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An Integrated Circular Intuitionistic Fuzzy SWARA-TOPSIS Framework for Supplier Selection: Evidence from Pia Cap Mangkok

Putri Rosmerry Retno Sahabir*, Vira Hari Krisnawati, and Marsudi

Mathematics Department of Brawijaya University

Abstract

In food industries, supplier evaluation and selection are strategic activities that influence product freshness, operational continuity, and supply chain sustainability. However, this process is often hindered by uncertainty and ambiguity in expert judgments. In response to these challenges, the present study proposes an integrated decision-making method that combines Circular Intuitionistic Fuzzy Set (CIFS), the Stepwise Weight Assessment Ratio Analysis (SWARA), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). CIFS capture uncertainty in expert opinions, SWARA determines systematic criteria weights, and TOPSIS—enhanced with the Garg et al. distance measure—ranks suppliers based on aggregated evaluations. The evaluation involves seven key criteria: flexibility, capacity, quality, service, reputation, price, and lead time, assessed across five potential suppliers. Applied to Toko Pia Cap Mangkok, a traditional snack producer in Malang, Indonesia, the method identifies lead time, capacity, and reputation as the most critical criteria. Among the alternatives, Supplier A_1 consistently ranks first across optimistic, pessimistic, and combined scenarios, confirming its robustness and reliability, followed by Supplier A_2, while others perform less competitively. This study advances fuzzy-based multi-criteria decision-making by integrating CIFS–SWARA–TOPSIS, ensuring reliable supplier selection under uncertainty and offering a replicable framework for decision-makers in the food industry.

Keywords: Circular Intuitionistic Fuzzy Set; Multi-Criteria Decision Making; Supplier Selection; SWARA; TOPSIS.

1 Introduction

Selecting suppliers in the food sector represents a critical strategic decision that strongly influences product quality, assurance of safety, and the long-term sustainability of supply chains. Food companies must secure reliable supplies of fresh raw materials that meet safety standards [1]. Since suppliers significantly influence supply chain performance, their evaluation requires systematic and accurate methods [2]. The growing complexity of food supply chains further challenges the identification of suppliers that meet diverse quality and sustainability requirements [3], [4]. However, many existing approaches still struggle to address uncertainty and ambiguity in expert judgments.

*Corresponding author. E-mail: putrisahabir96@gmail.com

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Uncertainty in food supplier selection arises from limited data, subjective preferences, and dynamic market conditions. To capture such vagueness, fuzzy set extensions have been widely used. Intuitionistic Fuzzy Sets (IFS), introduced by Atanassov, enhance classical fuzzy sets by incorporating both membership degrees (MD) and non-membership degrees (NMD), thereby reflecting hesitation more effectively. Building on IFS, Circular Intuitionistic Fuzzy Sets (CIFS) [5], [6] model uncertainty as circular regions defined by MD and NMD, enabling richer and more intuitive representations of ambiguous expert evaluations. Compared to conventional fuzzy and IFS approaches that treat MD and NMD independently, CIFS captures the interdependent and non-linear interaction between MD and NMD, preserving more information about expert hesitation and subjective uncertainty in complex decision-making scenarios.

Multi-criteria decision-making (MCDM) approaches such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [7] and criterion weighting methods like the Stepwise Weight Assessment Ratio Analysis (SWARA) [8], [9] are widely used to evaluate and rank alternatives. However, most studies apply these methods separately, limiting their ability to fully address uncertainty and subjectivity in expert judgments. The proposed CIFS–SWARA–TOPSIS framework integrates these techniques within a CIFS environment, which models uncertainty as circular regions defined by MD and NMD, capturing non-linear and interdependent hesitation that conventional fuzzy or IFS approaches cannot reflect. The SWARA procedure ensures transparent and consistent derivation of criterion weights from expert reasoning, while TOPSIS provides an interpretable ranking based on proximity to ideal solutions. By incorporating the distance measure developed by Garg et al. (2024) [10], which separately evaluates MD and NMD, the framework enhances discriminatory power and sensitivity to subtle differences in expert perceptions. Combined with sensitivity analysis, this integrated approach produces robust, consistent, and interpretable decision outcomes, making it particularly suitable for complex supplier selection problems characterized by uncertainty and subjective evaluations.

This research applies the integrated CIFS–SWARA–TOPSIS model to Pia Cap Mangkok, a traditional snack producer in Malang, Indonesia, which requires robust supplier selection to maintain quality, operational continuity, and sustainability. The contributions of this study are: (1) extending food supplier selection under uncertainty using CIFS; (2) applying SWARA for systematic and transparent criterion weighting; (3) adopting Garg's distance measure to refine CIFS–TOPSIS ranking precision; (4) incorporating sensitivity analysis to assess ranking consistency; and (5) providing a practical, replicable framework for supplier evaluation in the food industry.

2 Methods

This study integrates CIFS with the SWARA framework for criteria weighting, and TOPSIS for alternative ranking. The approach is designed to capture uncertainty in expert evaluations through CIFS, determine criterion weights systematically with SWARA, and perform ranking based on proximity to ideal solutions using TOPSIS. In the TOPSIS phase, the distance measure formulated by Garg et al. is employed to provide an efficient asymmetric distance formulation. This methodological integration is intended to strengthen the stability and precision of decisions in uncertain environments.

The research is conducted as a case study at Pia Cap Mangkok, a well-known souvenir store in Malang specializing in traditional pia products. The focus is on selecting the most suitable raw material suppliers, a decision that directly affects product quality, production continuity, and operational efficiency.

Evaluation criteria are determined through a review of literature on supplier selection and adjusted to the specific context of the case study. Data for this study are obtained from expert assessments of potential suppliers based on these criteria. These assessments are expressed using CIFS to model MD, NMD, and hesitation degrees in a circular representation. Expert respondents are selected based on their familiarity with the production process and supplier performance.

