RESEARCH ARTICLE

A Spherical Fuzzy Set-Based Decision Support System for Evaluation of Logistics Subcontractors in 3PL Operations

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Abstract

The increasing complexity of global supply chains has made third-party logistics (3PL) service providers essential for companies seeking operational flexibility and cost efficiency. On-time delivery, a critical performance metric, directly impacts customer satisfaction, long-term business partnerships, and corporate reputation. However, challenges such as subcontractor management, subjective performance evaluation, and uncertainty in data significantly affect the reliability of performance assessments. This study proposes a novel decision support system utilizing Interval-Valued Spherical Fuzzy Analytic Hierarchy Process (IVSF-AHP) and Interval-Valued Spherical Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (IVSF-TOPSIS) to evaluate the performance of logistics subcontractors. The IVSF-AHP method dynamically weights performance criteria, while the IVSF-TOPSIS model ranks subcontractor performance under uncertainty. The proposed model contributes to the literature by integrating fuzzy multi-criteria decision-making (MCDM) approaches to reflect both objective and subjective evaluations, offering a flexible and adaptive performance monitoring mechanism for 3PL firms. The framework is validated through a practical example, demonstrating its ability to support strategic and operational decisions in logistics subcontractor management.

Keywords: third-party logistics, spherical fuzzy sets, AHP, TOPSIS.

1 Introduction

Increasingly complex supply chain structures due to globalization have led businesses to outsource their logistics activities. In this context, third party logistics (3PL) service providers play a key role in the effective management of logistics operations, reducing costs and maintaining competitive advantage [1, 2]. On-time delivery is a critical factor for 3PL firms, not only for ensuring customer satisfaction but also for sustaining their competitive advantage in the industry [3, 4]. With the rapid growth of global e-commerce, increasing customer expectations, and deepening supply chain complexities, 3PL firms play a

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pivotal role in offering operational flexibility and cost advantages. The 3PL performance evaluation process is not only limited to strategic factors but it is also closely related to the service quality [5–7]. However, the effectiveness of these services largely hinges on adhering to promised delivery times. Timely deliveries are crucial for building customer trust and enhancing a company's corporate reputation. This also lays the groundwork for long-term collaborations. Conversely, delays can lead to customer dissatisfaction, breaches of contract, and ultimately, customer loss [1, 4, 8, 9]. Given that 3PL firms work with numerous clients, it's clear that disruptions with one customer can negatively impact the operations of others [10, 11]. Therefore, continuous improvement activities are essential, including effectively managing delivery processes, utilizing real-time tracking systems, anticipating supply chain risks, and developing efficient routing strategies. On-time delivery is not merely about ensuring customer satisfaction; it is an indispensable requirement for a firm's industry reputation and sustainable growth.

Particularly, during periods of increased customer demand and strained operational capacities, 3PL firms often outsource parts of their operations to subcontractor businesses, merely monitoring the process [5]. While this approach offers operational flexibility, it also necessitates effective monitoring and management of subcontractor performance. Existing performance evaluation methods typically rely on precise data, proving insufficient in handling subjective assessments like "good," "average," or "poor," or situations involving inherent uncertainty.

In recent years, fuzzy set extensions have been widely adopted in multi-criteria decision-making problems to better capture the ambiguity and hesitation in expert judgments. Traditional fuzzy sets (Type-1), Intuitionistic Fuzzy Sets (IFSs), and even Pythagorean and Spherical Fuzzy Sets (SFSs) have shown limitations in handling complex uncertainty, especially in problems involving subjective human evaluations. To overcome these limitations, this study adopts the Interval-Valued Spherical Fuzzy Set (IVSFS) approach, which provides a more flexible and expressive framework. In this context, this study aims to develop a decision support system for 3PL firms to evaluate the performance of their logistics subcontractors, utilizing the Interval-Valued Spherical Fuzzy AHP (IVSF-AHP) and TOPSIS (IVSF-TOPSIS) methods. Specifically, IVSF-AHP will be employed for the dynamic weighting of evaluation criteria, while the IVSF-TOPSIS method will be used for measuring the performance of existing businesses. This study offers the following significant contributions to literature:

- Developing an innovative IVSF-AHP and TOPSIS-based model for subcontractor performance evaluation in the logistics sector.
- Providing a more realistic and comprehensive evaluation by integrating uncertain and subjective performance criteria, addressing gaps in traditional methods.
- Establishing a flexible and adaptive performance monitoring mechanism to support operational decisions for 3PL firms.

The remainder of this study is structured as follows: Section 2 provides a comprehensive literature review on performance measurement for 3PL firms. Section 3 elaborates on the fundamental principles of the Spherical Fuzzy Sets methodology, Interval-valued spherical AHP, and TOPSIS Method. In Section 4, the proposed model for evaluating 3PL firms along with a practical example demonstrating its operation is given. Finally, Section 5 discusses the findings and concludes the study.

2 Related Work

The performance of 3PL service providers remains a critical area of research for business to reduce logistics costs, provide operational flexibility and maintain competitive advantage. Studies in this area provide methods to assess, manage and improve 3PL performance from different perspectives.

Recent studies have shown that 3PL performance is shaped by multiple interrelated factors, including service quality, organizational capabilities, strategic alignment, and technological integration. Core dimensions such as relationship management, operational efficiency, and trust have consistently emerged as critical to enhancing service outcomes [4, 10, 12–14]. However, the evolving demands of manufacturing and service sectors have necessitated a shift from cost-based outsourcing to value-added and innovation-driven 3PL partnerships [8, 15–17].

Strategic management perspectives have gained prominence in recent years. Studies suggest that dynamic capabilities, environmental factors, and strategic fit significantly mediate the relationship between logistics operations and organizational performance [18]. Furthermore, performance measurement frameworks—especially those involving structured indicator systems—are increasingly recognized as essential for avoiding decision errors and aligning 3PL outcomes with business goals [19].

An important methodological trend in literature is the widespread use of multi-criteria decision-making (MCDM) techniques to evaluate or select 3PL providers. Approaches such as AHP, TOPSIS, ELECTRE, and DEA have been widely applied to model complex decision problems and derive ranking preferences [13, 19–25]. Recent hybrid models combining fuzzy logic, interval-valued fuzzy sets, and goal programming highlight the growing interest in integrating uncertainty into performance evaluation [2, 26].

In parallel, technological innovation and digital decision support systems have gained traction. Studies have explored the use of tools such as digital twins, information system ratings, and IT-driven taxonomies to improve operational customization and strategic alignment [27–29]. Despite these advances, there remains a gap in integrating real-time data analytics and sustainability metrics into existing performance models, especially in the context of post-pandemic supply chain resilience.

