Journal of Quality Engineering and Production Optimization

Volume 9, Issue 2, Summer & Autumn 2024

http://jqepo.shahed.ac.ir

Research Paper

DOI: 10.22070/jqepo.2025.20674.1301

A Hybrid Group-MCDM Framework for Supplier Selection Problem in Organ Transplantation Networks under an Interval-Valued Fuzzy Environment

Reyhaneh Askarianzadeh[1], **Seyed Meysam Mousavi**[1*], **Mohammad Javad Barzegari**[1]

[1] *Department of Industrial Engineering, Shahed University, Tehran, Iran*

*** Corresponding Author:** *Seyed Meysam Mousavi (Email: sm.mousavi@shahed.ac.ir)*

Abstract – *Selecting appropriate suppliers in organ transplant affiliation networks is of critical importance due to its direct impact on service quality and increased life expectancy. This process is recognized as a complex group-multiple criteria decision-making (G-MCDM) problem, involving the evaluation of multiple supplier alternatives based on key criteria for organ transplantation. In this study, a new integrated model is proposed by combining the Borda and CoCoSo methods using Interval-Valued Fuzzy Sets (IVFSs) within a group decision-making environment. Leveraging the enhanced capabilities of fuzzy theory, the proposed method effectively addresses the inherent uncertainties present in real-world applications. The weights of the criteria are determined using an interval-valued fuzzy Shannon entropy (IVF-Shannon entropy) method, incorporating expert judgments. Subsequently, the hybrid Borda-CoCoSo approach is employed to rank supplier alternatives for organ transplant equipment within affiliation networks. An application example is presented to assess the performance of the proposed model, and both comparative and sensitivity analyses are conducted to investigate the influence of key parameters on the results. In addition, a comparative evaluation is performed with three existing methods from the literature. The results highlight the accuracy and efficiency of the proposed model in supplier selection and in improving decision-making within the organ transplant supply chain.*

Keywords*– Healthcare Supply Chain, Organ Transplantation, Group-Multiple Criteria Decision-Making (G-MCDM), Borda-CoCoSo Method, Interval-Valued Fuzzy Sets.*

I. INTRODUCTION

Healthcare systems, as the backbone of modern societies, play an indispensable role in the supply chain cycle, with objectives, such as promoting public health, increasing life expectancy, and improving quality of life. These systems integrate medical services, human resource management, and supply chain coordination to deliver effective and sustainable care (Liu et al., 2019). With the growing global demand for advanced medical services, particularly during critical situations, e.g., pandemics, healthcare systems have faced numerous challenges, including resource shortages, inadequate infrastructure, and the need for rapid and precise decision-making (Alsalem et al., 2022). These challenges necessitate novel managerial and decision-making approaches capable of effectively managing existing complexities. Among these, organ transplant networks represent one of the most sensitive components of healthcare systems, requiring special attention to supply chain management and the selection of appropriate resources (Jalilvand et al., 2023).

Manuscript Received: 17/08/2024 & Revised: 09/10/2024 & Accepted: 20/11/2024
ISSN: 2423-3781

Organ transplant networks serve as vital systems for treating organ failure, saving the lives of thousands of patients around the world and significantly improving their quality of life (Sabripour et al., 2024). This process involves complex coordination between donor hospitals, transplant centers, transportation systems, and recipient regions. The success of a transplant operation depends on several factors, including the quality of hospital resources, precise timing, and effective risk management within the supply chain (Salimian et al., 2023). With the increasing number of transplant procedures in recent decades, the need for advanced and reliable hospital resources has become more evident than ever. These resources must comply with international standards to minimize the risks associated with malfunction or delivery delays (Lo et al., 2022). However, the transplant process still faces challenges, such as uncertainty in resource quality, global supply chain fluctuations, and stringent safety requirements (Abdullah et al., 2025).

The selection of appropriate suppliers for hospital resources in organ transplant networks holds strategic importance due to its direct impact on surgical success, patient safety, and supply chain efficiency (Stević et al., 2020). This task is recognized as a multiple criteria decision-making (MCDM) problem that requires the simultaneous evaluation of both quantitative criteria (e.g., cost and delivery time) and qualitative factors (e.g., resource quality and reliability) (Salehi et al., 2021). The complexity of this decision-making arises from the diversity of criteria, the presence of vague and imprecise data, and the need to aggregate expert opinions. Traditional supplier selection methods, which are often limited to criteria, e.g., cost, prove inefficient in handling such complexities and uncertainties (Zolfani et al., 2020). Therefore, the use of advanced MCDM methods that can model uncertain data and integrate multiple criteria is essential.