2.1 Intuitionistic Fuzzy Set

The introduction of fuzzy set theory by Zadeh in 1965 [11] established a fundamental basis for dealing with vagueness and uncertainty in complex systems. Building on this foundation, Atanassov (1986) [12] proposed IFS as a broadening of fuzzy sets by introducing MD, NDM, and hesitation degrees. This development marked an important step in extending the expressive power of fuzzy theory, enabling more precise modeling of incomplete and uncertain information.

Definition 1. *[12]*
Let $E = x_1, x_2, ..., x_n$ denote the universe of discourse. An IFS A over E is defined as

$$A = \{\langle \mu_A(x), \nu_A(x)\rangle | x \in E\} \tag{1}$$

where $\mu_A : E \to [0,1]$ and $\nu_A : E \to [0,1]$, subject to the condition $0 \leq \mu_A(x)+\nu_A(x) \leq 1, \forall x \in E$. Here, $\mu_A(x)$ and $\nu_A(x)$ represent the MD and the NMD of element x in set A, respectively. Furthermore, the hesitation (or indeterminacy) degree $\pi_A(x)$ associated with x is given by:

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x). \tag{2}$$

Definition 2. *[10]*
Let $E = \{x_j, j = 1, 2, ..., m\}$ be a finite universe of discourse. Consider two IFS, $A = \langle \mu_A(x_j), \nu_A(x_j)\rangle$ and $B = \langle \mu_B(x_j), \nu_B(x_j)\rangle$. The distance between A and B, denoted as $d^w_{DG}(A, B)$, is defined as

$$d^w_{DG}(A, B) = \frac{3}{8}\Sigma^m_{j=1}\left[w_j|\mu_A(x_j) - \mu_B(x_j)| + |\nu_A(x_j) - \nu_B(x_j)| + w_j\frac{Cr(A, B)}{1 + Cr(A, B)}\right] \tag{3}$$

where

$$\begin{aligned} Cr(A, B) = \;& |min(\mu_A(x_j), \nu_B(x_j)) - min(\mu_B(x_j), \nu_A(x_j))| \\ & + |max(\mu_A(x_j), \nu_B(x_j)) - max(\mu_B(x_j), \nu_A(x_j))| \end{aligned} \tag{4}$$

and w_j represents the weights, subject to the condition $\Sigma^n_{j=1}w_j = 1$.

2.2 Circular Intuitionistic Set

Definition 3. *[5]*
Let E be a fixed universe. A CIFS $\mathcal{C}$ in E is described as

$$\mathcal{C} = \{\langle \mu_\mathcal{C}(x), \nu_\mathcal{C}(x); r\rangle | x \in E\} \tag{5}$$

with the condition

$$0 \leq \mu_\mathcal{C}(x) + \nu_\mathcal{C}(x) \leq 1 \tag{6}$$

where $r \in [0, 1]$ denotes the radius of the circle associated with each element $x \in E$. This structure is referred to as a CIFS, where $\mu_\mathcal{C}(x) : E \to [0, 1]$ and $\nu_\mathcal{C}(x) : E \to [0, 1]$ indicate the MD and NMD of element $x \in E$ in the set $\mathcal{C} \subseteq E$, respectively.

Definition 4. *[5]*
Let $\langle \mu_{i,1}, \nu_{i,1}\rangle, \langle \mu_{i,2}, \nu_{i,2}\rangle, ...$ denote a collection of IF pairs. The CIFS $\mathcal{C}i$ is derived from these pairs, where i indicates the index of the IFS and k_i represents the total number of pairs in the set. The arithmetic mean of this collection is defined as:

$$\mathcal{C}i = \langle \mu_\mathcal{C}(\mathcal{C}i), \nu_\mathcal{C}(\mathcal{C}i)\rangle = \left\langle \frac{\Sigma^{k_i}_{j=1}\mu_{i,j}}{k_i}, \frac{\Sigma^{k_i}_{j=1}\nu_{i,j}}{k_i} \right\rangle \tag{7}$$

Definition 5. *[13]*
Let $\{\langle\mu_{i,1},\nu_{i,1}\rangle,\langle\mu_{i,2},\nu_{i,2}\rangle,...\}$ represent a collection of Intuitionistic Fuzzy (IF) pairs. The aggregated result, which corresponds to the center of C_i, is obtained through the IF weighted geometric (IFWG) operator and yields another IF value:

$$C_i = IFWG_{W_i}(\langle\mu_{i,1},\nu_{i,1}\rangle,\langle\mu_{i,2},\nu_{i,2}\rangle,...) = \langle\prod_{j=1}^{n}\mu_{i,j}^{w_{i,j}}, 1-\prod_{j=1}^{n}(1-\nu_{i,j})^{w_{i,j}}\rangle \tag{8}$$

where $W_i = w_{i,1}, w_{i,2}, ..., w_{i,n}$ denotes the weight vector, with $w_{i,j}\in[0,1]$ and \$$\Sigma_{j=1}^{n} w_{i,j} = 1$. The radius r_i of C_i is determined ordinary least square method, given as [14]:

$$r_i = \sqrt{\frac{\Sigma_{j=1}^{k_i}\mathbf{l}_{ij}^2}{k_i}} \tag{9}$$

where

$$\mathbf{l}_{ij} = \sqrt{(\mu_C(x_i)-m_{i,j})^2+(\nu_C(x_i)-n_{i,j})^2} \tag{10}$$

Rather than adopting the maximum value approach [15], this study utilizes the Ordinary Least Squares (OLS) method. The reason is that estimating r through the maximum value technique tends to be affected by extreme observations, which may distort the representation of the original data. By contrast, the OLS-based estimation minimizes the total deviation between r and the original IF pairs, thereby preserving the intrinsic characteristics of the initial IF information.