In summary, the literature underscores that 3PL performance is a multidimensional phenomenon influenced by operational, strategic, and technological factors. While traditional MCDM and DEA methods remain popular, there is an emerging need for hybrid and adaptive models that address the complexity and dynamism of modern logistics environments. Sustainable evaluation and selection of 3PL providers has also been addressed using integrated MCDM approaches [37]. In this study, it is the first time we combine the IVSF-AHP and IVSF-TOPSIS techniques with practical performance indicators tailored to current industry challenges to measure the performance of 3PL logistics firms.

3 Methodology

In this section, the IVSF-AHP and IVSF-TOPSIS techniques are detailed after the foundational concepts of spherical fuzzy sets.

3.1 Spherical Fuzzy Sets

Spherical fuzzy sets (SFSs) are a modern generalization of intuitionistic fuzzy sets that introduce a three-dimensional membership framework consisting of membership, non-membership, and hesitancy degrees [30]. Unlike traditional fuzzy sets, SFSs require that the squared sum of these three parameters does not exceed 1, with any remaining difference from unity representing the refusal degree. This structure places SFSs within the broader family of three-parameter fuzzy set extensions, such as picture fuzzy sets and neutrosophic sets, while also relating them to other advanced fuzzy set theories like Pythagorean, Fermatean, and q-rung orthopair fuzzy sets that similarly expand the domain for degree assignments.

IVSFSs represent an advanced extension of fuzzy set theory where membership degrees are expressed as intervals rather than precise values. Formally, an IVSFS $\tilde{A}_S$ in universe U is characterized by three interval-valued functions: membership $[\mu^L_{A_S}(u), \mu^U_{A_S}(u)]$, non-membership $[\nu^L_{A_S}(u), \nu^U_{A_S}(u)]$, and hesitancy $[\pi^L_{A_S}(u), \pi^U_{A_S}(u)]$. These intervals must satisfy the conditions $[\mu^L_{A_S}(u), \mu^U_{A_S}(u)], [\nu^L_{A_S}(u), \nu^U_{A_S}(u)], [\pi^L_{A_S}(u), \pi^U_{A_S}(u)] \subset [0,1]$ and $(\mu^U_{A_S}(u))^2 + (\nu^U_{A_S}(u))^2 + (\pi^U_{A_S}(u))^2 \leq 1$, ensuring the squared sum of upper bounds does not exceed unity.

The algebraic operations for IVSFS $\tilde{a} = ([a,b],[c,d],[e,f])$, $\tilde{a}_1 = ([a_1,b_1],[c_1,d_1],[e_1,f_1])$, and $\tilde{a}_2 = ([a_2,b_2],[c_2,d_2],[e_2,f_2])$ are defined in Equations (1-4) where $i,j,k,l \geq 0$ [30]:

$$\tilde{a}_1 \oplus \tilde{a}_2 = \left\{ \begin{array}{c} \left[\begin{array}{c} \left(a_1^2 + a_2^2 - a_1^2 a_2^2\right)^{1/2}, \\ \left(b_1^2 + b_2^2 - b_1^2 b_2^2\right)^{1/2} \end{array} \right], \\ [c_1 c_2, d_1 d_2], \\ \left[\begin{array}{c} \left((1-a_2^2)e_1^2 + (1-a_1^2)e_2^2 - e_1^2 e_2^2\right)^{1/2}, \\ \left((1-b_2^2)f_1^2 + (1-b_1^2)f_2^2 - f_1^2 f_2^2\right)^{1/2} \end{array} \right], \end{array} \right\} \tag{1}$$

$$\tilde{a}_1 \otimes \tilde{a}_2 = \left\{ \begin{array}{c} , \\ \left[\begin{array}{c} \left(c_1^2 + c_2^2 - c_1^2 c_2^2\right)^{1/2}, \\ \left(d_1^2 + d_2^2 - d_1^2 d_2^2\right)^{1/2} \end{array} \right], \\ \left[\begin{array}{c} \left((1-c_2^2)e_1^2 + (1-c_1^2)e_2^2 - e_1^2 e_2^2\right)^{1/2}, \\ \left((1-d_2^2)f_1^2 + (1-d_1^2)f_2^2 - f_1^2 f_2^2\right)^{1/2} \end{array} \right] \end{array} \right\} \tag{2}$$

$$\lambda\tilde{\alpha} = \left\{ \begin{array}{c} \left[\begin{array}{c} \left(1-(1-a^2)^\lambda\right)^{1/2}, \\ \left(1-(1-b^2)^\lambda\right)^{1/2} \end{array} \right], \\ {[c^\lambda, d^\lambda]}, \\ \left[\begin{array}{c} \left((1-a^2)^\lambda-(1-a^2-e^2)^\lambda\right)^{1/2}, \\ \left((1-b^2)^\lambda-(1-b^2-f^2)^\lambda\right)^{1/2} \end{array} \right] \end{array} \right\} \tag{3}$$

$$\tilde{\alpha}^\lambda = \left\{ \begin{array}{c} \left[a^\lambda, b^\lambda\right], \\ \left[\begin{array}{c} \left(1-(1-c^2)^\lambda\right)^{1/2}, \\ \left(1-(1-d^2)^\lambda\right)^{1/2} \end{array} \right], \\ \left[\begin{array}{c} \left((1-c^2)^\lambda-(1-c^2-e^2)^\lambda\right)^{1/2}, \\ \left((1-d^2)^\lambda-(1-d^2-f^2)^\lambda\right)^{1/2} \end{array} \right] \end{array} \right\} \tag{4}$$

The Interval-Valued Spherical Weighted Arithmetic Mean (IVSWAM) operator aggregates a collection of IVSFSs $\tilde{\alpha}j = \langle [a_j, b_j], [c_j, d_j], [e_j, f_j] \rangle$ $(j = 1, 2, \ldots, n)$ with respect to a weight vector $w_j = (w_1, w_2, \ldots, w_n)$, where $w_j \in [0, 1]$ and $\sum j = 1^n w_j = 1$. The IVSWAM is defined as:

$$\begin{aligned} & \mathrm{IVSWAM}_w(\tilde{a}_1, \tilde{a}_2, \ldots, \tilde{a}_n) \\ =& w_1 \cdot \tilde{a}_1 \oplus w_2 \cdot \tilde{a}_2 \oplus \cdots \oplus w_n \cdot \tilde{a}_n \\ =& \left\{ \begin{array}{c} \left[\begin{array}{c} \left(1-\prod_{j=1}^n (1-a_j^2)^{w_j}\right)^{1/2}, \\ \left(1-\prod_{j=1}^n (1-b_j^2)^{w_j}\right)^{1/2} \end{array} \right], \\ \left[\prod_{j=1}^n c_j^{w_j}, \prod_{j=1}^n d_j^{w_j}\right], \\ \left[\begin{array}{c} \left(\prod_{j=1}^n (1-a_j^2)^{w_j} - \prod_{j=1}^n (1-a_j^2-e_j^2)^{w_j}\right)^{1/2}, \\ \left(\prod_{j=1}^n (1-b_j^2)^{w_j} - \prod_{j=1}^n (1-b_j^2-f_j^2)^{w_j}\right)^{1/2} \end{array} \right] \end{array} \right\} \end{aligned} \tag{5}$$