MCDM approaches have been widely applied in various fields, including supply chain and healthcare management, due to their ability to break down complex problems into smaller components and evaluate alternatives based on diverse criteria (Yilmaz et al., 2020). Fuzzy set theory, particularly interval-valued fuzzy sets (IVFSs), has increasingly been utilized in complex decision-making problems because of its ability to handle imprecise and incomplete data (Chakraborty et al., 2023). IVFSs provide enhanced fuzzy modeling capabilities that allow for a more accurate representation of uncertainty compared to traditional fuzzy sets. This feature is especially valuable in vital environments, like organ transplant networks (Pamucar et al., 2023).

This research aims to develop a group-multiple criteria decision-making (G-MCDM) method based on a new integration of the Borda and CoCoSo approaches within interval-valued fuzzy (IVF) environments for the supplier selection problem in organ transplant networks. The study further involves calculating the criteria weights using interval-valued fuzzy Shannon entropy and evaluating the efficiency of the model through sensitivity analysis and comparative assessment with existing methods.

According to the existing literature, Jalilvand et al. (2023) proposed a bi-objective MINLP model for designing organ transplant networks, aiming to minimize costs and unmet demands while considering cold chain allocation and prioritization of high-risk recipients. Lo et al. (2022) employed the Analytic Network Process (ANP) to investigate psychological factors influencing family decisions regarding organ donation. Their findings revealed that attitude, with a weight of 31.5%, plays a key role in the donation decision-making process. Salimian et al. (2023) developed a group-multiple criteria decision-making (G-MCDM) model for selecting transportation modes within organ transplant networks under interval-valued intuitionistic fuzzy uncertainty. This model used the CRITIC method and integrated subjective judgments and similarity measures to evaluate three transportation modes, with validation conducted through sensitivity analysis.

Sabripour et al. (2024) proposed a fuzzy hybrid MCDM model based on F-FMEA to assess post-transplant risks. This model achieved expert approval with an accuracy rate of 91.67%. It prioritized 20 key risks, including medication non-adherence and ischemia time. Abdullah et al. (2025) introduced interval-valued neutrosophic hypersoft Fermatean sets for medical decision-making. This approach utilizes algebraic operations to prioritize patients for organ transplants based on criteria such as organ compatibility and urgency, effectively handling uncertainty. Liu et al. (2019) developed a hybrid model (DDANPMV) for promoting mobile health services, which examined critical factors such as social norms and consumer trust. Yilmaz et al. (2020) explored the application of MCDM methods in military healthcare systems. Their study highlighted the lack of integrated approaches in this field and emphasized the need to develop and implement these methods for more effective decision-making in military health systems.

Zolfani et al. (2020) presented a decision support framework using CRITIC and CoCoSo methods for selecting temporary hospital locations for COVID-19 patients. A case study conducted in Istanbul demonstrated the efficiency and practical applicability of the proposed approach. Alghawli et al. (2021) evaluated and compared the level of organizational health literacy in hospitals using the FAHP-FDM method. The multi-stage fuzzy model demonstrated higher accuracy and discrimination capability compared to the traditional qualitative AHP. The findings indicated that hospitals with lower scores require greater financial support. Chen and Lin (2022) proposed a fuzzy MCDM approach based on FGM, which divides the fuzzy judgment matrix into diverse and consistent sub-estimations. The proposed method enabled the identification of multiple optimal smart technologies in post-COVID-19 healthcare.

Alsalem et al. (2022) proposed an intelligent framework for the emergency transfer of mesenchymal stem cells (MSCs) during COVID-19 crises. Using MCDM techniques, this study prioritized patients based on the level of urgency, thereby facilitating effective MSC transfers under critical conditions. The findings highlighted that individual resilience played a key role in improving immune performance in both genders. Salehi et al. (2023) applied entropy and MCDM methods to examine the impact of occupational stress, individual resilience, and organizational flexibility on the safety performance of healthcare staff during the COVID-19 pandemic. Their results showed that organizational flexibility was more influential for older personnel, while individual flexibility had a greater impact on younger and less experienced staff.