Definition 6. *[16]*
Let $Q = [q_{ij}]_{m\times n}$ denote a collective decision matrix (or CIF decision matrix) with dimensions $m\times n$, where i corresponds to the alternatives $(i = 1,2,\dots,m)$ and j refers to the criteria $(j = 1,2,\dots,n)$. Each entry of Q is characterized by a CIF value expressed as $q_{ij} = \langle\mu_{ij},\nu_{ij};r_{ij}\rangle$. Based on Q, the optimistic and pessimistic decision matrices, denoted by Q^{O_d} and Q^{P_d} respectively, are defined as follows:

$$Q^{O_d} = \begin{bmatrix} q_{11}^O & q_{12}^O & \cdots & q_{1n}^O \\ q_{21}^O & q_{22}^O & \cdots & q_{2n}^O \\ \vdots & \vdots & \ddots & \vdots \\ q_{m1}^O & q_{m2}^O & \cdots & q_{mn}^O \end{bmatrix} \text{ and } Q^{P_d} = \begin{bmatrix} q_{11}^P & q_{12}^P & \cdots & q_{1n}^P \\ q_{21}^P & q_{22}^P & \cdots & q_{2n}^P \\ \vdots & \vdots & \ddots & \vdots \\ q_{m1}^P & q_{m2}^P & \cdots & q_{mn}^P \end{bmatrix} \tag{11}$$

where

$$\begin{aligned} q_{ij}^O = \langle\mu_{ij}^O,\nu_{ij}^O\rangle &= \left\langle \mu_{ij}+\frac{r_{ij}}{2}\sqrt{2}, \nu_{ij}-\frac{r_{ij}}{2}\sqrt{2}\right\rangle, \\ q_{ij}^P = \langle\mu_{ij}^P,\nu ij^P\rangle &= \left\langle \mu_{ij}-\frac{r_{ij}}{2}\sqrt{2}, \nu_{ij}+\frac{r_{ij}}{2}\sqrt{2},\right\rangle \end{aligned} \tag{12}$$

such that $\mu_{ij}^O,\nu_{ij}^O \in [0,1]$ and $\mu_{ij}^P,\nu_{ij}^P \in [0,1]$, representing the corresponding optimistic and pessimistic IF values derived from the CIF information.

The aforementioned formulation adheres to the fundamental properties of IFS, which are outlined below:

$$0 \le \mu_{ij}^O+\nu_{ij}^O = \left(\mu_{ij}+\frac{r_{ij}}{2}\sqrt{2}\right)+\left(\nu_{ij}-\frac{r_{ij}}{2}\sqrt{2}\right) = \mu_{ij}+\nu_{ij} \le 1$$
$$0 \le \mu_{ij}^P+\nu_{ij}^P = \left(\mu_{ij}-\frac{r_{ij}}{2}\sqrt{2}\right)+\left(\nu_{ij}+\frac{r_{ij}}{2}\sqrt{2}\right) = \mu_{ij}+\nu_{ij} \le 1$$

2.3 CIFS TOPSIS SWARA

The steps of supplier selection are developed through the integration of the CIFS–SWARA model developed by Alinejad et al. [17] and the CIFS–TOPSIS method introduced by Buyukselcuk et al.[18] Instead of applying these procedures in full, selected components are synthesized and refined, resulting in an extended framework tailored to supplier evaluation under uncertainty, and the method proceeds as follows:

1. Define the set of alternatives $\mathcal{A} = \{A_1, A_2, ..., A_m\}$ and the set of evaluation criteria $C = \{C_1, C_2, ..., C_n\}$.
2. Establish the expert set $\mathcal{E} = \mathcal{E}_1, \mathcal{E}_2, ..., \mathcal{E}_p$ and construct decision matrices from their evaluations, employing linguistic labels defined in Table 1.

Table 1: Criteria-based scale for assessing the alternatives

Linguistic Labels	(μ, ν)
Extremely high level (EHL)	(0.90,0.10)
Very high level (VHL)	(0.80,0.15)
High level (HL)	(0.70,0.25)
Above average level (AAL)	(0.60,0.35)
Average level (AL)	(0.50,0.45)
Below average level (BAL)	(0.40,0.55)
Low Level (LL)	(0.30,0.65)
Very low level (VLL)	(0.20,0.75)
Extremely low level (ELL)	(0.10,0.90)

3. Convert the decision matrices (d) provided by the experts into IF numbers according to Table 1. Then, construct $\mathcal{E}p = (e_{ijp})_{n\times m} = \langle \mu_{ij}, \nu_{ij} \rangle$, where e_{ijp} shows the evaluation of alternative A_i under criterion C_j by the p^{th} expert.
4. Aggregate all experts' decision matrices using Eq. 7 to construct the CIF decision matrix, and then calculate the radius of each CIF value according to Eq. 9.
5. Obtain the optimistic and pessimistic decision matrices, denoted as (Q^{O_d}, Q^{P_d}), based on Eq. 11 and Eq. 12.
6. Rank the criteria with experts judgments, where the experts are asked to provide their rankings using the linguistic labels presented in Table 2.

Table 2: Scale for assessing the relative importance of criteria

Linguistic Labels	(μ, ν)
Absolutely low level (AL)	(0.05,0.85)
Very low level (VLL)	(0.15,0.75)
Low level (LL)	(0.25,0.65)
Medium low level (MLL)	(0.35,0.55)
Almost Equal level (AEL)	(0.45,0.45)
Medium High level (MHL)	(0.55,0.35)
High level (HL)	(0.65,0.25)
Very high level (VHL)	0.75,0.15)
Absolutely high level (AHL)	(0.85,0.05)

7. Calculate the weights of experts using the following equation:

$$\omega_l = \frac{\left[\mu_l + \pi_l(\frac{\mu_l}{1-\pi_l})\right]}{\Sigma_{j=1}^{l}\left[\mu_j + \pi_l(\frac{\mu_l}{1-\pi_l})\right]}, \Sigma_{j=1}^{p}\omega_l = 1 \tag{13}$$

where $\pi_l = 1 - \mu_l - \nu_l$.