The Interval-Valued Spherical Weighted Geometric Mean (IVSWGM) operator for the same IVSFSs and weights is defined as:

$$\begin{aligned} & \mathrm{IVSWGM}_w(\tilde{\alpha}_1, \tilde{\alpha}_2, \ldots, \tilde{\alpha}_n) \\ &= \tilde{\alpha}_1^{w_1} \otimes \tilde{\alpha}_2^{w_2} \otimes \ldots \otimes \tilde{\alpha}_n^{w_n} \\ &= \left\{ \begin{array}{c} \left[\prod_{j=1}^n a_j^{w_j}, \prod_{j=1}^n b_j^{w_j}\right], \\ \left[\begin{array}{c} \left(1-\prod_{j=1}^n (1-c_j^2)^{w_j}\right)^{1/2}, \\ \left(1-\prod_{j=1}^n (1-d_j^2)^{w_j}\right)^{1/2} \end{array} \right], \\ \left[\begin{array}{c} \left(\prod_{j=1}^n (1-c_j^2)^{w_j} - \prod_{j=1}^n (1-c_j^2-e_j^2)^{w_j}\right)^{1/2}, \\ \left(\prod_{j=1}^n (1-d_j^2)^{w_j} - \prod_{j=1}^n (1-d_j^2-f_j^2)^{w_j}\right)^{1/2} \end{array} \right] \end{array} \right\} \end{aligned} \tag{6}$$

The score function and accuracy function of an IVSF number $\tilde{a}$ are defined as in Eq. (7) and Eq. (8), respectively, where $S(\tilde{a}) \in [-1, +1]$ and $H(\tilde{a}) \in [0, 1]$.

$$\mathrm{Score}(\tilde{a}) = S(\tilde{a}) = \frac{a^2 + b^2 - c^2 - d^2 - (e/2)^2 - (f/2)^2}{2} \tag{7}$$

$$\mathrm{Accuracy}(\tilde{a}) = H(\tilde{a}) = \frac{a^2 + b^2 + c^2 + d^2 + e^2 + f^2}{2} \tag{8}$$

The score and accuracy functions are used to rank IVSF numbers. $\tilde{a}_1 < \tilde{a}_2$ if and only if $S(\tilde{a}_1) < S(\tilde{a}_2)$ or $S(\tilde{a}_1) = S(\tilde{a}_2)$ and $H(\tilde{a}_1) < H(\tilde{a}_2)$.

3.2 Interval-valued spherical AHP

The IVSF-AHP method, proposed by Kutlu Gündoğdu et al. [32], involves the following steps:

Step 1. Problem Definition and Hierarchical Structure: Clearly outline the problem and develop its hierarchical framework.

Step 2. Pairwise Comparison Matrices: Construct pairwise comparison matrices using linguistic terms, as defined in Table 1.

Step 3. Construct Comparison Matrices

Table 1. Linguistic terms and their corresponding interval-valued spherical fuzzy numbers [38].

Linguistic terms	IVSF Numbers $\tilde{A}_S = \left([\mu^L_{A_S}(u), \mu^U_{A_S}(u)], [\nu^L_{A_S}(u), \nu^U_{A_S}(u)], [\pi^L_{A_S}(u), \pi^U_{A_S}(u)]\right)$	Saaty's Scale
Absolutely more Importance (AMI)	$([0.85, 0.85], [0.10, 0.15], [0.05, 0.15])$	9
Very High Importance (VHI)	$([0.75, 0.85], [0.15, 0.20], [0.15, 0.20])$	7
High Importance (HI)	$([0.65, 0.75], [0.20, 0.25], [0.20, 0.25])$	5
Slightly More Importance (SMI)	$([0.55, 0.65], [0.25, 0.30], [0.25, 0.30])$	3
Equally Importance (EI)	$([0.50, 0.55], [0.45, 0.55], [0.30, 0.40])$	1
Slightly Low Importance (SLI)	$([0.25, 0.30], [0.55, 0.65], [0.25, 0.30])$	1/3
Low Importance (LI)	$([0.20, 0.25], [0.65, 0.75], [0.20, 0.25])$	1/5
Very Low Importance (VLI)	$([0.15, 0.20], [0.75, 0.85], [0.15, 0.20])$	1/7
Absolutely Low Importance (ALI)	$([0.10, 0.15], [0.85, 0.95], [0.05, 0.15])$	1/9

Table 2. Linguistic terms and their corresponding IVSF numbers [38].

Linguistic terms	IVSF Numbers $\tilde{A}_s = \left([\mu^L_{A_s}(u), \mu^U_{A_s}(u)], [\nu^L_{A_s}(u), \nu^U_{A_s}(u)], [\pi^L_{A_s}(u), \pi^U_{A_s}(u)]\right)$
Absolutely High (AH)	$([0.85, 0.95], [0.10, 0.15], [0.05, 0.15])$
Very High (VH)	$([0.75, 0.85], [0.15, 0.20], [0.15, 0.20])$
High (H)	$([0.65, 0.75], [0.20, 0.25], [0.20, 0.25])$
Above Average (AA)	$([0.55, 0.65], [0.25, 0.30], [0.25, 0.30])$
Average (A)	$([0.50, 0.55], [0.45, 0.55], [0.30, 0.40])$
Below Average (BA)	$([0.25, 0.30], [0.55, 0.65], [0.25, 0.30])$
Low (L)	$([0.20, 0.25], [0.65, 0.75], [0.20, 0.25])$
Very Low (VL)	$([0.15, 0.20], [0.75, 0.85], [0.15, 0.20])$
Absolutely Low (AL)	$([0.10, 0.15], [0.85, 0.95], [0.05, 0.15])$

Pairwise comparison matrices are developed for each decision-maker using the linguistic scale from Table 3, expressed as interval-valued spherical fuzzy numbers. The matrix for the kth decision-maker is structured as:

$$\tilde{A}^{(k)}_s = \begin{bmatrix} 1 & \tilde{a}^{(k)}_{s12} & \cdots & \tilde{a}^{(k)}_{s1n} \\ \tilde{a}^{(k)}_{s21} & 1 & \cdots & \tilde{a}^{(k)}_{s2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}^{(k)}_{sn1} & \tilde{a}^{(k)}_{sn2} & \cdots & 1 \end{bmatrix} \quad (9)$$

Let $\tilde{\alpha}^{(k)}_{sij} = \langle [\mu^L_{i,j}, \mu^U_{i,j}], [\nu^L_{i,j}, \nu^U_{i,j}], [\pi^L_{i,j}, \pi^U_{i,j}] \rangle$ denote the number expressing the comparison of criterion i to j provided by the k-th decision-maker.

Step 4. Consistency Check of Fuzzy Pairwise Comparison Matrices.

