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Supplier selection using Fuzzy DEA credibility constrained and relative closeness index: A case of Indonesian manufacturing industry

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Abstract: Supplier selection plays a crucial role in enhancing the competitiveness and operational efficiency of manufacturing industries. In the Indonesian manufacturing sector, where market conditions are dynamic and complex, the need for an effective supplier selection methodology is particularly critical. The suggested method converts conventional DEA (Data Envelopment Analysis) models into fuzzy events through the application of credibility measures. Additionally, the relative closeness (RC) index is employed to enhance the differentiating capability of traditional DEA. This article incorporates three input criteria and five output criteria. The findings suggest that higher values of the RC Index correspond to superior performance by the supplier. Furthermore, the study's outcomes reveal that the credibility index influences the RC index. Imposing stricter credibility constraints can diminish the value of the RC index.

Subjects: Operations Research; Engineering Mathematics; Logistics; Supply Chain Management;

Keywords: Fuzzy DEA; credibility constraint; relative closeness; MCDM; supplier evaluation

1. Introduction

Supplier evaluation refers to the examination, assessment, and continuous observation of supplier performance, along with the analysis of business procedures and methods, intending to minimize expenses and mitigate risks (Gordon, 2008). Supplier evaluation holds significant significance within supply chain management, as opting for the appropriate supplier can enable the supply chain to accomplish its objectives and secure a competitive edge (Abel et al., 2020). In the production process, a variety of suppliers play a vital role by providing essential raw materials that meet specific criteria. These suppliers are carefully selected to ensure the smooth functioning of the production line. Their involvement is crucial in maintaining the overall resilience of the supply chain, as they contribute to the consistent and timely availability of the required materials. The effectiveness and productivity of a company can be influenced by its purchasing activities. Changes in purchase prices and issues such as insufficient supply or low-quality materials can disrupt the production process (Stainer et al., 2016). During the implementation of purchasing strategies, various challenges arise due to suppliers, including non-compliant raw materials, delivery delays, and discrepancies between ordered and received quantities. These issues are caused by poor supplier performance. Suppliers play a crucial role in meeting the product, component, and material requirements of a company, which are essential for maintaining a competitive edge (Bai & Sarkis, 2010). Choosing appropriate suppliers ensures a productive supply chain and overall customer satisfaction (T.-C. Wen et al., 2020).

In the field of procurement, companies are closely intertwined with their suppliers, as suppliers can have a significant impact on a company's legal compliance and reputation (Bai & Sarkis, 2010). Therefore, it is crucial for companies to carefully choose their suppliers. Supplier selection involves the process of identifying appropriate suppliers who can deliver products and/or services at the right price, quantity, and time (Dargi et al., 2014). The issue of supplier selection is highly critical within the supply chain system (C. T. Chen et al., 2006). Opting for the right supplier can yield substantial benefits such as cost reduction in procurement, shorter production lead times, enhanced customer satisfaction, and increased company competitiveness (Soner Kara, 2011). Price typically holds the utmost significance in supplier selection, as companies aim to maximize profits (Baskaran et al., 2012). However, a study by Kannan and Tan (2002) indicated that quality and delivery accuracy have emerged as primary criteria in supplier selection. This suggests that previous supplier selection criteria only encompassed price, quality, delivery, and service (Molamohamadi et al., 2013). Notably, there has been limited research incorporating attributes like product defect rate, flexibility to accommodate order changes and hygiene. This paper aims to incorporate these three criteria for supplier selection in the context of Indonesian manufacturing, specifically frozen food production.

Bai and Sarkis (2010) conducted a study indicating that the decision-making process for supplier selection can be unclear. To address this ambiguity, various approaches have been explored in research. For instance, Rashidi and Cullinane (2019) utilized Fuzzy DEA (Data Envelopment Analysis) and Fuzzy TOPSIS (Technique for Order Preference by Similarities to Ideal Solution) in sustainable supplier selection; Tavassoli et al. (2020) introduced stochastic Fuzzy DEA to evaluate supplier sustainability. Moreover, Zhou et al. (2016) employed Type-2 fuzzy multi-objective DEA to asses sustainable supplier evaluation; Mirmousa and Dehnavi (2016) developed criteria for supplier selection using Fuzzy DEMATEL (Decision-Making Trial and Evaluation Laboratory). In addition, Chin-Nung (2012) utilized Fuzzy MSGP (Multi-Segment Goal Programming) for green supplier selection. Nevertheless, a major challenge arises when the final scores for different suppliers are equal, making it difficult for the decision-maker to make a choice. J. Wang et al. (2016) in their study indicated that A major drawback is evident when the decision-maker is confronted with the dilemma of deciding as the final score becomes indistinguishable. Similarly, Mohammadnazari et al. (2022) believed that one issue lies in the fact that when the final score reaches an identical value, the decision-maker faces a significant challenge in reaching a decision. Hence, the main aim of this research is to employ Fuzzy DEA Credibility Constrained and Relative Closeness (RC) Index approaches in order to identify the most suitable supplier. According to Wardana et al. (2021), increasing the credibility level enhances the ability to differentiate effectively without sacrificing any information. Consequently, this study also demonstrates the influence of credibility level on the ultimate score.

The structure of this paper is as follows. In section 2, we review the assessment standards and the method used to evaluate suppliers. Following that, we elaborate on our proposed approach in section 3. Section 5 delves into the fuzzification of numbers and the consistency of rankings, including a comparison of the results obtained through different methods. Section 6 discusses the practical and theoretical implications, while section 7 provides a conclusion for the paper.

2. Literature review

2.1. Supplier evaluation

According to Fei et al. (2018), supplier selection is a part of Multi-Criteria Decision Making (MCDM). Their study utilizes the D-S VIKOR (Dempster—Shafer Višekriterijumsko Kompromisno Rangiranje) approach to determine the optimal supplier. Numerous investigations have been carried out in the field of supplier selection. Another study by Toloo and Nalchigar (2011) also researched supplier selection. They used the cardinal and ordinal data DEA method with 18 supplier selection specifications. Moreover, Dargi et al. (2014) researched supplier selection using the Fuzzy Analytical Network Process (Fuzzy-ANP) method implemented in the automotive sector with five supplier assessment specifications. Based on the research conducted by Bulgurcu and Nakiboglu (2018), it has been established that the AHP (Analytic Hierarchy Process), DEA, and TOPSIS techniques are extensively employed for supplier evaluation and selection. In this particular study, the Fuzzy DEA Credibility Constrained method and the Relative Closeness Index methodologies are utilized to address and resolve any uncertainties or ambiguities. This innovative approach combines the Fuzzy DEA Credibility Constrained method with the Relative Closeness Index to create an updated evaluation method. The Relative Closeness Index is employed to tackle ambiguity, while the credibility constraint is applied to handle ambiguities.

2.2. Assessment of criteria

The process of decision-making, particularly when it comes to choosing suppliers, involves the crucial task of selecting appropriate criteria (K.-L. Chen et al., 2014). K.-L. Chen et al. (2014) stated that companies evaluate their suppliers according to various standards, which can vary depending on specific circumstances and contexts. Previous research has explored several studies focused on supplier selection, as outlined below.

Table 1 illustrates that numerous types of research delve into the topic of supplier choice. The analysis reveals that the commonly employed factors comprise cost, excellence, on-time delivery, service excellence, adaptability for order modifications, and the supplier's reputation. Presently, the supplier selection process primarily integrates MCDM techniques alongside fuzzy methods, as indicated in Table 1.