8. Aggregate experts' opinions of the criteria through the Eq. 8.
9. Compute the radius from the decision matrix of all experts using Eq. 9.
10. Apply the score function Eq. 14 to convert each aggregated CIF value into a crisp value, and use the resulting crisp values-denoted as Relative Significance Factors (RSF_j)- as inputs for the weighting process [17].

$$RSF_j = \frac{(1-\nu_j)(1+\mu_j)+\mu_j}{3} \times \left(\frac{\frac{1}{r_j}}{\sqrt{\Sigma_{j=1}^{n} \frac{1}{r_j^2}}} \right)^{\theta}, \theta = 0.01 \tag{14}$$

where θ indicates the uncertainty in the membership of an element within a set. A smaller value of this parameter indicates lower uncertainty. In this study, θ is set to 0.01.

11. Determine the relative importance of each criterion (S_k) by comparing it with the criterion ranked immediately. This step identifies how significant each criterion is relative to others, and the value of S_k is obtained using Eq. 15.

$$S_k = RSF_k - RSF_{k-1} \tag{15}$$

where RSF_k represents the score function of criterion arranged in descending order, from the highest to the lowest. In this variant of SWARA, the pairwise comparison phase is excluded. Instead, the difference between each ranked criterion score and the one immediately below it is calculated and incorporated into the subsequent SWARA weighting computation [17], [19], [20].

12. Determine the coefficient K_k. In this step, the index k refers to the position of a criterion in the decreasing order of scores obtained in the previous step, where $k = 1$ corresponds to the criterion with the highest score, $k = 2$ to the next, and so forth. This process establishes the adjustment factor for each criterion, and the coefficient K_k is then determined using the following equation:

$$K_k = \begin{cases} 1, k = 1 \\ S_k + 1, k > 1 \end{cases} \tag{16}$$

13. Determine the criterion weights using the following equation:

$$q_k = \begin{cases} 1, k = 1 \\ \frac{q_{k-1}}{K_k}, k > 1 \end{cases} \tag{17}$$

Next, q_k will be adjusted according to the initial criteria prior to the ranking of criterion scores.

14. Normalize the criterion weights using the following equation:

$$W_j = \frac{q_j}{\Sigma_{j=1}^{n} q_j}, j = 1, 2, ..., n \tag{18}$$

15. Determine the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) from the optimistic and pessimistic decision matrices using the following equations:

$$S_O^* = \left\{ \langle (\max_i \mu_{ij}^O, \min_i \nu_{ij}^O \mid j \in J_1), (\min_i \mu_{ij}^O, \max_i \nu_{ij}^O \mid j \in J_2) \rangle \right\} \tag{19}$$

$$S_O^- = \left\{ \langle (\min_i \mu_{ij}^O, \max_i \nu_{ij}^O \mid j \in J_1), (\max_i \mu_{ij}^O, \min_i \nu_{ij}^O \mid j \in J_2) \rangle \right\} \tag{20}$$

The PIS and NIS based on the pessimistic decision matrix are obtained using the following equations:

$$S_P^* = \left\{ \langle (\max_i \mu_{ij}^P, \min_i \nu_{ij}^P \mid j \in J_1), (\min_i \mu_{ij}^P, \max_i \nu_{ij}^P \mid j \in J_2) \rangle \right\} \tag{21}$$

$$S_P^- = \left\{ \langle (\min_i \mu_{ij}^P, \max_i \nu_{ij}^P \mid j \in J_1), (\max_i \mu_{ij}^P, \min_i \nu_{ij}^P \mid j \in J_2) \rangle \right\} \tag{22}$$

Here, μ_{ij} and ν_{ij} represent the membership and non-membership degrees of the i^{th} alternative with respect to the j^{th} criterion. The PIS (S^*) corresponds to the most desirable values that maximize the MD and minimize the NMD for benefit criteria, while the NIS (S^-) represents the least desirable values that minimize the MD and maximize the NMD for cost criteria. In this context, J_1 and J_2 denote the sets of benefit and cost criteria, respectively.

16. Compute the distances from every alternative to the PIS and NIS using the distance formula proposed by Garg et al. (2024) as shown in Eq. 3 and Eq. 4.
17. Calculate the Closeness Coefficient (CC) based on the optimistic and pessimistic matrices using the following equation:

$$CC_i^O = \frac{D_i^{O-}}{D_i^{O-} + D_i^{O*}} \tag{23}$$

$$CC_i^P = \frac{D_i^{P-}}{D_i^{P-} + D_i^{P*}} \tag{24}$$

18. Rank the alternatives utilizing Eq. 25 to calculate the score ratio of each alternative.

$$CC_i^{CR} = \alpha \times CC_i^O + (1 - \alpha) \times CC_i^P \tag{25}$$

where α denotes the weighting given to experts' optimistic and pessimistic judgments.

19. Arrange the alternatives according to their computed scores, identifying the most suitable option in decreasing order of CC_i^{CR}.
20. Conduct a sensitivity analysis to evaluate the consistency of the rankings.

3 Results and Discussion

Before presenting the numerical outcomes, this section first reports the empirical results of applying the proposed CIFS–SWARA–TOPSIS framework to the Pia Cap Mangkok supplier dataset. The intention is to show, in a stepwise manner, how expert judgments are transformed into CIF values, how criteria weights are derived, and how supplier rankings are finally obtained. After the results are outlined, the subsequent part of this section discusses their managerial and methodological implications.

3.1 Results

In this research application at Pia Cap Mangkok, seven criteria are employed, as presented in Table 3. These criteria are established based upon a detailed review of prior studies on supplier selection and provide a comprehensive foundation for evaluating suppliers, ensuring that the selection process incorporates both theoretical knowledge and practical applicability. Furthermore, five alternative suppliers were assessed with the involvement of five domain experts from Pia Cap Mangkok who are directly engaged in supplier selection decision-making.