The consistency of each matrix is verified using score indices (Table 3) and Saaty's classical consistency ratio (CR) formula [33]. A matrix is deemed consistent if $CR < 0.1$.

Step 5. Aggregate Matrices.

For multiple decision-makers, evaluations are combined using the Interval-Valued Spherical Fuzzy Weighted Geometric Mean (IVSFWGM) operator (Eq. (10)), where w_k is the weight of the k-th decision-maker ($\sum_{k=1}^{s} w_k = 1$).

$$\tilde{w}_{s_{ij}} = \begin{bmatrix} \prod_{k=1}^{s} \mu_{ij}^{L^{(k)} w_k}, \prod_{k=1}^{s} \mu_{ij}^{U^{(k)} w_k} \\ \left(1 - \prod_{k=1}^{s}\left(1 - (\nu_{ij}^{L^{(k)^2}})\right)^{w_k}\right)^{1/2}, \\ \left(1 - \prod_{k=1}^{s}\left(1 - (\nu_{ij}^{U^{(k)^2}})\right)^{w_k}\right)^{1/2} \\ \left(\prod_{k=1}^{s}\left(1 - (\nu_{ij}^{L^{(k)^2}})\right)^{w_k} - \prod_{k=1}^{s}\left(1 - (\nu_{ij}^{L^{(k)^2}}) - (\pi_{ij}^{L^{(k)^2}})\right)^{w_k}\right)^{1/2}, \\ \left(\prod_{k=1}^{s}\left(1 - (\nu_{ij}^{U^{(k)^2}})\right)^{w_k} - \prod_{k=1}^{s}\left(1 - (\nu_{ij}^{U^{(k)^2}}) - (\pi_{ij}^{U^{(k)^2}})\right)^{w_k}\right)^{1/2} \end{bmatrix} \quad (10)$$

Step 6. Compute Local and Global Weights.

Local Weights: Calculated using the Interval-Valued Spherical Weighted Arithmetic Mean (IVSWAM) operator (Eq. 11), where $w_j = 1/n$.

$$\tilde{w}_{sj} = \left\{ \begin{array}{c} \left[\left(1 - \prod_{j=1}^{n} (1 - (\mu_j^L)^2)^{w_j}\right)^{1/2}, \\ \left(1 - \prod_{j=1}^{n} (1 - (\mu_j^U)^2)^{w_j}\right)^{1/2} \right], \\ \left[\prod_{j=1}^{n} (\nu_j^L)^{w_j}, \prod_{j=1}^{n} (\nu_j^U)^{w_j} \right], \\ \left[\left(\prod_{j=1}^{n} (1 - (\mu_j^L)^2)^{w_j} - \prod_{j=1}^{n} (1 - (\mu_j^L)^2 - (\pi_j^L)^2)^{w_j} \right)^{1/2}, \\ \left(\prod_{j=1}^{n} (1 - (\mu_j^U)^2)^{w_j} - \prod_{j=1}^{n} (1 - (\mu_j^U)^2 - (\pi_j^U)^2)^{w_j} \right)^{1/2} \right] \end{array} \right\} \tag{11}$$

Global Weights: Calculated applying a modified score function given in Eq. (12) for the defuzzification and then normalizing the weights using Eq. (13).

$$S(\tilde{w}_{sj}) = \frac{(\mu_j^L)^2 + (\mu_j^U)^2 - (\nu_j^L)^2 - (\nu_j^U)^2 - \left(\frac{\pi_j^L}{2}\right)^2 - \left(\frac{\pi_j^U}{2}\right)^2 + 1}{2} \tag{12}$$

$$\tilde{w}_{sj} = \frac{S(\tilde{w}_{sj})}{\sum_{j=1}^{n} S(\tilde{w}_{sj})} \tag{13}$$

Step 7. Determine Final Weights.

Multiply the global weights at each hierarchical level by the corresponding sub-criterion weights to obtain the final aggregated weights.

3.3 TOPSIS Method

The steps of the IVSF-TOPSIS method are as follows [31]:

Step 1. Construct Individual Decision Matrices

Each decision-maker evaluates alternatives using the linguistic scale (defined in Table 2), forming a separate decision matrix.

Step 2. Aggregate Decision Matrices.

Combine evaluations from all decision-makers using the IVSWAM operator (Eq. 14).

$$\tilde{A}_s = \begin{array}{c|cccc} & X_1 & X_2 & \cdots & X_n \\ \hline f_1 & \tilde{f}_{s11} & \tilde{f}_{s12} & \cdots & \tilde{f}_{s1n} \\ f_2 & \tilde{f}_{s21} & \tilde{f}_{s22} & \cdots & \tilde{f}_{s2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_m & \tilde{f}_{sm1} & \tilde{f}_{sm2} & \cdots & \tilde{f}_{smn} \end{array} \tag{14}$$

Step 3. Develop the Weighted IVSF Decision Matrix

The aggregated decision matrix is transformed into a weighted matrix $\bar{Y}_{sw}$ by multiplying each element with the corresponding criterion weight. This step ensures that the relative importance of each criterion is properly incorporated into the evaluation.

$$\bar{Y}_{s_{1v}} = \begin{array}{c|cccc} & X_1 & X_2 & \cdots & X_n \\ \hline f_1 & \tilde{V}_{s11} & \tilde{V}_{s12} & \cdots & \tilde{V}_{s1n} \\ f_2 & \tilde{V}_{s21} & \tilde{V}_{s22} & \cdots & \tilde{V}_{s2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_m & \tilde{V}_{sm1} & \tilde{V}_{sm2} & \cdots & \tilde{V}_{smn} \end{array} \tag{15}$$

where

$$\begin{aligned} \tilde{V}_{s_{ij}} &= \tilde{W}_{s_i} \otimes \tilde{f}_{s_{ij}} \\ &= ([\mu_{ijv}^L(u), \mu_{ijv}^U(u)], \\ &\quad [\nu_{ijv}^L(u), \nu_{ijv}^U(u)], \\ &\quad [\pi_{ijv}^L(u), \pi_{ijv}^U(u)]) \end{aligned} \tag{16}$$

Step 4. Defuzzify the Weighted Decision Matrix.