The evaluation process relies on the crucial task of establishing criteria, which entails considering alternative qualifications (Soner Kara, 2011). Within the DEA method, the criteria can be categorized into two groups: input and output. Output criteria aim to be maximized, while input criteria aim to be minimized (Mousavi-Nasab & Sotoudeh-Anvari, 2017). A criterion with a higher value is referred to as maximizing, whereas a lower value is considered minimizing. The forthcoming study will employ the following criteria.

2.2.1. Input

–Price

The cost of the product plays a significant role in its overall expenses. Consequently, the procurement department aims to acquire the commodity at the most economical price to minimize the overall costs (Kilincci & Onal, 2011; Masudin, Ramadhani, et al., 2021).

–Location

The geographical position of the supplier company holds importance due to its impact on shorter delivery times, reduced transportation costs, and quicker technical support required (Kilincci & Onal, 2011).

–Product Defect Rate

The level of damage observed in previous agreements with suppliers (Aydin & Kahraman, 2010).

2.2.2. Output

–Quality

Requirements for goods must be met by suppliers according to the company's specifications (Aydin & Kahraman, 2010).

–Delivery Accuracy

Table 1. Assessment standards utilized in prior studies

Author's	Approaches	Criteria
Rashidi and Cullinane (2019)	Fuzzy DEA and Fuzzy TOPSIS	Inputs: logistics costs, energy, and resource consumption
		Output: quality of logistics services, environmental management system, occupational health & safety of workers, social responsibility
Karsak and Dursun (2014)	QFD (Quality Function Deployment) and DEA	Output: product volume, delivery, payment method, product variety, reliability, experience, supplier reputation, management system, geographic location
Jauhar and Pant (2017)	DEA with DE (Differential Evolution) and MODE (Multi-Objective Differential Evolution)	Input: lead time, quality, price
		Output: service quality, CO2 emission
Toloo and Nalchigar (2011)	DEA	Input: total shipping cost, supplier reputation
		Output: an invoice from the supplier
Dobos and Vörösmarty (2014)	DEA	Input: lead time, quality, price
		Output: reusability, CO2 emission
Wu (2009)	DEA, decision tree and neural network	Inputs: quality management systems and practices, independent documentation and auditing, process/manufacturing capabilities, enterprise management, design and development capabilities, cost reduction capabilities
		Output: quality, price, delivery, cost reduction ability
Tavassoli et al. (2020)	Fuzzy DEA	Inputs: delivery delays, prices, shipping costs, total annual electricity costs, worker health and safety costs
		Output: energy consumption efficiency, supplier experience, quality
Zhou et al. (2016)	Type-2 fuzzy multi-objective DEA	Inputs: technological capability, financial capacity, environmental maintenance costs, worker health and safety costs
		Output: on-time delivery quantity, invoice without error
Azadi et al. (2015)	Fuzzy DEA	Inputs: technological capability, financial capacity, environmental maintenance costs, worker health and safety costs
		Output: on-time delivery quantity, invoice without error
Rajesh and Malliga (2013)	AHP-QFD	Price, quality, delivery time, service quality, location, quality assurance, shipping costs
Mirmousa and Dehnavi (2016)	Fuzzy DEMATEL	Price, quality, prompt delivery, flexibility to change orders, quality assurance
Chin-Nung (2012)	Fuzzy MSGP	Quality, service quality, supplier reputation
Kilincci and Onal (2011)	Fuzzy AHP	Price, quality, location, providing information

(*Continued*)

Table 1. (*Continued*)

Author's	Approaches	Criteria
Sevkli (2009)	Fuzzy ELECTRE (Elimination and Choice Translating Reality)	Price, quality, prompt delivery,
Zaim et al. (2003)	Fuzzy Analytical Hierarchy	Quality, service quality, flexibility to change orders
Aydin and Kahraman (2010)	Fuzzy AHP	Price, quality, prompt delivery, service quality, location

Suppliers are expected to follow the agreed-upon delivery schedule accurately.

–Service quality

The benefits offered by a service supplier can be assessed using service performance criteria. These criteria should always be considered when selecting a supplier, as purchasing involves various service levels like order processing and information provision (Aydin & Kahraman, 2010; Masudin et al., 2020).

–Flexibility to Order Changes

Suppliers need to be flexible and adapt to changes in orders as required.

–Hygiene

Suppliers must ensure the cleanliness of raw materials during delivery. The condition of delivery vehicles and equipment should be checked during each delivery, and the delivered products must meet the expected level of quality (Masudin, LAU, et al., 2021; Trafialek, 2019).

2.3. Supplier evaluation method

Supplier evaluation is a part of Multi-Criteria Decision Making (MCDM) and involves various techniques for selecting suppliers. Past research has utilized MCDM to evaluate supplier performance, including studies by Hoseini et al. (2020), who employed the Fuzzy sets-Z number method to identify 13 criteria for supplier assessment. Moreover, Kara et al. (2022) also conducted a literature review and gathered opinions to investigate sustainable suppliers. Their approach involved using the Fuzzy DEA credibility constrained and relative closeness index.

2.3.1. Data envelopment analysis (DEA) model

Data Envelopment Analysis (DEA) is a technique focused on data that assesses the performance of Decision-Making Units (DMUs), which are entities capable of converting multiple inputs into multiple outputs (Cooper et al., 2011). According to Mousavi-Nasab and Sotoudeh-Anvari (2017), there exists a methodological relationship between DEA and MCDM, where parameters to be maximized are treated as outputs and parameters to be minimized are considered inputs, as depicted in Figure 1. In addition, Karsak and Dursun (2014) also explain that inputs correspond to parameters that need to be minimized, while outputs refer to parameters that should be maximized. Cook et al. (2014) conducted a study and found that in general comparative scenarios, inputs are typically performance measures where a lower value is desirable, whereas outputs are usually performance measures where a higher value is desirable. Additionally, the determination of whether a parameter is considered an input or output depends on the specific problem being evaluated.

Charnes, Cooper, and Rhodes (CCR) first introduced the Data Envelopment Analysis model in 1978 as a mathematical measurement model with a nonparametric method that can evaluate several activities by measuring the efficiency of the DMU (Cooper et al., 2011). The DEA model used in the followings the CCR model used to evaluate the DMU:

$$Ej = \frac{\sum_{r=1}^{m} u_r y_{rj}}{\sum_{i=1}^{n} v_i x_{ij}}$$

Subject to:

Table 2. Notation definition

Notation	Definition
Ej	Efficiency of DMUj
u_r	Output Weight
v_i	Input Weight
x_{ij}	Input DMUj
y_{rj}	Output DMUj
θ_{IDMU}	Efficiency of IDMU
y_r^{max}	Output IDMU
x_i^{min}	Input IDMU
θ_{IDMU}^*	Optimum efficiency of IDMU
θj	Optimum efficiency of DMU
φ_{ADMU}	Efficiency ADMU
y_r^{min}	Output ADMU
x_i^{max}	Input ADMU
φ_{ADMU}^*	Optimum efficiency of ADMU
φj	Efficiency Score DMUj
φ_j^*	Optimal Efficiency Score of DMUj
RCj	Relative Closeness
α	Credibility constrained for function
βj	Credibility constrained for DMU
$\tilde{y}_r^{max}$	Fuzzy output IDMU
$\tilde{x}_i^{min}$	Fuzzy input IDMU
$\tilde{y}_{rj}$	Fuzzy output DMU j
$\tilde{x}_{ij}$	Fuzzy input DMU i
$\tilde{y}_r^{min}$	Fuzzy output ADMU
$\tilde{x}_i^{max}$	Fuzzy input ADMU
$y_r^{1^{max}}$	Fuzzy Output r with the lower value of IDMU
$y_r^{2^{max}}$	Fuzzy Output r with the middle value of IDMU
$x_i^{3^{min}}$	Fuzzy Input i with the upper value of IDMU
$x_i^{2^{min}}$	Fuzzy Input i with the middle value of IDMU
y_{rj}^3	Fuzzy Output r with the upper value of DMU j
y_{rj}^2	Fuzzy Output r with the middle value of DMU j
x_{ij}^1	Fuzzy Input i with the lower value of DMU j
x_{ij}^2	Fuzzy Input i with the middle value of DMU j
y_{rj}^1	Fuzzy Output r with the lower value of DMU j
x_{ij}^3	Fuzzy Input i with the upper value of DMU j
$y_r^{3^{min}}$	Fuzzy Output r with the upper value of ADMU
$y_r^{2^{min}}$	Fuzzy Output r with the middle value of ADMU

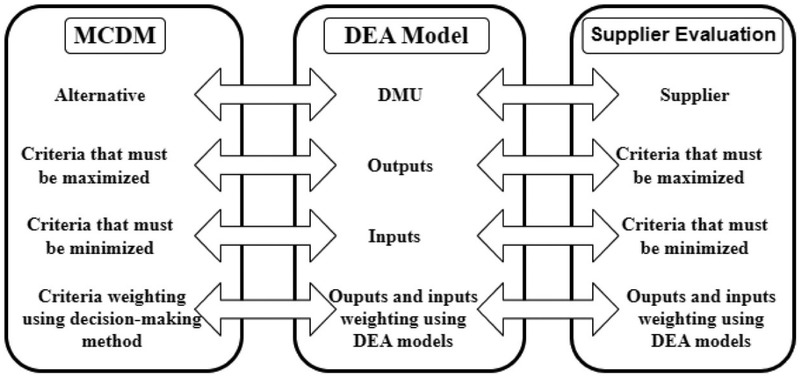

Figure 1. MCDM and DEA process of decision making.

$$\frac{\sum_{r=1}^{m} u_r y_{rj}}{\sum_{i=1}^{n} v_i x_{ij}} \leq 1, \forall j$$

$$v_i u_r \geq 0 \forall i, r \quad (1)$$

Where:

Ej : Efficiency of DMUj

u_r : Output weight

v_i: Input weight

x_{ij}: Input DMUj

y_{rj}: Output DMUj

In addition to supplier selection, the DEA method has been applied in previous studies to various scenarios. For instance, Peixoto et al. (2020) employed the DEA method to evaluate the performance of hospital management. Similarly, the DEA model serves as a helpful tool in assessing the quality of radiotherapy treatment plans for patients with head and neck cancer, as demonstrated by Raith et al (Raith et al., 2021). Furthermore, Eftekhari et al. (2020) utilized the DEA method to assess ground motion prediction in their research.

2.3.2. DEA and RC index model

Data Envelopment Analysis (DEA) is a nonparametric technique utilized to evaluate the relative efficiency of decision-making units (DMUs) by considering multiple inputs and outputs (M. Wen et al., 2009). DEA has garnered significant theoretical and practical attention since its introduction in 1978. Over time, several theoretical extensions have been developed based on the fundamental DEA model. The conventional DEA model yields the same efficiency value for DMUs, posing a challenge in determining the best-performing DMU (Wardana et al., 2021). Therefore, to avoid this, in his research, Kim et al. (2019) incorporated the Relative Closeness index into the DEA approach in their research. They compared two virtual DMUs, namely the ideal DMU (IDMU) and anti-ideal DMU (ADMU), and ranked them based on their relative closeness. The IDMU model can be solved through a linear programming model, as demonstrated below:

$$\theta_{IDMU} = \max \frac{\sum_{r=1}^{m} u_r y_r^{max}}{\sum_{i=1}^{n} v_i x_i^{min}}$$

Subjected to:

$$\frac{\sum_{r=1}^{m} u_r y_{rj}}{\sum_{i=1}^{n} v_i x_{ij}} \le 1, \forall j$$

$$v_i u_r \ge 0 \forall i, r \tag{2}$$

The inputs and outputs of IDMU, denotes as y_r^{max} and x_i^{min}, respectively, are obtained from the maximum value of $y_r^{max} = max_y\{y_{rj}\}$ and the minimum value of $x_i^{min} = min_x\{x_{ij}\}$. The optimal efficiency of IDMU is represented as θ^*_{IDMU}. The subsequent task involves comparing the efficiency of each DMU with the optimal efficiency value of the DMU. The following model describes this process:

$$\theta j = max \frac{\sum_{r=1}^{m} u_r y_{rj}}{\sum_{i=1}^{n} v_i x_{ij}}$$

Subjected to:

$$\sum_{r=1}^{m} u_r y_r^{max} - \sum_{i=1}^{n} v_i \left(\theta^*_{IDMU} x_i^{min}\right) = 0$$

$$\frac{\sum_{r=1}^{m} u_r y_{rj}}{\sum_{i=1}^{n} v_i x_{ij}} \le 1, \forall j$$

$$v_i u_r \ge 0 \forall i, r \tag{3}$$

θj represents the efficiency rating of DMU_j in relation to the efficiency rating of. The subsequent stage involves calculating the efficiency score of ADMU (ϕ_{ADMU}) using the following model:

$$\varphi_{ADMU} = min \frac{\sum_{r=1}^{m} u_r y_r^{min}}{\sum_{i=1}^{n} v_i x_i^{max}}$$

Subject to:

$$\frac{\sum_{r=1}^{m} u_r y_{rj}}{\sum_{i=1}^{n} v_i x_{ij}} \le 1, \forall j$$

$$v_i u_r \ge 0 \forall i, r \tag{4}$$

y_r^{min} and x_i^{max} are ADMU inputs and outputs derived from $y_r^{min} = min_y\{y_{rj}\}$ dan $x_i^{max} = max_x\{x_{ij}\}$. φ^*_{ADMU} is the optimal efficiency of the ADMU, the next step is to compare the efficiency value of each DMU with the optimal efficiency value of the DMU. The modeling is as follows:

$$\varphi j = min \frac{\sum_{r=1}^{m} u_r y_{rj}}{\sum_{i=1}^{n} v_i x_{ij}}$$

Subject to:

$$\sum_{r=1}^{m} u_r y_r^{min} - \sum_{i=1}^{n} v_i \left(\theta^*_{ADMU} x_i^{max}\right) = 0$$

$$\frac{\sum_{r=1}^{m} u_r y_{rj}}{\sum_{i=1}^{n} v_i x_{ij}} \le 1, \forall j$$

$$v_i u_r \ge 0 \forall i, r \tag{5}$$

φj represents the efficiency score of DMU_j which is compared with the efficiency score of φ_{ADMU}. After determining the score $\theta^*_{IDMU}, \theta j, \varphi_{ADMU}, \varphi j$, the next step is to calculate the relative closeness as follows:

$$RCj = \frac{\varphi_j^* - \varphi_{ADMU}^*}{(\varphi_j^* - \varphi_{ADMU}^*) + \left(\theta_{IDMU}^* - \theta_j^*\right)} \tag{6}$$

Y.-M. Wang and Y (2006) also use the DEA method and the RC index to illustrate solving the DMU selection problem.