Table 3: Definition of Criteria

Criterion	Type	Definition
Flexibility (C_1) [21], [22]	Benefit	The responsiveness of a supplier in accommodating variations in demand and external dynamics while ensuring consistent quality and uninterrupted performance.
Capacity (C_2) [4], [22], [23]	Benefit	The ability of a supplier to consistently meet the required volume of customer demand, thereby ensuring product availability in accordance with supply chain needs.
Quality (C_3) [24], [25], [26]	Benefit	The degree to which food products comply with required standards and customer expectations, encompassing aspects of product quality, safety, and consistency.
Service (C_4) [21], [22]	Benefit	The behavior, ethics, and service orientation demonstrated by a supplier in business interactions, which contribute to the establishment of long-term, mutually beneficial relationships.
Reputation (C_5) [27], [28]	Benefit	The image and track record of a supplier within the industry, reflected through recognition of product or service quality, integrity, consistent performance, and experience in collaborating with various enterprises, including large-scale companies.
Price (C_6) [22], [26]	Cost	The cost offered by a supplier for the provided products, where lower prices reflect cost efficiency and enhance competitiveness in supplier selection.
Lead Time (C_7) [29], [30], [31]	Cost	The duration required by a supplier to complete the food delivery process, from order placement to receipt by the customer. Shorter lead times indicate better supplier performance in maintaining distribution efficiency and product freshness.

Subsequently, Table 4 presents the evaluations provided by the experts for each alternative supplier, assessed in accordance with the established criteria.

Table 4: Experts' Evaluation of Alternatives

Criteria	Experts	Alternatives				
		A_1	A_2	A_3	A_4	A_5
C_1	$\mathcal{E}1$	EHL	VHL	VHL	VHL	VHL
	$\mathcal{E}2$	VHL	VHL	VHL	HL	VHL
	$\mathcal{E}3$	EHL	VHL	VHL	VHL	EHL
	$\mathcal{E}4$	EHL	VHL	EHL	AAL	HL
	$\mathcal{E}5$	EHL	EHL	HL	HL	HL
C_2	$\mathcal{E}1$	EHL	VHL	HL	AL	AAL
	$\mathcal{E}2$	EHL	EHL	HL	AAL	VHL
	$\mathcal{E}3$	EHL	EHL	EHL	VHL	EHL
	$\mathcal{E}4$	EHL	EHL	EHL	AAL	HL
	$\mathcal{E}5$	VHL	VHL	HL	HL	HL

Continued on next page

Table 4 (continued)

Criteria	Experts	Alternatives				
		A_1	A_2	A_3	A_4	A_5
C_3	$\mathcal{E}1$	EHL	EHL	HL	HL	VHL
	$\mathcal{E}2$	EHL	EHL	EHL	HL	VHL
	$\mathcal{E}3$	EHL	VHL	VHL	VHL	VHL
	$\mathcal{E}4$	EHL	EHL	EHL	AAL	HL
	$\mathcal{E}5$	VHL	VHL	HL	HL	HL
C_4	$\mathcal{E}1$	EHL	VHL	EHL	VHL	EHL
	$\mathcal{E}2$	EHL	HL	EHL	EHL	EHL
	$\mathcal{E}3$	EHL	HL	VHL	VHL	EHL
	$\mathcal{E}4$	EHL	EHL	EHL	HL	VHL
	$\mathcal{E}5$	VHL	VHL	VHL	VHL	VHL
C_5	$\mathcal{E}1$	EHL	VHL	VHL	HL	VHL
	$\mathcal{E}2$	EHL	EHL	EHL	VHL	EHL
	$\mathcal{E}3$	EHL	EHL	EHL	EHL	EHL
	$\mathcal{E}4$	EHL	EHL	EHL	AAL	VHL
	$\mathcal{E}5$	VHL	VHL	VHL	HL	VHL
C_6	$\mathcal{E}1$	ELL	VLL	VLL	LL	VLL
	$\mathcal{E}2$	ELL	LL	BAL	AL	BAL
	$\mathcal{E}3$	VLL	LL	LL	LL	LL
	$\mathcal{E}4$	VLL	LL	LL	BAL	BAL
	$\mathcal{E}5$	VLL	LL	LL	LL	LL
C_7	$\mathcal{E}1$	ELL	ELL	VLL	LL	LL
	$\mathcal{E}2$	VLL	VLL	BAL	LL	LL
	$\mathcal{E}3$	ELL	ELL	VLL	VLL	ELL
	$\mathcal{E}4$	VLL	VLL	AAL	AAL	VLL
	$\mathcal{E}5$	VLL	VLL	BAL	BAL	BAL

Then, the evaluations were converted into CIF numbers based on Table 1, and then aggregated using the arithmetic mean as defined in Eq. 7. The final outcomes are consolidated into a single table, which reports the aggregated expert assessments alongside the radius, the latter being determined through Eq. 9.

Table 5: Aggregation with radius (CIF Decision matrix)

Criteria	A_1	A_2	A_3	A_4	A_5
C_1	$\langle 0.880, 0.110; 0.045\rangle$	$\langle 0.820, 0.140; 0.045\rangle$	$\langle 0.800, 0.160; 0.080\rangle$	$\langle 0.720, 0.230; 0.106\rangle$	$\langle 0.780, 0.180; 0.096\rangle$
C_2	$\langle 0.880, 0.110; 0.045\rangle$	$\langle 0.860, 0.120; 0.055\rangle$	$\langle 0.780, 0.190; 0.122\rangle$	$\langle 0.640, 0.310; 0.144\rangle$	$\langle 0.740, 0.220; 0.050\rangle$
C_3	$\langle 0.880, 0.110; 0.045\rangle$	$\langle 0.860, 0.120; 0.055\rangle$	$\langle 0.800, 0.170; 0.112\rangle$	$\langle 0.700, 0.250; 0.089\rangle$	$\langle 0.760, 0.190; 0.103\rangle$
C_4	$\langle 0.880, 0.110; 0.045\rangle$	$\langle 0.780, 0.180; 0.096\rangle$	$\langle 0.860, 0.120; 0.055\rangle$	$\langle 0.800, 0.170; 0.075\rangle$	$\langle 0.860, 0.120; 0.055\rangle$
C_5	$\langle 0.880, 0.110; 0.045\rangle$	$\langle 0.860, 0.120; 0.055\rangle$	$\langle 0.860, 0.120; 0.055\rangle$	$\langle 0.740, 0.220; 0.134\rangle$	$\langle 0.840, 0.130; 0.055\rangle$
C_6	$\langle 0.160, 0.810; 0.088\rangle$	$\langle 0.280, 0.670; 0.057\rangle$	$\langle 0.300, 0.650; 0.089\rangle$	$\langle 0.360, 0.590; 0.113\rangle$	$\langle 0.320, 0.630; 0.106\rangle$
C_7	$\langle 0.160, 0.810; 0.088\rangle$	$\langle 0.160, 0.810; 0.088\rangle$	$\langle 0.360, 0.590; 0.212\rangle$	$\langle 0.360, 0.590; 0.192\rangle$	$\langle 0.260, 0.700; 0.156\rangle$