Convert the weighted IVSF decision matrix into crisp values using Eq. (16) to enable quantitative comparisons.

$$S(\bar{Y}_{s,w}) = \frac{(\mu_j^L)^2 + (\mu_j^U)^2 - (\nu_j^L)^2 - (\nu_j^U)^2 - \left(\frac{\pi_j^L}{2}\right)^2 - \left(\frac{\pi_j^U}{2}\right)^2}{2} + 1 \tag{17}$$

Step 5. Identify Ideal Solutions

IVSF-PIS (Positive Ideal Solution): Determine the optimal benchmark using either Eq. (17) or Eq. (18), selecting the most favorable values across all criteria.

$$IVSF\text{-}PIS = \{C_j, \max\langle S(\bar{Y}_{s_{1v}})\rangle \mid j = 1, 2, \ldots, n\} \tag{18}$$

$$\begin{aligned} IVSF\text{-}PIS = &\{\langle C_1, (\mu_1^{L+}, \mu_1^{U+}), [\nu_1^{L+}, \nu_1^{U+}], \\ &[\pi_1^{L+}, \pi_1^{U+}]\rangle, \ldots, \langle C_n, (\mu_n^{L+}, \mu_n^{U+}), \\ &[\nu_n^{L+}, \nu_n^{U+}], [\pi_n^{L+}, \pi_n^{U+}]\rangle\} \end{aligned} \tag{19}$$

IVSF-NIS (Negative Ideal Solution): Derive the worst-case benchmark using Eq. (19) or Eq. (20), representing the least desirable performance.

$$IVSF\text{-}NIS = \{C_j, \min\langle S(\bar{Y}_{s_{1v}})\rangle \mid j = 1, 2, \ldots, n\} \quad (20)$$

$$\begin{aligned} IVSF\text{-}NIS = &\{\langle C_1, (\mu_1^{L-}, \mu_1^{U-}), [\nu_1^{L-}, \nu_1^{U-}], \\ &[\pi_1^{L-}, \pi_1^{U-}]\rangle, \ldots, \langle C_n, (\mu_n^{L-}, \mu_n^{U-}), \\ &[\nu_n^{L-}, \nu_n^{U-}], [\pi_n^{L-}, \pi_n^{U-}]\rangle\} \end{aligned} \quad (21)$$

Step 6. Compute Distances

Calculate the distance from IVSF-PIS (D_i^+) and distance from IVSF-NIS (D_i^-) for each alternative using the normalized distance formula [34, 35]:

$$D_i^+ = \frac{1}{4n}\sum_{j=1}^{n}\begin{pmatrix} \left|\mu_{ij}^{L^2} - \mu_j^{+^2}\right| + \left|\mu_{ij}^{U^2} - \mu_j^{+^2}\right| + \\ \left|\nu_{ij}^{L^2} - \nu_j^{+^2}\right| + \left|\nu_{ij}^{U^2} - \nu_j^{+^2}\right| + \\ \left|\pi_{ij}^{L^2} - \pi_j^{+^2}\right| + \left|\pi_{ij}^{U^2} - \pi_j^{+^2}\right| \end{pmatrix} \quad (22)$$

$$D_i^- = \frac{1}{4n}\sum_{j=1}^{n}\begin{pmatrix} \left|\mu_{ij}^{L^2} - \mu_j^{-^2}\right| + \left|\mu_{ij}^{U^2} - \mu_j^{-^2}\right| + \\ \left|\nu_{ij}^{L^2} - \nu_j^{-^2}\right| + \left|\nu_{ij}^{U^2} - \nu_j^{-^2}\right| + \\ \left|\pi_{ij}^{L^2} - \pi_j^{-^2}\right| + \left|\pi_{ij}^{U^2} - \pi_j^{-^2}\right| \end{pmatrix} \quad (23)$$

Step 7. Determine Relative Closeness.

Compute the relative closeness coefficient (Ci) for each alternative:

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \quad (24)$$

where a higher C_i indicates better performance.

Step 8: Rank Alternatives.

Sort alternatives in descending order of C_i values, with the highest C_i representing the optimal choice.

4 Application in Logistics Sector

This case study presents a real-world application to evaluate the top five contractors of a leading logistics firm in Turkey, based on annual transaction volume. The methodology employed in this application is consistent with recent advancements in spherical fuzzy MCDM, including the evaluation of sustainable vehicle technologies for freight transportation using spherical fuzzy AHP and TOPSIS [36]. The firm's existing evaluation framework prioritizes three core criteria: Delivery Performance, Operational Efficiency, and Communication & Collaboration, each broken down into several sub-criteria. The criteria and sub criteria are defined as follows:

- C1. *Delivery Performance:* Evaluates the efficiency and reliability of the delivery process.
- C11. *On-Time Delivery Rate (Benefit):* Measures the percentage of shipments delivered within the promised timeframe.
- C12. *Average Delivery Delay Time (Cost):* Quantifies the mean delay duration for late shipments in hours.
- C13. *First-Attempt Delivery Success Rate (Benefit):* This tracks the percentage of shipments successfully delivered on the first attempt without requiring redelivery, derived from (Successful first deliveries/Total deliveries) × 100. Higher percentages reflect better performance.
- C2. *Operational Efficiency:* Examines the effectiveness and quality of operational processes.
- C21. *Compliance with Delivery Time Window (Benefit):* Assesses adherence to scheduled delivery slots.
- C22. *Damage/Loss Rate (Cost):* Monitors shipment integrity by measuring the percentage of damaged or lost items.
- C23. *Customer Satisfaction (Benefit):* This criterion captures service quality perceptions.
- C3. *Communication and Collaboration:* Evaluates the effectiveness of communication and cooperation between stakeholders.
- C31. *Information Flow (Benefit):* This evaluates documentation completeness and timeliness, measured by digital record completion percentage.
- C32. *Flexibility (Benefit):* This criterion indicates the subcontractor firm's ability to respond agilely to changing work orders.
- C33. *Contract Compliance (Benefit):* This assesses fulfillment of contractual obligations through expert review of documentation and performance records.

The pairwise comparison of the criteria are done by three experts and the linguistic statements are given

Table 3. Pairwise comparisons of criteria.

	Expert 1			Expert 2			Expert 3		
Criteria	C1	C2	C3	C1	C2	C3	C1	C2	C3
C1	EI	VIH/EI	SMI/HI	EI	EI	HI	EI	EI	HI
C2	EI	HI	SLI/EI	HI	EI	EI	EI	SMI	HI
C3	VLI/LI	EI	LI	EI	LI	SLI/EI	EI	EI	HI
Sub-criteria for C1									
	Expert 1			Expert 2			Expert 3		
	C11	C12	C13	C11	C12	C13	C11	C12	C13
C11	HI	SMI/EI	VIH/HI	EI	VIH/SMI	HI	HI	HI	HI
C12	EI	EI	VLI/EI	SLI	VLI/EI	EI	EI	EI	HI
C13	SLI/EI	EI	LI	SMI/EI	SLI/HI	HI	HI	HI	EI
Sub-criteria for C2									
	Expert 1			Expert 2			Expert 3		
	C21	C22	C23	C21	C22	C23	C21	C22	C23
C21	EI	SMI/HI	EI	SMI/SMI/EI	SMI/HI	HI	HI	HI	HI
C22	SLI/EI	SMI/SLI/EI	SLI/SLI/EI	HI	HI	HI	HI	HI	HI
C23	LI	SLI/EI	SLI/SLI/EI	EI	EI	EI	EI	EI	HI
Sub-criteria for C3									
	Expert 1			Expert 2			Expert 3		
	C31	C32	C33	C31	C32	C33	C31	C32	C33
C31	EI	SMI/SMI/EI	HI	VIH/EI	SMI/HI	HI	HI	HI	HI
C32	SLI/EI	EI	LI	EI	SMI/SLI/EI	HI	HI	HI	HI
C33	SLI/EI	EI	VLI/SLI/EI	EI	LI	SLI/EI	HI	HI	HI

in Table 3. Consistency ratios of the comparisons are all calculated below 0.10.