3. Proposed approach

3.1. Fuzzy DEA credibility constrained and RC index

The conventional DEA model assumes that all inputs and outputs are represented as precise numbers. Nevertheless, this assumption may not hold true in practical situations. To address this issue, fuzzy DEA's credibility is restricted, mainly due to the presence of uncertainty caused by obscurity. As a solution, the RC index model is introduced as a linear programming model to tackle real-world problems (Wardana et al., 2020, 2021). Following that, we proceed with the fundamental idea of credibility theory and implement it within the framework (2–5), resulting in a novel model constrained by the fuzzy DEA credibility and RC index. Ultimately, in a conducted investigation undertaken by Wardana et al. (2021), The credibility of the DEA is utilized to address the uncertainty, while the RC index is employed to resolve the ambiguity.

Definition 1 Let be ξ as a fuzzy variable with a distribution function μ: $\mathcal{R}$ → [0,1]. The fuzzy variable (ξ) is normal if it comes from a real number r so that μ (r) = 1.

Definition 2 Let Pos and Nec be two specific fuzzy measures defined at ($\mathcal{R}$, U), where U is the set of $\mathcal{R}$. Furthermore, Pos and Nec are a pair of multiple fuzzy measures, and the model is Pos {A} = 1 - Nec {A^C} where A^C is the complement of A.

Definition 3 The credibility measurement model is as follows:

$$Cr(A) = \frac{1}{2}(Pos\{A\} + Nec\{A\}) \tag{7}$$

For any $A \in U$

Consider ξ as a triangular fuzzy number (k^1,k^2,k^3) knowing the value of $k^1 \geq k^2 \geq k^3$, so the membership function is as follows:

$$\mu(r) = \begin{cases} \frac{r-k^2}{k^2-k^1} \\ \frac{r-k^3}{k^2-k^3} \\ 0 \end{cases} \tag{8}$$

Based on this definition, the fuzzy probability constraint model can be formulated as follows (X. LI & B, 2006):

$$Min \sum_{j=1}^{n} C_j x_j$$

Subject to:

$$Cr\left\{\sum_{j=1}^{n} a_{ij} x_j \leq \tilde{b}_i\right\} \geq \lambda i, i = 1, \ldots, m.$$

$$x_j \geq 0, i = 1, \ldots, n. \tag{9}$$

Based on the model (9), the first constraint $\sum_{j=1}^{n} a_{ij}x_j \leq \widetilde{b_i}$ must be greater than or equal to λ_i. The λ_i is the Credibility level scalar, and usually, the credibility level should be greater than 0.5 (Meng & Y, 2007). Moreover, it is advantageous to have a deterministic model for the fuzzy probability constraint model in order to streamline the optimization model. Ultimately, theory 1 is employed to transform FCCP into an equivalent crisp representation.

Theory 1 Let K_i be an independent triangular fuzzy number (k_i^1, k_i^2, k_i^3) and $\check{s}_o$ be an independent triangular fuzzy number (s_o^1, s_o^2, s_o^3) with a level credibility α ∊ [0,5, 1].

$Cr\{\sum_j^n u_i\tilde{k}_i / \sum_j^n h_o\tilde{s}_o \leq c\} \geq \alpha$ *if and only if*

$$\frac{(2\alpha - 1)\sum_j^n u_i k_i^3 + 2(1-\alpha)\sum_j^n u_i k_i^2}{(2\alpha - 1)\sum_o^n h_o s_o^1 + 2(1-\alpha)\sum_o^n h_o s_o^2} \leq c; \tag{10}$$

$Cr\{\sum_j^n u_i\tilde{k}_i / \sum_j^n h_o\tilde{s}_o \leq c\} \geq \alpha$ *if and only if*

$$\frac{(2\alpha - 1)\sum_j^n u_i k_i^1 + 2(1-\alpha)\sum_j^n u_i k_i^2}{(2\alpha - 1)\sum_o^n h_o s_o^3 + 2(1-\alpha)\sum_o^n h_o s_o^2} \leq c; \tag{11}$$

According to the FCCP concept, models (2), (3), (4), and (5) can be transformed into a credibility-limited model as follows:

$\max \theta_{IDMU}$

Subject to:

$$\left\{\frac{\sum_{r=1}^{m} u_r\tilde{y}_r^{max}}{\sum_{i=1}^{n} v_i\tilde{x}_i^{min}} \geq \theta_{IDMU}\right\} \geq \alpha$$

$$\left\{\frac{\sum_{r=1}^{m} u_r\tilde{y}_{rj}}{\sum_{i=1}^{n} v_i\tilde{x}_{ij}} \leq 1\right\} \geq \beta j, \forall j$$

$$v_i u_r \geq 0 \ \forall i, r \tag{12}$$

$\max \theta j$

$$\left\{\frac{\sum_{r=1}^{m} u_r\tilde{y}_{rj}}{\sum_{i=1}^{n} v_i\tilde{x}_{ij}} \geq \theta j\right\} \geq \alpha$$

$$\sum_{r=1}^{m} u_r y_r^{max} - \sum_{i=1}^{n} v_i\left(\theta_{IDMU}^{*} x_i^{min}\right) = 0$$

$$\left\{\frac{\sum_{r=1}^{m} u_r\tilde{y}_{rj}}{\sum_{i=1}^{n} v_i\tilde{x}_{ij}} \leq 1\right\} \geq \beta j, \forall j$$

$$v_i u_r \geq 0 \forall i, r \tag{13}$$

$\min \varphi_{ADMU}$

Subjected to:

$$\left\{\frac{\sum_{r=1}^{m} u_r\tilde{y}_r^{min}}{\sum_{i=1}^{n} v_i\tilde{x}_i^{max}} \leq \varphi_{ADMU}\right\} \geq \alpha$$

$$\left\{\frac{\sum_{r=1}^{m} u_r \tilde{y}_{rj}}{\sum_{i=1}^{n} v_i \tilde{x}_{ij}} \leq 1\right\} \geq \beta j, \forall j$$

$$v_i u_r \geq 0 \forall i, r \tag{14}$$

$$\min \varphi j$$

Subjected to:

$$\left\{\frac{\sum_{r=1}^{m} u_r \tilde{y}_{rj}}{\sum_{i=1}^{n} v_i \tilde{x}_{ij}} \leq \varphi j\right\} \geq \alpha$$

$$\sum_{r=1}^{m} u_r y_r^{min} - \sum_{i=1}^{n} v_i \left(\varphi^*_{ADMU} x_i^{max}\right) = 0$$

$$\left\{\frac{\sum_{r=1}^{m} u_r \tilde{y}_{rj}}{\sum_{i=1}^{n} v_i \tilde{x}_{ij}} \leq 1\right\} \geq \beta j, \forall j$$

$$v_i u_r \geq 0 \ \forall i, r \tag{15}$$

The conversion process outlined in theorem 1 transforms models (14), (15), (16), and (17) into crisp equivalents as follows:

$$\max \theta_{IDMU}$$

Subjected to:

$$\frac{(2\alpha - 1)\sum_r^m u_r y_r^{1^{max}} + 2(1-\alpha)\sum_r^m u_r y_r^{2^{max}}}{(2\alpha - 1)\sum_i^n v_i x_i^{3^{min}} + 2(1-\alpha)\sum_i^n v_i x_i^{2^{min}}} \geq \theta_{IDMU}$$

$$\frac{(2\beta_J - 1)\sum_r^m u_r y_{rj}^3 + 2\left(1-\beta_j\right)\sum_r^m u_r y_{rj}^2}{\left(2\beta_j - 1\right)\sum_i^n v_i x_{ij}^1 + 2\left(1-\beta_j\right)\sum_i^n v_i x_{ij}^2} \leq 1, \forall j$$

$$v_i u_r \geq 0 \ \forall i, r \tag{16}$$

$$\max \theta j$$

Subjected to:

$$\frac{(2\alpha - 1)\sum_r^m u_r y_{rj}^1 + 2(1-\alpha)\sum_r^m u_r y_{rj}^2}{(2\alpha - 1)\sum_i^n v_i x_{ij}^3 + 2(1-\alpha)\sum_i^n v_i x_{ij}^2} \geq \theta_j$$

$$\sum_{r=1}^{m} u_r y_r^{2^{max}} - \sum_{i=1}^{n} v_i \left(\theta^*_{IDMU} x_i^{2^{min}}\right) = 0$$

$$\frac{(2\beta_J - 1)\sum_r^m u_r y_{rj}^3 + 2\left(1-\beta_j\right)\sum_r^m u_r y_{rj}^2}{\left(2\beta_j - 1\right)\sum_i^n v_i x_{ij}^1 + 2\left(1-\beta_j\right)\sum_i^n v_i x_{ij}^2} \leq 1, \forall j$$

$$v_i u_r \geq 0 \ \forall i, r \tag{17}$$

$$\min \varphi_{ADMU}$$

Subjected to:

$$\frac{(2\alpha - 1)\sum_r^m u_r y_r^{3^{min}} + 2(1-\alpha)\sum_r^m u_r x_r^{2^{min}}}{(2\alpha - 1)\sum_i^n v_i x_{ij}^3 + 2(1-\alpha)\sum_i^n v_i x_{ij}^2} \leq \varphi_{ADMU}$$

$$\frac{(2\beta_J - 1)\sum_r^m u_r y_{rj}^3 + 2\left(1 - \beta_j\right)\sum_r^m u_r y_{rj}^2}{\left(2\beta_j - 1\right)\sum_i^n v_i x_{ij}^1 + 2\left(1 - \beta_j\right)\sum_i^n v_i x_{ij}^2} \leq 1, \forall j$$

$$v_i u_r \geq 0 \ \forall i, r \tag{18}$$

$$\min \varphi_J$$

Subjected to:

$$\frac{(2\alpha - 1)\sum_r^m u_r y_{rj}^3 + 2(1 - \alpha)\sum_r^m u_r y_{rj}^2}{(2\alpha - 1)\sum_i^n v_i x_{ij}^1 + 2(1 - \alpha)\sum_i^n v_i x_{ij}^2} \leq \varphi_j$$

$$\sum_{r=1}^m u_r y_r^{2^{min}} - \sum_{i=1}^n v_i (\varphi_{ADMU}^* x_i^{2^{max}}) = 0$$

$$\frac{(2\beta_J - 1)\sum_r^m u_r y_{rj}^3 + 2\left(1 - \beta_j\right)\sum_r^m u_r y_{rj}^2}{\left(2\beta_j - 1\right)\sum_i^n v_i x_{ij}^1 + 2\left(1 - \beta_j\right)\sum_i^n v_i x_{ij}^2} \leq 1, \forall j$$

$$v_i u_r \geq 0 \ \forall i, r \tag{19}$$

The models numbered 16, 17, 18, and 19 correspond to the subsequent models listed below.

$$\theta_{IDMU} = \max(2\alpha - 1)\sum_r^m u_r y_r^{1^{max}} + 2(1 - \alpha) u_r y_r^{2^{max}}$$

Subjected to:

$$(2\alpha - 1)\sum_r^m v_i x_i^{3^{min}} + 2(1 - \alpha)\sum_r^m v_i x_i^{2^{min}} = 1$$

$$(2\beta_J - 1)(\sum_r^m u_r y_{rj}^3 - \sum_i^n v_i x_{ij}^1) + 2\left(1 - \beta_j\right)(\sum_r^m u_r y_{rj}^2 - \sum_i^n v_i x_{ij}^2) \leq 0, \forall j$$

$$v_i u_r \geq 0 \ \forall i, r \tag{20}$$

$$\theta_j = max(2\alpha - 1)\sum_r^m u_r y_{rj}^1 + 2(1 - \alpha)\sum_r^m u_r y_{rj}^2$$

Subjected to:

$$(2\alpha - 1)\sum_i^n v_i x_{ij}^3 + 2(1 - \alpha)\sum_i^n v_i x_{ij}^2 = 1$$

$$\sum_{r=1}^m u_r y_r^{2^{max}} - \sum_{i=1}^n v_i \left(\theta_{IDMU}^* x_i^{2^{min}}\right) = 0$$

$$(2\beta_J - 1)(\sum_r^m u_r y_{rj}^3 - \sum_i^n v_i x_{ij}^1) + 2\left(1 - \beta_j\right)(\sum_r^m u_r y_{rj}^2 - \sum_i^n v_i x_{ij}^2) \leq 0, \forall j$$

$$v_i u_r \geq 0 \ \forall i, r \tag{21}$$

$$\varphi_{ADMU} = min(2\alpha - 1)\sum_r^m u_r y_r^{3^{min}} + 2(1 - \alpha)\sum_r^m u_r x_r^{2^{min}}$$

Subjected to:

$$(2\alpha - 1)\sum_i^n v_i x_i^{1^{max}} + 2(1 - \alpha)\sum_i^n v_i x_i^{2^{max}} = 1$$

$$(2\beta_J - 1)(\sum_r^m u_r y_{rj}^3 - \sum_i^n v_i x_{ij}^1) + 2\left(1 - \beta_j\right)(\sum_r^m u_r y_{rj}^2 - \sum_i^n v_i x_{ij}^2) \leq 0, \forall j$$

$$v_i u_r \geq 0 \ \forall i, r \tag{22}$$

$$\varphi_j = min(2\alpha - 1)\sum_r^m u_r y_{rj}^3 + 2(1 - \alpha)\sum_r^m u_r y_{rj}^2$$

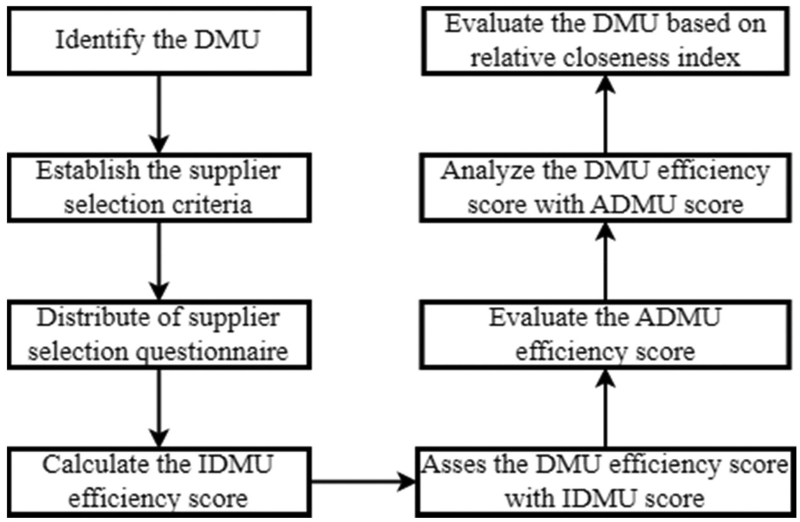

Figure 2. Supplier selection flowchart.

