma M, Joshi S. Digital supplier selection reinforcing supply chain quality management systems to enhance firm's performance. TQM J. 2023;35(1):102–30.

[6] Kanike UK. Factors disrupting supply chain management in manufacturing industries. J Supply Chain Manag Sci. 2023;4(1–2):1–24.

[7] Tong LZ, Wang J, Pu Z. Sustainable supplier selection for SMEs based on an extended PROMETHEE II approach. J Clean Prod. 2022;330:129830.

[8] Teng Y, Zhang J, Sun T. Data-driven decision-making model based on artificial intelligence in higher education system of colleges and universities. Expert Syst. 2023;40(4):e12820.

[9] Moradi H, Meybodi HB. A Systematic Review and Bibliometric Analysis of the Scientific Literature on DEA models under the Common Set of Weights. Iran J Oper Res. 2023;14(1):49–79.

[10] Hosseinzadeh Lotfi F, Allahviranloo T, Shafiee M, Saleh H. Data Envelopment Analysis. In: Supply Chain Performance Evaluation: Application of Data Envelopment Analysis. Springer; 2023. p. 179–241.

[11] Babaei-Meybodi H, Moradi H, Abbaszadeh M. Evaluation of the Proficiency of Distinguished Countries in Managing COVID-19. Heal Inf Manag. 2021;18(1):19–26.

[12] Seuring S, Aman S, Hettiarachchi BD, de Lima FA, Schilling L, Sudusinghe JI. Reflecting on theory development in sustainable supply chain management. Clean Logist Supply Chain. 2022;3(November 2021):100016.

[13] Oliver RK, Webber MD. Supply-chain management: logistics catches up with strategy. In 1982.

[14] Rezapour S, Farahani RZ, Pourakbar M. Resilient supply chain network design under competition: A case study. Eur J Oper Res. 2017;259(3):1017–35.

[15] Chanchaichujit J, Balasubramanian S, Charmaine NSM. A systematic literature review on the benefit-drivers of RFID implementation in supply chains and its impact on organizational competitive advantage. Cogent Bus Manag. 2020;7(1).

[16] Marzband A. Precise services and supply chain prioritization in manufacturing companies using cost analysis provided in a fuzzy environment. J Fuzzy Ext Appl. 2020;1(1):41–56.

[17] Mzougui I, Carpitella S, Certa A, El Felsoufi Z, Izquierdo J. Assessing supply chain risks in the automotive industry through a modified MCDM-based FMECA. Processes. 2020;8(5):579.

[18] Moradi H, Rabbani M, Babaei Meybodi H, Honari M. Novel approaches for determining exogenous weights in dynamic network DEA. Iran J Manag Stud. 2023;(x):accepted and under publish.

[19] Moradi H, Rabbani M, Babaei Meybodi H, Honari MT. Sustainable Supplier Selection : A New Integrated Approach of Fuzzy Interpretive Structural Modeling and Dynamic Network Data Envelopment Analysis. 2021;12(2):14–36.

[20] Saavedra-Nieves A, Fiestras-Janeiro MG. Analysis of the impact of DMUs on the overall efficiency in the event of a merger. Expert Syst Appl. 2022;195:116571.

[21] Shetty U, Pakkala TPM. Ranking efficient DMUs based on single virtual inefficient DMU in DEA. Opsearch. 2010;47:50–72.

[22] Veiga GL, Pinheiro de Lima E, Gouvea da Costa SE. An Efficiency-Frontier Based Procedure to Improve Operations Strategy. J Ind Integr Manag. 2022;7(03):367–99.

[23] Podinovski V V. Returns to scale in convex production technologies. Eur J Oper Res. 2017;258(3):970–82.

[24] Garcia Sanchez IM. Technical and scale efficiency in Spanish urban transport: Estimating with data envelopment analysis. Adv Oper Res. 2009;2009.

[25] Sharma S, Sharma M. Analyzing the technical and scale efficiency of small industries in India: state-wise cluster study. Meas Bus Excell. 2010;14(2):54–65.

[26] Kirigia JM, Asbu EZ. Technical and scale efficiency of public community hospitals in Eritrea: an exploratory study. Health Econ Rev. 2013;3(1):1–16.

[27] Wanke PF, Barros CP. Public-private partnerships and scale efficiency in Brazilian ports: Evidence from two-stage DEA analysis. Socioecon Plann Sci. 2015;51:13–22.

[28] Havidz SAH, Jianmu Y, Aima MH, Ali H. Technical and scale efficiency employing data envelopment analysis: Empirical evidence from Islamic public banks in Indonesia. Int J Appl or Innov Eng Manag. 2017;6(8):85–94.

[29] Yousef AN, Al-Salih R, Obaid MA. Measuring the Relative Efficiency and Scale Efficiencyof Health Organization in Thi Qar Province Using BCC Model. NeuroQuantology. 2023;21(3):288–94.