Linguistic evaluations of experts are first converted to IVSF numbers using the scale given in Table 1 and then the evaluations are aggregated using IVSFWGM operator. The aggregated decision matrix is given in Table 4.

The main criteria weights are calculated as:

- C1: $([0.58, 0.66], [0.32, 0.4], [0.26, 0.33])$,
- C2: $([0.52, 0.59], [0.36, 0.44], [0.27, 0.34])$,
- C3: $([0.34, 0.39], [0.58, 0.68], [0.25, 0.32])$.

Table 5 shows the global and local weights of the sub-criteria.

Following the determination of IVSF weights for each criterion, five contractors are evaluated using the IVSF-TOPSIS approach. The conversion process from crisp values to spherical fuzzy numbers involves normalization, spherical fuzzy number conversion and interval valued extension. All raw performance values are first normalized to the $[0, 1]$ interval to ensure comparability across criteria. The normalization approach differs for benefit and cost criteria. For benefit criteria (where higher values indicate better performance):

$$\mu = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}}, \quad \nu = 1 - \mu$$

For cost criteria (where lower values indicate better performance):

$$\nu = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}}, \quad \mu = 1 - \nu$$

The hesitancy degree is fixed at $\pi = 0.05$ for all conversions to maintain consistency. After transforming crisp data into SFNs using the

Table 4. Aggregated decision matrix.

Criteria	C1	C2	C3
C1	$([0.5, 0.55], [0.45, 0.5], [0.19, 0.23])$	$([0.52, 0.58], [0.4, 0.49], [0.19, 0.23])$	$([0.68, 0.78], [0.18, 0.23], [0.19, 0.23])$
C2	$([0.4, 0.45], [0.49, 0.5], [0.28, 0.37])$	$([0.5, 0.55], [0.45, 0.55], [0.3, 0.4])$	$([0.61, 0.72], [0.22, 0.27], [0.22, 0.27])$
C3	$([0.18, 0.23], [0.69, 0.79], [0.18, 0.23])$	$([0.22, 0.27], [0.62, 0.72], [0.3, 0.4])$	$([0.5, 0.55], [0.45, 0.55], [0.3, 0.4])$

Criteria	C11	C12	C13
C11	$([0.5, 0.55], [0.45, 0.5], [0.19, 0.23])$	$([0.72, 0.82], [0.17, 0.22], [0.19, 0.23])$	$([0.58, 0.68], [0.23, 0.28], [0.23, 0.28])$
C12	$([0.17, 0.22], [0.72, 0.82], [0.19, 0.23])$	$([0.5, 0.55], [0.45, 0.55], [0.3, 0.4])$	$([0.29, 0.35], [0.56, 0.66], [0.25, 0.31])$
C13	$([0.23, 0.28], [0.59, 0.69], [0.23, 0.28])$	$([0.56, 0.64], [0.32, 0.4], [0.3, 0.4])$	$([0.5, 0.55], [0.45, 0.55], [0.3, 0.4])$

Criteria	C21	C22	C23
C21	$([0.5, 0.55], [0.45, 0.5], [0.19, 0.23])$	$([0.55, 0.65], [0.25, 0.3], [0.19, 0.23])$	$([0.61, 0.72], [0.22, 0.27], [0.19, 0.23])$
C22	$([0.25, 0.3], [0.55, 0.6], [0.19, 0.23])$	$([0.5, 0.55], [0.45, 0.55], [0.3, 0.4])$	$([0.58, 0.68], [0.23, 0.28], [0.23, 0.28])$
C23	$([0.22, 0.27], [0.62, 0.72], [0.19, 0.23])$	$([0.23, 0.28], [0.59, 0.69], [0.19, 0.23])$	$([0.5, 0.55], [0.45, 0.55], [0.3, 0.4])$

Criteria	C31	C32	C33
C31	$([0.5, 0.55], [0.45, 0.5], [0.19, 0.23])$	$([0.58, 0.68], [0.23, 0.28], [0.21, 0.25])$	$([0.64, 0.75], [0.2, 0.25], [0.21, 0.25])$
C32	$([0.23, 0.28], [0.59, 0.69], [0.19, 0.23])$	$([0.5, 0.55], [0.45, 0.55], [0.3, 0.4])$	$([0.53, 0.61], [0.33, 0.41], [0.27, 0.35])$
C33	$([0.2, 0.25], [0.66, 0.7], [0.2, 0.25])$	$([0.31, 0.37], [0.52, 0.62], [0.3, 0.4])$	$([0.5, 0.55], [0.45, 0.55], [0.3, 0.4])$

Table 5. Sub-criteria weights obtained from Spherical Fuzzy AHP.

Criteria	Local Weights	Global Weights
C11	$([0.61, 0.71], [0.26, 0.32], [0.23, 0.30])$	$([0.40, 0.47], [0.61, 0.67], [0.19, 0.27])$
C12	$([0.36, 0.40], [0.57, 0.67], [0.25, 0.33])$	$([0.31, 0.36], [0.76, 0.80], [0.15, 0.21])$
C13	$([0.46, 0.53], [0.44, 0.53], [0.27, 0.35])$	$([0.35, 0.41], [0.69, 0.74], [0.17, 0.24])$
C21	$([0.56, 0.65], [0.29, 0.35], [0.26, 0.32])$	$([0.34, 0.40], [0.66, 0.72], [0.19, 0.26])$
C22	$([0.47, 0.55], [0.39, 0.47], [0.26, 0.34])$	$([0.32, 0.37], [0.71, 0.76], [0.18, 0.24])$
C23	$([0.35, 0.40], [0.55, 0.65], [0.26, 0.34])$	$([0.27, 0.32], [0.78, 0.82], [0.15, 0.21])$
C31	$([0.58, 0.67], [0.28, 0.34], [0.25, 0.31])$	$([0.22, 0.26], [0.80, 0.85], [0.17, 0.22])$
C32	$([0.45, 0.51], [0.45, 0.54], [0.27, 0.36])$	$([0.19, 0.22], [0.84, 0.89], [0.15, 0.20])$
C33	$([0.37, 0.42], [0.54, 0.64], [0.26, 0.34])$	$([0.18, 0.20], [0.87, 0.91], [0.13, 0.18])$

normalization rules for benefit and cost criteria, SFNs are extended to interval-valued SFNs to capture uncertainty more robustly. The conversion process is defined as follows: For benefit criteria, the IV-SFN membership and non-membership intervals are constructed by:

$$\mu_{ij}^U = \mu_{ij}, \quad \mu_{ij}^L = \max(\mu_{ij} - 0.05, 0)$$

and

$$\nu_{ij}^L = (1 - \mu_{ij}^U), \quad \nu_{ij}^U = (1 - \mu_{ij}^L)$$

while maintaining $\pi = [0.05, 0.05]$.