Subjected to:

$$(2\alpha - 1)\sum_i^n v_i x_{ij}^1 + 2(1-\alpha)\sum_i^n v_i x_{ij}^2$$

$$\sum_{r=1}^m u_r y_r^{2^{min}} - \sum_{i=1}^n v_i\left(\varphi_{ADMU}^* x_i^{2^{max}}\right) = 0$$

$$(2\beta_J - 1)\left(\sum_r^m u_r y_{rj}^3 - \sum_i^n v_i x_{ij}^1\right) + 2\left(1-\beta_j\right)\left(\sum_r^m u_r y_{rj}^2 - \sum_i^n v_i x_{ij}^2\right) \le 0, \forall j$$

$$v_i u_r \ge 0 \ \forall i, r \quad (23)$$

According to the study conducted by Wardana et al. (2021), the decision-making technique involving the combination of fuzzy DEA credibility constrained and the RC index is represented in Figure 2.

(1) Identify the DMU

The DMU can be determined by conducting an interview with the company's expert to establish the number of suppliers currently utilized.

(2) Establish the criteria for supplier selection

The criteria for supplier selection are determined by consulting with the company's expert to determine the suitable criteria that align with the company's requirements.

(3) Distribute the questionnaire for supplier selection

The supplier performance evaluation questionnaires were distributed to the company's expert.

(4) Calculate the efficiency score of the IDMU

The IDMU efficiency score can be computed using Equation (20).

(5) Assess the DMU efficiency score using the IDMU value

Compare the DMU efficiency score with the IDMU value by utilizing the solving model (17) or (21).

(6) Evaluate the efficiency score of the ADMU

Determine the ADMU efficiency score through the solution model (18) or by employing equation (22)

(7) Analyze the DMU efficiency score with the ADMU score

Compare the DMU efficiency score with the ADMU score using the solving model (19) or equation (23)

(8) Evaluate the DMU rating based on the calculation of the relative closeness value

This research was conducted in the frozen food manufacturing industry in Indonesia. The data collection for this research comes from the experts, so this research needs to identify the experts.

Table 3. Fuzzy number

Linguistic Variable	Fuzzy Number
Worst	(0, 0.5,1.5)
Very Poor	(1, 2, 3)
Poor	(2, 3.5, 5)
Fair	(3, 5, 7)
Good	(5, 6.5, 8)
Very Good	(7, 8, 9)
Excellent	(8.5, 9.5, 10)

The expert meaning has been discussed in the previous sections and the expert who becomes our data source should have enough knowledge about frozen shrimp quality and production, supplier criteria, and all of the attributes of this research. In this study, the experts are the managers of the logistics and purchasing divisions. The questionnaire was designed according to the desired criteria such as price, supplier location, product return rate, quality, delivery, service, order flexibility, and hygiene. The rating scale of the questions in the questionnaire for respondents in this study used 7 scales namely excellent, very good, good, fair, poor, and very poor. In this study, GAMS software was used to complete steps 7 and 8.

4. Results and discussion

4.1. Fuzzification

After gathering data from the survey, the obtained results are converted into fuzzy values for further analysis. The process of transforming the findings involves assigning fuzzy numbers to represent the collected data. Table 3 provides a comprehensive overview of the fuzzy numbers utilized in the analysis, offering a consolidated representation of the fuzzy values employed in the evaluation. Table 4 and Table 5 display the outcomes obtained by transforming the linguistic variables of each DMU into fuzzy numbers. These fuzzy numbers will serve as inputs for coding the GAMS software. Table 2 show the definationof notation that used in this article.

Based on the provided table, it is evident that DMU 3 ranks first, followed by DMU 15, DMU 7, DMU 11, DMU 6, DMU 13, DMU 10, DMU 9, DMU 1, DMU 4, DMU 8, DMU 12, DMU 5, DMU 2, and finally DMU 14. Some DMUs, namely DMU 4, DMU 6, DMU 8, and DMU 11 have identical IDMU values of 0.732. Among these four DMUs, it is observed that higher ADMU values correspond to greater RC Index values. Therefore, it can be inferred that an increase in the ADMU value leads to a higher RC Index value, and the same principle applies to an increase in the IDMU value. When employing the Fuzzy DEA Credibility Constrained method and the RC Index for supplier selection, it was found that certain suppliers obtained low scores on multiple criteria, resulting in their subpar performance.

4.2. Ranking consistency

Table 7 displays the outcomes of the supplier evaluation, which are additionally reassessed with various credibility constraints. This reassessment aims to determine the level of ranking consistency associated with each credibility constraint being employed. The credibility constraints employed include values of 0.6, 0.7, 0.8, 0.9, and 1. Table 6 show score of IDMU, ADMU, and RC index using credibility constrained 0.7.

Based on Table 7, it is evident that the RC Index value changed when the Credibility constraint increased by 0.1. Multiple prior studies also employed credibility constraints and achieved similar outcomes (X. M. LI et al., 2015; Wardana et al., 2021; Zhang & P, 2017). However, the variance in DMU ratings for each credibility constraint is negligible. Additionally, it can be observed that the IDMU value of each DMU decreases as the credibility constraint increases, while the ADMU score

Table 4. Fuzzy number input criteria

DMU	INPUTS								
	PRICE ($\tilde{x}_{1j}$)			LOCATION ($\tilde{x}_{2j}$)			PRODUCTS DEFECT RATE ($\tilde{x}_{3j}$)		
	x^1_{1J}	x^2_{1J}	x^3_{1J}	x^1_{2J}	x^2_{2J}	x^3_{2J}	x^1_{3J}	x^2_{3J}	x^3_{3J}
1	5	6.5	8	8.5	9.5	10	8.5	9.5	10
2	7	8	9	8.5	9.5	10	8.5	9.5	10
3	7	8	9	2	3.5	5	8.5	9.5	10
4	5	6.5	8	7	8	9	5	6.5	8
5	5	6.5	8	7	8	9	8.5	9.5	10
6	5	6.5	8	2	3.5	5	7	8	9
7	7	8	9	2	3.5	5	8.5	9.5	10
8	5	6.5	8	8.5	9.5	10	5	6.5	8
9	5	6,5	8	5	6.5	8	8.5	9.5	10
10	5	6.5	8	3	5	7	8.5	9.5	10
11	5	6.5	8	2	3.5	5	5	6.5	8
12	5	6.5	8	7	8	9	7	8	9
13	5	6.5	8	3	5	7	8.5	9.5	10
14	7	8	9	8.5	9.5	10	8.5	9.5	10
15	7	8	9	3	5	7	8.5	9.5	10
IDMU	x_1^{1min}	x_1^{2min}	x_1^{3min}	x_2^{1min}	x_2^{2min}	x_2^{3min}	x_3^{1min}	x_3^{2min}	x_3^{3min}
	5	6.5	8	2	3,5	5	5	6,5	8
ADMU	x_1^{1max}	x_1^{2max}	x_1^{3max}	x_2^{1max}	x_2^{2max}	x_2^{3max}	x_3^{1max}	x_3^{2max}	x_3^{3max}
	7	8	9	8.5	9.5	10	8.5	9.5	10

rises with the increasing credibility constraint. These findings align with the research conducted by Wardana et al. (2021). Figure 3 depicts the pattern of the RC Index based on different Credibility constraints.