The optimistic and the pessimistic matrix are obtained from Eq. 11 and Eq. 12, and are presented in Table 6 and Table 7, respectively.

Table 6: Optimistic decision matrix

Criteria	A_1	A_2	A_3	A_4	A_5
C_1	$\langle 0.912, 0.078\rangle$	$\langle 0.852, 0.108\rangle$	$\langle 0.857, 0.103\rangle$	$\langle 0.795, 0.155\rangle$	$\langle 0.848, 0.112\rangle$
C_2	$\langle 0.912, 0.078\rangle$	$\langle 0.899, 0.081\rangle$	$\langle 0.867, 0.103\rangle$	$\langle 0.742, 0.208\rangle$	$\langle 0.775, 0.185\rangle$
C_3	$\langle 0.912, 0.078\rangle$	$\langle 0.899, 0.081\rangle$	$\langle 0.879, 0.091\rangle$	$\langle 0.763, 0.187\rangle$	$\langle 0.833, 0.117\rangle$
C_4	$\langle 0.912, 0.078\rangle$	$\langle 0.848, 0.112\rangle$	$\langle 0.899, 0.081\rangle$	$\langle 0.853, 0.117\rangle$	$\langle 0.899, 0.081\rangle$
C_5	$\langle 0.912, 0.078\rangle$	$\langle 0.899, 0.081\rangle$	$\langle 0.899, 0.081\rangle$	$\langle 0.835, 0.125\rangle$	$\langle 0.879, 0.091\rangle$
C_6	$\langle 0.222, 0.748\rangle$	$\langle 0.320, 0.630\rangle$	$\langle 0.363, 0.587\rangle$	$\langle 0.440, 0.510\rangle$	$\langle 0.395, 0.555\rangle$
C_7	$\langle 0.222, 0.748\rangle$	$\langle 0.222, 0.748\rangle$	$\langle 0.510, 0.440\rangle$	$\langle 0.496, 0.454\rangle$	$\langle 0.370, 0.590\rangle$

Table 7: Pessimistic decision matrix

Criteria	A_1	A_2	A_3	A_4	A_5
C_1	$\langle 0.848, 0.142\rangle$	$\langle 0.788, 0.172\rangle$	$\langle 0.743, 0.217\rangle$	$\langle 0.645, 0.305\rangle$	$\langle 0.712, 0.248\rangle$
C_2	$\langle 0.848, 0.142\rangle$	$\langle 0.821, 0.159\rangle$	$\langle 0.693, 0.277\rangle$	$\langle 0.538, 0.412\rangle$	$\langle 0.705, 0.255\rangle$
C_3	$\langle 0.848, 0.142\rangle$	$\langle 0.821, 0.159\rangle$	$\langle 0.721, 0.249\rangle$	$\langle 0.637, 0.313\rangle$	$\langle 0.687, 0.263\rangle$
C_4	$\langle 0.848, 0.142\rangle$	$\langle 0.712, 0.248\rangle$	$\langle 0.821, 0.159\rangle$	$\langle 0.747, 0.223\rangle$	$\langle 0.821, 0.159\rangle$
C_5	$\langle 0.848, 0.142\rangle$	$\langle 0.821, 0.159\rangle$	$\langle 0.821, 0.159\rangle$	$\langle 0.645, 0.315\rangle$	$\langle 0.801, 0.169\rangle$
C_6	$\langle 0.098, 0.872\rangle$	$\langle 0.240, 0.710\rangle$	$\langle 0.237, 0.713\rangle$	$\langle 0.280, 0.670\rangle$	$\langle 0.245, 0.705\rangle$
C_7	$\langle 0.098, 0.872\rangle$	$\langle 0.098, 0.872\rangle$	$\langle 0.210, 0.740\rangle$	$\langle 0.224, 0.726\rangle$	$\langle 0.150, 0.810\rangle$

At this stage, the calculation of the criteria weights is executed using the SWARA method. Prior to this, the experts' weights were first determined using Eq. 13. The evaluation of the experts' importance was conducted with reference to Table 2, based on the length of their experience in this field and the resulting weights are presented in the following table.

Table 8: Expert's weights

Experts	Importance Level	Weight
$\mathcal{E}1$	AHL	0.221
$\mathcal{E}2$	AHL	0.221
$\mathcal{E}3$	VHL	0.195
$\mathcal{E}4$	VHL	0.195
$\mathcal{E}5$	HL	0.169

Following this, the experts evaluate the criteria with reference to Table 2. The aggregated opinions are then calculated using Eq. 8 with the radius calculated using Eq. 9, and the score function is obtained through Eq. 14. The outcomes are presented in Table 9.