For cost criteria, the IV-SFN membership and non-membership intervals are constructed by:

$$\nu_{ij}^L = \nu_{ij}, \quad \nu_{ij}^U = \min((\nu_{ij} + 0.05), 1)$$

$$\mu_{ij}^L = (1 - \nu_{ij}^U), \quad \mu_{ij}^U = (1 - \nu_{ij}^L)$$

while maintaining $\pi = [0.05, 0.05]$.

Using the transformation and aggregation of linguistic assessments given in Table 6, the aggregated decision matrix for the alternatives is computed as in Table 7.

Table 6. The crisp and linguistic evaluation data for the alternatives.

Alternatives	C11	C12	C13	C21	C22	C23	C31	C32	C33
A1	0.92	3.2	0.94	0.9	1.5	4.4	0.96	(H, VH, H)	(AH, VH, AH)
A2	0.88	5.1	0.89	0.84	3	3.8	0.9	(A, AA, AA)	(H, VH, VH)
A3	0.95	2	0.97	0.93	0.8	4.7	0.98	(VH, H, VH)	(AH, AH, VH)
A4	0.85	6.5	0.82	0.8	4.2	3.5	0.85	(BA, A, AA)	(AA, H, A)
A5	0.9	4.3	0.91	0.88	2.1	4.1	0.92	(A, BA, BA)	(VH, H, AA)

Table 7. Aggregated decision matrix.

Part 1: Criteria C11–C13

Alternatives	C11	C12	C13
A1	$([0.65, 0.70], [0.30, 0.35], [0.05, 0.05])$	$([0.68, 0.73], [0.27, 0.32], [0.05, 0.05])$	$([0.75, 0.80], [0.20, 0.25], [0.05, 0.05])$
A2	$([0.25, 0.30], [0.70, 0.75], [0.05, 0.05])$	$([0.26, 0.31], [0.69, 0.74], [0.05, 0.05])$	$([0.42, 0.47], [0.53, 0.58], [0.05, 0.05])$
A3	$([0.95, 1.00], [0.05, 0.05], [0.05, 0.05])$	$([0.95, 1.00], [0.05, 0.05], [0.05, 0.05])$	$([0.95, 1.00], [0.05, 0.05], [0.05, 0.05])$
A4	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$
A5	$([0.45, 0.50], [0.50, 0.55], [0.05, 0.05])$	$([0.44, 0.49], [0.51, 0.56], [0.05, 0.05])$	$([0.55, 0.60], [0.40, 0.45], [0.05, 0.05])$

Part 2: Criteria C21–C23

Alternatives	C21	C22	C23
A1	$([0.72, 0.77], [0.23, 0.28], [0.05, 0.05])$	$([0.74, 0.79], [0.21, 0.26], [0.05, 0.05])$	$([0.70, 0.75], [0.25, 0.30], [0.05, 0.05])$
A2	$([0.26, 0.31], [0.69, 0.74], [0.05, 0.05])$	$([0.30, 0.35], [0.65, 0.70], [0.05, 0.05])$	$([0.20, 0.25], [0.75, 0.80], [0.05, 0.05])$
A3	$([0.95, 1.00], [0.05, 0.05], [0.05, 0.05])$	$([0.95, 1.00], [0.05, 0.05], [0.05, 0.05])$	$([0.95, 1.00], [0.05, 0.05], [0.05, 0.05])$
A4	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$
A5	$([0.57, 0.62], [0.38, 0.43], [0.05, 0.05])$	$([0.57, 0.62], [0.38, 0.43], [0.05, 0.05])$	$([0.45, 0.50], [0.50, 0.55], [0.05, 0.05])$

Part 3: Criteria C31–C33

Alternatives	C31	C32	C33
A1	$([0.80, 0.85], [0.15, 0.20], [0.05, 0.05])$	$([0.69, 0.79], [0.18, 0.23], [0.18, 0.23])$	$([0.82, 0.93], [0.11, 0.17], [0.09, 0.17])$
A2	$([0.33, 0.38], [0.62, 0.67], [0.05, 0.05])$	$([0.53, 0.62], [0.30, 0.37], [0.27, 0.33])$	$([0.72, 0.82], [0.17, 0.22], [0.17, 0.22])$
A3	$([0.95, 1.00], [0.05, 0.05], [0.05, 0.05])$	$([0.72, 0.82], [0.17, 0.22], [0.17, 0.22])$	$([0.82, 0.93], [0.11, 0.17], [0.09, 0.17])$
A4	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$	$([0.46, 0.53], [0.40, 0.48], [0.27, 0.34])$	$([0.57, 0.66], [0.28, 0.35], [0.25, 0.32])$
A5	$([0.49, 0.54], [0.46, 0.51], [0.05, 0.05])$	$([0.36, 0.41], [0.51, 0.61], [0.27, 0.35])$	$([0.66, 0.77], [0.20, 0.25], [0.20, 0.25])$

Using Eq. (15) fuzzy weighted decision matrix is constructed as given in Table 8.

Using the defuzzified values the best and worst alternative for each criterion is determined and the positive ideal solution is found as:

$$\begin{aligned}\text{IVSF-PIS} = \{&([0.3827, 0.4693], [0.6105, 0.6118], [0.1964, 0.2681]),\\ &([0.2902, 0.3587], [0.7610, 0.8018], [0.1531, 0.2131]),\\ &([0.3323, 0.4094], [0.6950, 0.7450], [0.1734, 0.2394]),\\ &([0.3265, 0.4009], [0.6642, 0.7203], [0.1925, 0.2578]),\\ &([0.3028, 0.3725], [0.7055, 0.7559], [0.1798, 0.2419]),\\ &([0.2583, 0.3187], [0.7787, 0.8182], [0.1551, 0.2102]),\\ &([0.2122, 0.2561], [0.7955, 0.8517], [0.1690, 0.2251]),\\ &([0.1404, 0.1838], [0.8461, 0.8912], [0.1677, 0.2126]),\\ &([0.1443, 0.1870], [0.8714, 0.9090], [0.1373, 0.1873])\}\end{aligned}$$

and negative ideal solution is found as:

$$\begin{aligned}\text{IVSF-NIS} = \{&([0.00, 0.00], [1.00, 1.00], [0.0384, 0.0346]),\\ &([0.00, 0.00], [1.00, 1.00], [0.0316, 0.0280]),\\ &([0.00, 0.00], [1.00, 1.00], [0.0349, 0.0312]),\\ &([0.00, 0.00], [1.00, 1.00], [0.0362, 0.0323]),\\ &([0.00, 0.00], [1.00, 1.00], [0.0343, 0.0305]),\\ &([0.00, 0.00], [1.00, 1.00], [0.0304, 0.0268]),\\ &([0.00, 0.00], [1.00, 1.00], [0.0291, 0.0237]),\\ &([0.0701, 0.0913], [0.8861, 0.9305], [0.1887, 0.2132]),\\ &([0.1006, 0.1335], [0.8806, 0.9180], [0.1736, 0.2064])\}\end{aligned}$$

At last distance of each alternative to the positive ideal solution and negative ideal solution are calculated and relative closeness coefficient of each alternative are computed. The results and the final rankings based on the relative closeness coefficients are given in Table 9.