Figure 3 illustrates that when the Credibility Ratio falls within the range of 0.6 to 0.8, the rankings of DMUs remain relatively consistent or show only slight deviations. This suggests that the evaluation results are dependable and can be trusted. On the other hand, when the Credibility Ratio exceeds the range of 0.9 to 1, the credibility diminishes substantially. This indicates that the reliability of the rankings obtained is compromised, and caution should be exercised in interpreting the evaluation outcomes.

4.3. Comparison results of conventional DEA with Fuzzy DEA credibility constrained and relative closeness index

After acquiring the questionnaire results, calculations were conducted utilizing Conventional DEA to compare the outcomes of both approaches. The subsequent analysis contrasts the calculations performed using Conventional DEA alongside Fuzzy DEA Credibility Constrained and Relative Closeness Index.

According to the table, it is evident that several DMUs possess identical efficiency values when evaluated using Conventional DEA. As a result, determining the top-performing DMU becomes challenging. This can be seen from the many values of ranking 1 generated using conventional DEA, making it difficult for decision-makers to choose the best DMU. Kim et al. (2019) noted that the use of Conventional DEA often leads to multiple DMUs having the same efficiency value, making it difficult to distinguish the best performer. This phenomenon can also be caused by the presence of outliers or

Table 5. Fuzzy number output criteria

DMU	OUTPUT														
	QUALITY ($\tilde{y}_{1j}$)			DELIVERY ACCURACY ($\tilde{y}_{2j}$)			SERVICE QUALITY ($\tilde{y}_{3j}$)			FLEXIBILITY TO ORDER CHANGES ($\tilde{y}_{4j}$)			HYGIENE ($\tilde{y}_{5j}$)		
	y^1_{1J}	y^2_{1J}	y^3_{1J}	y^1_{2J}	y^2_{2J}	y^3_{2J}	y^1_{3J}	y^2_{3J}	y^3_{3J}	y^1_{4J}	y^2_{4J}	y^3_{4J}	y^1_{5J}	y^2_{5J}	y^3_{5J}
1	5	6.5	8	8.5	9.5	10	5	6.5	8	0	0.5	1.5	7	8	9
2	7	8	9	8.5	9.5	10	5	6.5	8	0	0.5	1.5	8.5	9.5	10
3	7	8	9	8.5	9.5	10	7	8	9	1	2	3	8.5	9.5	10
4	5	6.5	8	7	8	9	5	6.5	8	0	0.5	1.5	7	8	9
5	5	6.5	8	7	8	9	5	6.5	8	0	0.5	1.5	7	8	9
6	5	6.5	8	7	8	9	7	8	9	0	0.5	1.5	7	8	9
7	7	8	9	7	8	9	5	6.5	8	0	0.5	1.5	8.5	9.5	10
8	5	6.5	8	7	8	9	5	6.5	8	0	0.5	1.5	5	6.5	8
9	7	8	9	7	8	9	7	8	9	0	0.5	1.5	7	8	9
10	5	6.5	8	8.5	9.5	10	7	8	9	0	0.5	1.5	7	8	9
11	5	6.5	8	7	8	9	7	8	9	0	0.5	1.5	7	8	9
12	5	6.5	8	7	8	9	5	6.5	8	0	0.5	1.5	5	6.5	8
13	7	8	9	8.5	9.5	10	7	8	9	0	0.5	1.5	8.5	9.5	10
14	7	8	9	7	8	9	7	8	9	0	0.5	1.5	7	8	9
15	7	8	9	8.5	9.5	10	8,5	9.5	10	1	2	3	7	8	9
IDMU	y_1^{1max}	y_1^{2max}	y_1^{3max}	y_2^{1max}	y_2^{2max}	y_2^{3max}	y_3^{1max}	y_3^{2max}	y_3^{3max}	y_4^{1max}	y_4^{2max}	y_4^{3max}	y_4^{1max}	y_4^{2max}	y_4^{3max}
	7	8	9	8.5	9.5	10	8.5	9.5	10	1	2	3	8.5	9.5	10
ADMU	y_1^{1min}	y_1^{2min}	y_1^{3min}	y_2^{1min}	y_2^{2min}	y_2^{3min}	y_3^{1min}	y_3^{2min}	y_3^{3min}	y_4^{1min}	y_4^{2min}	y_4^{3min}	y_4^{1min}	y_4^{2min}	y_4^{3min}
	5	6,5	8	7	8	9	5	6,5	8	0	0,5	1,5	5	6,5	8

Table 6. Score IDMU, ADMU, and RC index using credibility constrained 0.7

DMU	θ_j	φ_j	RC
1	0.795	4.383	0.92413
2	0.709	3.812	0.88452
3	0.782	15.033	0.98000
4	0.732	4.875	0.91908
5	0.666	4.386	0.89212
6	0.732	7.019	0.94669
7	0.719	7.407	0.94794
8	0.732	4.869	0.91896
9	0.771	4.872	0.92777
10	0.795	5.715	0.94468
11	0.732	7.026	0.94675
12	0.698	4.389	0.89995
13	0.795	5.873	0.94640
14	0.694	3.811	0.88022
15	0.781	14.011	0.97838

extreme values within the dataset can also impact the DEA results and pose challenges in determining the best DMU accurately. According to Berghäll and Nisar (2016), the outlier values within the dataset can distort the efficiency scores and rankings, potentially leading to misinterpretations or misleading conclusions. Therefore, it is essential to carefully consider the limitations and uncertainties associated with the DEA method when attempting to determine the most efficient DMU.

Meanwhile, the use of the fuzzy DEA and credibility-constrained approach (see Table 8) shows better results than the conventional DEA approach. This is indicated by the decrease in the number of DMUs ranked 1 when compared to conventional DEA. However, there are still two DMUs with the same ranking, for example, a DMU ranked 13th, which would also make it difficult for decision-makers to choose the best DMU. When employing fuzzy DEA, the concept of credibility becomes crucial in ensuring the reliability of the obtained results. Credibility refers to the degree of trustworthiness or believability of the evaluation outcomes. Meng et al. (2011) believed that credibility-constrained are imposed on the fuzzy DEA model. These constraints define a range of credibility ratios within which the rankings of DMUs are considered reliable. For instance, a credibility ratio value between 0.6 and 0.8 May indicate a stable ranking, while a value above 0.9 suggests low credibility (Konings et al., 2006).