Table 9: Criteria Evaluation

Criteria	Experts					Aggregate; radius	RSF
	$\mathcal{E}1$	$\mathcal{E}2$	$\mathcal{E}3$	$\mathcal{E}4$	$\mathcal{E}5$		
C_1	VHL	VHL	AHL	AHL	AHL	$\langle 0.804, 0.096; 0.005\rangle$	0.32321
C_2	AHL	AHL	VHL	AHL	AHL	$\langle 0.830, 0.070; 0.003\rangle$	0.32678
C_3	AHL	VHL	VHL	AHL	VHL	$\langle 0.790, 0.110; 0.005\rangle$	0.32182
C_4	VHL	VHL	VHL	AHL	AHL	$\langle 0, 782, 0.115; 0.005\rangle$	0.32124
C_5	VHL	AHL	AHL	AHL	AHL	$\langle 0, 827, 0.073; 0.003\rangle$	0.32655
C_6	VHL	AHL	AHL	AHL	VHL	$\langle 0.810, 0.090; 0.005\rangle$	0.32375
C_7	AHL	AHL	AHL	AHL	VHL	$\langle 0.832, 0.068; 0.003\rangle$	0.32698

At this stage, the computation of the criteria weights is summarized in this table, with the complete calculation details provided in the supplementary file.

Table 10: Computation of criteria weights

Criteria	Skor	Sk	Kk	Qk	Qj
C_7	0.32698	-	1.00000	1.00000	0.14324
C_2	0.32678	0.00020	1.00020	0.99980	0.14321
C_5	0.32655	0.00024	1.00024	0.99956	0.14317
C_6	0.32375	0.00280	1.00280	0.99677	0.14277
C_1	0.32321	0.00054	1.00054	0.99624	0.14270
C_3	0.32182	0.00139	1.00139	0.99485	0.14250
C_4	0.32124	0.00058	1.00058	0.99427	0.14242

Based on the calculations, the prioritization of criteria reveals that Lead Time emerges as the most influential factor, followed by Capacity, Reputation, Price, Flexibility, Quality, and Service. This ordering highlights the relative importance of operational and performance-related aspects in the supplier selection process.

By employing Eq. 19–22, the PIS and NIS based on the optimistic and pessimistic matrices are presented in Table 11. The determination of these ideal solutions follows the same classification of benefit-type (J_1) and cost-type (J_2) criteria as defined earlier in Table 3, ensuring consistency in the evaluation framework.

Table 11: PIS and NIS

Optimistic Matrix		Pessimistic Matrix	
PIS	NIS	PIS	NIS
$\langle 0.912, 0.078\rangle$	$\langle 0.795, 0.155\rangle$	$\langle 0.848, 0.142\rangle$	$\langle 0.645, 0.305\rangle$
$\langle 0.912, 0.078\rangle$	$\langle 0.742, 0.208\rangle$	$\langle 0.848, 0.142\rangle$	$\langle 0.538, 0.412\rangle$
$\langle 0.912, 0.078\rangle$	$\langle 0.763, 0.187\rangle$	$\langle 0.848, 0.142\rangle$	$\langle 0.637, 0.313\rangle$
$\langle 0.912, 0.078\rangle$	$\langle 0.848, 0.117\rangle$	$\langle 0.848, 0.142\rangle$	$\langle 0.712, 0.248\rangle$
$\langle 0.912, 0.078\rangle$	$\langle 0.835, 0.125\rangle$	$\langle 0.848, 0.142\rangle$	$\langle 0.645, 0.315\rangle$
$\langle 0.222, 0.748\rangle$	$\langle 0.440, 0.510\rangle$	$\langle 0.098, 0.872\rangle$	$\langle 0.280, 0.670\rangle$
$\langle 0.222, 0.748\rangle$	$\langle 0.510, 0.440\rangle$	$\langle 0.098, 0.872\rangle$	$\langle 0.224, 0.726\rangle$

The separation measure, calculated using Eq. 3 and Eq. 4, represents the distance between the PIS and the NIS for every alternative. Specifically, D_i^{O*} denotes the distance of alternative i from the PIS in the optimistic matrix, D_i^{O-} its distance from the NIS in the optimistic matrix, D_i^{P*} the distance of alternative i from the PIS in the pessimistic matrix, and D_i^{P-} its distance from the NIS in the pessimistic matrix. These distances are presented in Table 12.

Table 12: Distances from PIS and NIS to Each Alternative

	A_1	A_2	A_3	A_4	A_5
D_i^{O*}	0.00000	0.04523	0.10405	0.18555	0.11475
D_i^{O-}	0.18816	0.14760	0.08979	0.00351	0.08343
D_i^{P*}	0.00000	0.07536	0.12953	0.23478	0.12873
D_i^{P-}	0.24014	0.17130	0.12339	0.00621	0.12461

The relative closeness coefficient built upon optimistic and pessimistic matrix is computed using Eq. 23 and Eq. 24 and displayed in Table 13.

Table 13: The relative closeness coefficient and ranking of the alternatives

	A_1	A_2	A_3	A_4	A_5
CC_i^O	1.00000	0.76545	0.46323	0.01858	0.42100
Rank	1	2	3	5	4
CC_i^P	1.00000	0.69450	0.48787	0.02576	0.49186
Rank	1	2	4	5	3

Finally, the alternatives are ranked using Eq. 25, with the parameter set to $\alpha = 0.5$. The result is shown in Table 14.

Table 14: Overall CC

For $\alpha = 0.5$	A_1	A_2	A_3	A_4	A_5
CC_i^{CR}	1.00000	0.72997	0.47555	0.02217	0.45643
Rank	1	2	3	5	4

The findings indicate that Lead Time (C_7) holds the highest significance in supplier selection, followed by Capacity (C_2) and Reputation (C_5). Regarding supplier ranking, Supplier A_1 consistently achieved the highest score across optimistic, pessimistic, and combined evaluations, while Supplier A_2 ranked second. The other suppliers (A_3, A_5, and A_4) showed comparatively lower performance.

A sensitivity analysis is performed to examine how the issue behaves across various scenarios. Table 15 displays the rankings of the alternatives for several α values.