Table 8. Weighted decision matrix.

Part 1: Criteria C11–C13

Alternatives	**C11**	**C12**	**C13**
A1	$([0.26, 0.33], [0.66, 0.72], [0.19, 0.25])$	$([0.21, 0.26], [0.78, 0.82], [0.15, 0.20])$	$([0.26, 0.33], [0.71, 0.76], [0.17, 0.23])$
A2	$([0.10, 0.14], [0.82, 0.85], [0.14, 0.18])$	$([0.08, 0.11], [0.88, 0.92], [0.11, 0.15])$	$([0.15, 0.19], [0.79, 0.84], [0.15, 0.20])$
A3	$([0.38, 0.47], [0.61, 0.61], [0.20, 0.27])$	$([0.29, 0.36], [0.76, 0.80], [0.15, 0.21])$	$([0.33, 0.41], [0.70, 0.75], [0.17, 0.24])$
A4	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$
A5	$([0.18, 0.23], [0.73, 0.75], [0.17, 0.23])$	$([0.13, 0.18], [0.83, 0.87], [0.13, 0.18])$	$([0.19, 0.25], [0.75, 0.80], [0.16, 0.21])$

Part 2: Criteria C21–C23

Alternatives	**C21**	**C22**	**C23**
A1	$([0.25, 0.31], [0.69, 0.75], [0.18, 0.23])$	$([0.24, 0.30], [0.72, 0.77], [0.18, 0.23])$	$([0.19, 0.24], [0.79, 0.84], [0.15, 0.20])$
A2	$([0.09, 0.12], [0.84, 0.89], [0.14, 0.17])$	$([0.10, 0.13], [0.84, 0.88], [0.14, 0.18])$	$([0.05, 0.08], [0.91, 0.94], [0.11, 0.13])$
A3	$([0.33, 0.40], [0.66, 0.72], [0.19, 0.26])$	$([0.30, 0.37], [0.71, 0.76], [0.18, 0.24])$	$([0.26, 0.32], [0.78, 0.82], [0.16, 0.21])$
A4	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$
A5	$([0.19, 0.25], [0.72, 0.78], [0.18, 0.23])$	$([0.18, 0.23], [0.76, 0.81], [0.17, 0.22])$	$([0.12, 0.16], [0.84, 0.88], [0.14, 0.18])$

Part 3: Criteria C31–C33

Alternatives	**C31**	**C32**	**C33**
A1	$([0.18, 0.22], [0.80, 0.86], [0.17, 0.22])$	$([0.13, 0.18], [0.85, 0.89], [0.17, 0.22])$	$([0.14, 0.19], [0.87, 0.91], [0.14, 0.19])$
A2	$([0.07, 0.10], [0.88, 0.92], [0.13, 0.17])$	$([0.10, 0.14], [0.86, 0.90], [0.20, 0.23])$	$([0.13, 0.17], [0.87, 0.91], [0.15, 0.19])$
A3	$([0.21, 0.26], [0.80, 0.85], [0.17, 0.23])$	$([0.14, 0.18], [0.85, 0.89], [0.17, 0.21])$	$([0.14, 0.19], [0.87, 0.91], [0.14, 0.19])$
A4	$([0.00, 0.00], [1.00, 1.00], [0.05, 0.05])$	$([0.09, 0.12], [0.87, 0.91], [0.19, 0.23])$	$([0.10, 0.13], [0.88, 0.92], [0.17, 0.21])$
A5	$([0.11, 0.14], [0.84, 0.89], [0.15, 0.19])$	$([0.07, 0.09], [0.89, 0.93], [0.19, 0.21])$	$([0.12, 0.15], [0.87, 0.91], [0.16, 0.20])$

Table 9. Distance to positive and negative ideal solutions and ranks of the alternatives.

Alternatives	D_i^+	D_i^-	C_i	**Rank**
A1	0.0347	0.2106	0.8585	2
A2	0.1345	0.1113	0.4528	4
A3	0.0000	0.2452	1.0000	1
A4	0.2433	0.0022	0.0090	5
A5	0.0812	0.1640	0.6688	3

Based on the results shown in Table 9, Alternative 3 is selected as the best contractor among the examined alternatives.

5 Conclusion

The growing complexity of global supply chains has made the evaluation of logistics subcontractors a critical challenge for providers. Traditional performance assessment methods often fall short in addressing the inherent uncertainties and subjective judgments involved in real-world logistics operations. This study addresses these limitations by adapting and implementing a decision support framework based on methods. The integrated approach provided a more nuanced and realistic way to evaluate subcontractor performance by effectively handling both quantitative metrics and qualitative expert judgments under uncertain conditions.

Through the IVSF-AHP method, the weights of key performance criteria are determined dynamically, including delivery reliability, operational efficiency, and communication effectiveness. The IVSF-TOPSIS model then enabled a comprehensive ranking of subcontractors, accounting for the vagueness and imprecision common in logistics performance data. The practical application of this framework demonstrated its effectiveness, with the third alternative emerging as the top-performing subcontractor due to its consistent results across critical indicators such as on-time delivery rates, minimal shipment damages, and high customer satisfaction scores.

This research contributes to logistics management practice by showcasing how advanced fuzzy multi-criteria decision-making techniques can be successfully adapted to address real-world subcontractor evaluation challenges. The framework provides logistics managers with a structured yet flexible tool that accommodates both objective performance data and subjective expert assessments.

Future research could explore the integration of real-time data analytics to enable dynamic performance monitoring or examine the model's applicability across different logistics sectors with varying operational requirements. Comparative studies with other fuzzy MCDM approaches could also provide additional insights into method selection for specific evaluation scenarios.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

Ersin Şengül is affiliated with the Department of Project and Integration, Horoz Lojistik Kargo Hiz. ve Tic.A.Ş., Istanbul, Turkey. The authors declare that this affiliation had no influence on the study design, data collection, analysis, interpretation, or the decision to publish, and that no other competing interests exist.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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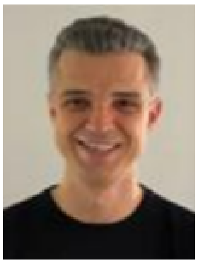

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