Conversely, the Fuzzy DEA Credibility Constrained and Relative Closeness Index produced dissimilar outcomes for each DMU. When employing credibility constraints, if the RC Index yields identical results, the credibility constraint can be adjusted to clarify the superior DMU (Wardana et al., 2021). This adjustment is attributed to the influence of the credibility index on the RC index, whereby an increase in the credibility index leads to a decrease in the RC index value. In addition, LIN and LU (2023) argued that the Fuzzy DEA Credibility Constrained approach and Relative Closeness Index are superior due to their ability to handle uncertainty and provide a comprehensive evaluation of DMU performance. These methods go beyond traditional approaches, allowing decision-makers to make more informed decisions based on a realistic understanding of the rankings and proximity to optimal performance

5. Managerial and theoretical implications

Based on the previous discussion, stakeholders can implement various managerial policies regarding the criteria for selecting suppliers to ensure that the chosen supplier is the most suitable for

Table 7. Ranking consistency

0.6		0.7		0.8		0.9		1	
Ranking	**DMU**	**Ranking**	**DMU**	**Ranking**	**DMU**	**Ranking**	**DMU**	**Ranking**	**DMU**
1	DMU 3	1	DMU 3	1	DMU 3	1	DMU 3	1	DMU 3
2	DMU 15	2	DMU 15	2	DMU 15	2	DMU 15	2	DMU 15
3	DMU 11	3	DMU 7	3	DMU 13	3	DMU 13	3	DMU 7
4	DMU 7	4	DMU 11	4	DMU 10	4	DMU 7	4	DMU 13
5	DMU 6	5	DMU 6	5	DMU 7	5	DMU 10	5	DMU 10
6	DMU 13	6	DMU 13	6	DMU 11	6	DMU 11	6	DMU 11
7	DMU 10	7	DMU 10	7	DMU 6	7	DMU 6	7	DMU 6
8	DMU 4	8	DMU 9	8	DMU 1	8	DMU 1	8	DMU 9
9	DMU 9	9	DMU 1	9	DMU 9	9	DMU 9	9	DMU 1
10	DMU 8	10	DMU 4	10	DMU 4	10	DMU 4	10	DMU 4
11	DMU 12	11	DMU 8	11	DMU 8	11	DMU 8	11	DMU 8
12	DMU 1	12	DMU 12	12	DMU 5	12	DMU 5	12	DMU 5
13	DMU 5	13	DMU 5	13	DMU 12	13	DMU 2	13	DMU 12
14	DMU 2	14	DMU 2	14	DMU 2	14	DMU 12	14	DMU 2
15	DMU 14	15	DMU 14	15	DMU 14	15	DMU 14	15	DMU 14

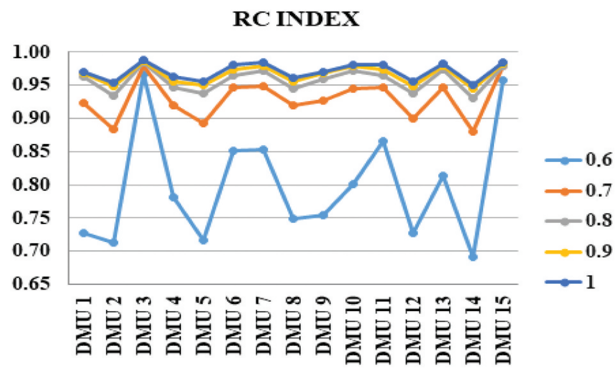

Figure 3. Relative Closeness Index.

Table 8. Comparison of results using DEA vs Fuzzy DEA and credibility constrained

DMU	DEA Conventional		Fuzzy DEA and Fuzzy Credibility Constrained (0.7)		Fuzzy DEA Credibility Constrained and RC Index (0.7)	
	Efficiency	Ranking	RC Index	Ranking	RC Index	Ranking
1	1	1	0.749	9	0.924	9
2	0.923	13	0.707	13	0.885	14
3	1	1	0.813	1	0.980	1
4	1	1	0.721	12	0.919	10
5	0.886	15	0.743	11	0.892	13
6	1	1	0.757	7	0.947	5
7	1	1	0.805	3	0.948	3
8	1	1	0.745	10	0.919	11
9	1	1	0.750	8	0.928	8
10	1	1	0.793	5	0.945	7
11	1	1	0.786	6	0.947	4
12	0.932	12	0.707	13	0.900	12
13	1	1	0.801	4	0.946	6
14	0.923	13	0.676	15	0.880	15
15	1	1	0.809	2	0.978	2

industry needs. Decision-makers must consistently assess the necessary supplier criteria. Furthermore, personnel responsible for supplier selection should enhance their skills in adapting to change. Decision-makers also need to understand the digital technology advancements that suppliers possess. Therefore, regular training activities and skill development in information technology are essential. A well-planned training program is necessary to empower individuals, reduce internal levels within the organization, and foster quality improvement (Hanaysha, 2016). Moreover, periodic training would enhance the purchasing staff's ability to choose the optimal supplier for the business (Masudin, Aprilia, et al., 2021).

Another aspect that decision-makers must take into account during the supplier selection process is the connection between the buyer and the supplier. It is crucial for decision-makers on both sides, buyers, and suppliers, to establish a strong working relationship. A favorable and stable working relationship regarding supply and demand activities ensures the satisfaction of requirements based on industry standards. Additionally, this buyer-supplier relationship facilitates efficient and effective information sharing between the two parties (Zaim et al., 2003). A strong and dependable working relationship concerning supply and demand activities guarantees the fulfillment of needs according to industry criteria. Moreover, this buyer-supplier relationship aids in the efficient and effective exchange of information between the two entities. The occurrence of information distortion between buyers and suppliers in business-to-business interactions has a significant impact on meeting demand (Souza et al., 2000).

The findings of this study indicated that the valid data flows from buyers and suppliers impact significantly the quality of the information received by the stakeholders involved. In enhancing communication and information exchange, it is beneficial to make use of technology solutions and data-sharing platforms. Technology solutions and data-sharing platforms play a significant role in facilitating seamless communication within and across organizations. These platforms could provide a centralized and accessible space where relevant stakeholders can share information, collaborate, and coordinate their activities. Duong et al. (2021) believed that by utilizing such platforms, companies can eliminate the need for time-consuming manual communication methods and ensure that accurate and up-to-date information is readily available to all involved parties.

Theoretically, implementing the fuzzy DEA credibility constrained and relative closeness index approach for supplier selection can decrease the uncertainty of supplier selection outcomes caused by inaccurate data. Nevertheless, traditional methods employed in supplier selection reveal that the outcomes become unclear when multiple suppliers receive the same evaluation score (Bai & Sarkis, 2010). Hence, the findings of the research indicating that enhancing the Credibility index will decrease the value of the RC index offer crucial insights for minimizing the ambiguity observed in previous theories related to supplier selection.

The integration of the Fuzzy DEA credibility-constrained approach and the RC index not only reduces uncertainty but also offers a practical solution to the long-standing issue of ambiguity in supplier selection. The theoretical advancements of this study provide a foundation for future research in supplier selection methodologies, enabling a more reliable and informed decision-making process in various industrial contexts.

6. Conclusion

This study aimed to enhance the validity of the supplier selection approach's outcomes. The conventional approach currently used exhibits uncertainty in the supplier selection results, as they often yield similar assessment scores. The proposed method called the Fuzzy DEA Credibility Constrained and Relative Closeness Index, introduces a valuable aspect as information to alleviate the ambiguity in the supplier selection process results. The study's findings suggest that an increase in the Credibility index level leads to a decrease in the relative closeness index value.

In light of these research findings, it is important to address several considerations regarding managerial policies. It is crucial to periodically enhance the competence and skills of staff involved in the supplier selection process. Moreover, policymakers responsible for supplier selection should prioritize the level of relationship between buyers and suppliers. This aspect relates to the implementation of information-sharing policies between the two parties. As for future research, it is worth considering the impact of the COVID-19 pandemic on the criteria selection process. Therefore, incorporating health criteria could be a valuable addition to the next study.

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