Table 15: CC_i^{CR} for each alternative at different α levels

Alternative	**0.0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1.0**
A1	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
A2	0.69450	0.70159	0.70869	0.71578	0.72288	0.72997	0.73707	0.74416	0.75126	0.75835	0.76545
A3	0.48787	0.48540	0.48294	0.48047	0.47801	0.47555	0.47308	0.47062	0.46815	0.46569	0.46323
A4	0.02576	0.02505	0.02433	0.02361	0.02289	0.02217	0.02146	0.02074	0.02002	0.01930	0.01858
A5	0.49186	0.48478	0.47769	0.47060	0.46352	0.45643	0.44934	0.44226	0.43517	0.42808	0.42100

Although α varies, the results demonstrate consistency, with the top two alternatives maintaining their positions and the lowest-ranked alternative remaining unchanged. The following presents the Kendall's τ stability matrix used for the sensitivity analysis under three scenarios: (i) perturbation of the highest weight (w_7), (ii) equal weighting of experts, and (iii) application of a different distance measure, namely the weighted Euclidean distance. The analytical steps remain consistent with the proposed framework, with modifications applied only to the parameters being analyzed.

Table 16: Kendall's τ correlation matrix among different scenario

Scenario	**Original**	$\mathbf{w_7 - 20\%}$	$\mathbf{w_7 - 15\%}$	$\mathbf{w_7 - 10\%}$	$\mathbf{w_7 + 10\%}$	$\mathbf{w_7 + 15\%}$	$\mathbf{w_7 + 20\%}$	**Equal**	**Euclidean**
Original	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.80
$w_7 - 20\%$		1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.80
$w_7 - 15\%$			1.00	1.00	1.00	1.00	1.00	1.00	0.80
$w_7 - 10\%$				1.00	1.00	1.00	1.00	1.00	0.80
$w_7 + 10\%$					1.00	1.00	1.00	1.00	0.80
$w_7 + 15\%$						1.00	1.00	1.00	0.80
$w_7 + 20\%$							1.00	1.00	0.80
Equal ω_j								1.00	0.80
Euclidean									1.00

The full ranking outcomes for all sensitivity scenarios and the algorithm (pseudo code) are provided in the supplementary file.

3.2 Discussion

The findings highlight that timely delivery and supplier reliability are more decisive than quality and service in the food industry. This aligns with the characteristics of food supply chains, where product freshness and operational continuity depend on time efficiency and production capacity. These results are consistent with previous studies such as the Entropy–AHP Weighted TOPSIS approach [23] and the Pythagorean fuzzy AHP and fuzzy TOPSIS methodology [32], where Lead Time and Capacity also rank among the top three criteria in supplier selection.

The consistent ranking of Supplier A1 across all evaluation scenarios demonstrates robustness and reliability, making it a strategic partner for maintaining operational continuity. Supplier A2's stability further underscores the managerial importance of engaging suppliers with dependable delivery and production capabilities. Although the top-ranked supplier was intuitively preferred by the decision makers, the proposed method quantitatively confirmed the appropriateness of this choice, ensuring that the final decision was derived from a consistent and objective evaluation process. Strategically, firms should prioritize partnerships with suppliers offering strong responsiveness and production flexibility to enhance supply chain resilience.

The integration of CIFS, SWARA, and TOPSIS effectively captures expert subjectivity and uncertainty, providing a transparent and structured evaluation framework. However, this study is limited to the specific case analyzed, particularly in the number of experts and supplier alternatives, which may restrict the generalizability of the results. Future research should involve broader datasets and industrial contexts to validate and extend the applicability of the proposed model.

4 Conclusion

This study addresses the supplier choice problem in the food industry, with a practical application at Pia Cap Mangkok. The objective is to develop a decision-making framework by integrating CIFS, TOPSIS, and the SWARA method. This framework endeavors to manage inconsistency in expert appraisal while systematically quantifying the influence of each criterion.

The analysis reveals that Lead Time is the dominant criterion, followed by Capacity, Reputation, Price, Flexibility, Quality, and Service, emphasizing the critical role of timely delivery and operational reliability in food supply chains. For the alternatives, the model yields a stable ranking in which A_1 attains the highest score, followed by A_2, A_3, A_5, and A_4.Although experts intuitively favored the top supplier, the integrated approach substantiates this ranking quantitatively, ensuring that the decision results from a systematic and objective assessment. These findings offer actionable insights for Pia Cap Mangkok to enhance its supplier management and strengthen long-term partnerships. From a strategic standpoint, food firms are advised to engage suppliers with strong responsiveness and flexible production, which bolster supply chain robustness and maintain continuity in operations where timing is crucial.

The core contribution of this study lies in the integration of CIFS-based assessments with the SWARA weighting procedure and the TOPSIS ranking mechanism. This hybridization effectively accommodates expert uncertainty while maintaining transparency in the aggregation and evaluation process. It also provides a replicable and structured tool for supporting managerial decision-making in supplier evaluation, particularly under conditions of imprecise or subjective judgments.

Nevertheless, this study has several limitations. The analysis focuses on a single case and a limited number of decision-makers and supplier alternatives, which may restrict the generalizability of the results. Although the findings are consistent with previous studies that identified Lead Time and Capacity as key determinants in supplier selection, the comparative scope remains narrow. Future research should extend this framework to broader industrial contexts, include larger expert panels, or compare its performance against other advanced fuzzy MCDM techniques to further validate and strengthen the model's practical relevance.

CRediT Authorship Contribution Statement

Putri Rosmerry Retno Sahabir: Conceptualization, Methodology, Writing–Original Draft. **Vira Hari Krisnawati:** Validation, Data Curation and Supervision. **Marsudi:** Validation, Data Curation and Supervision.

Declaration of Generative AI and AI-assisted technologies

In preparing this manuscript, Generative AI (ChatGPT, GPT-5 by OpenAI) was used to aid in refining grammar, clarity, and overall flow, in addition to providing paraphrasing and language polishing support.

Declaration of Competing Interest

The authors declare no competing interests.

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Data and Code Availability

The data and code that underpin this study can be obtained from the corresponding author upon reasonable request, subject to confidentiality agreements, as the dataset contains interview responses from company representatives.

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