Bouraima et al. (2024) used the AROMAN method to rank sustainable outsourcing strategies in the Kisumu healthcare system in Kenya, emphasizing infrastructure development and human resource enhancement. Alabool (2025) identified nine main criteria and twelve sub-criteria in healthcare through the Delphi method and interviews with 38 experts. These criteria were then weighted and ranked using the FAHP decision-making approach. This method facilitated the management of uncertainty and the determination of the relative importance of the criteria. Stević et al. (2020) introduced the MARCOS method for sustainable supplier selection at Ghetaldus Polyclinic. By evaluating eight suppliers based on 21 sustainability criteria, their approach demonstrated high decision-making accuracy and robustness through sensitivity analysis. Chakraborty et al. (2023) presented a comparative analysis of the MABAC model for healthcare supplier selection across seven fuzzy environments. The study found that the best and worst suppliers remained consistent across different fuzzy settings, confirming the model's effectiveness in handling uncertainty and expert judgment. Pamucar et al. (2023) proposed a fuzzy decision-making approach for supplier selection in healthcare supply chain management during the COVID-19 pandemic. The study utilized MACBETH and CODAS methods under fuzzy rough numbers (FRNs) to address supplier selection in Turkish hospitals.

Rishabh and Das (2025) developed a hybrid model (AHP-PSO-TOPSIS) for healthcare supplier selection in India. This method integrated AHP and TOPSIS within a PSO optimization environment to extract precise weights from fuzzy decision matrices and validated performance through sensitivity analysis and comparisons. Salimian et al. (2022) introduced a hybrid model based on E-VIKOR and MARCOS under interval-valued intuitionistic fuzzy sets (IVIFSs) for sustainable supplier selection in organ transplant networks. This approach aimed to manage uncertainty and ranked medical device suppliers based on economic, social, and environmental sustainability criteria.

According to Table 1, despite significant advancements in the application of MCDM and fuzzy methods in organ transplantation and supplier selection, specific gaps are observed in the literature. Most studies have focused on pre-transplantation issues, such as member allocation or network design, and the selection of hospital resource suppliers in organ transplant networks has received less attention. The IVFSs are of great importance due to their capability to accurately model complex uncertainties, particularly in critical environments, e.g., organ transplant networks. By defining ranges for memberships, IVFSs provide greater flexibility than traditional fuzzy sets in handling ambiguous

Table 1. Comparison of Previous Studies

No.	Authors (Year)	Ranking Approach/Methods			Criteria Weighting Method		Uncertainty		
		COCOSO	BORDA	Others	Shannon Entropy-GDM	Others	Fuzzy Set	Interval-Valued Fuzzy Set	Others
1	Liu et al. (2019)			✓		✓			
2	Zolfani et al. (2020)	✓				✓	✓		
3	Yilmaz et al. (2020)			✓		✓			✓
4	Stević et al. (2020)			✓		✓	✓		
5	Alsalem et al. (2022)			✓		✓			
6	Lo et al. (2022)			✓		✓			✓
7	Salimian et al. (2022)			✓					✓
8	Salehi et al. (2023)			✓		✓			✓
9	Jalilvand et al. (2023)						✓		
10	Pamucar et al. (2023)			✓		✓	✓		
11	Chakraborty et al. (2023)			✓		✓	✓		
12	Salimian et al. (2023)			✓		✓			✓
13	Karami et al. (2023)	✓		✓		✓		✓	
14	Barzegari et al. (2023)			✓		✓		✓	
15	Sabripour et al. (2024)			✓			✓		
16	Bouraima et al. (2024)			✓		✓			✓
17	Abdullah et al. (2025)			✓		✓		✓	
18	Rishabh and Das (2025)			✓		✓	✓		
This study		✓	✓		✓			✓	

data and aggregating expert group judgments. However, many previous studies have not utilized this approach. For instance, Pamucar et al. (2023) employed Fuzzy Rough Numbers (FRN) in their supplier selection model, which has limited ability to manage interval uncertainties and cannot fully capture the complexity of multiple judgments. Similarly, Sabripour et al. (2024), in their F-FMEA study for assessing post-transplant risks, relied on traditional fuzzy sets and overlooked the potential of IVFSs for more precise modeling of uncertainties. Such limitations reduce decision-making accuracy in strategic contexts, as IVFSs enable more effective management of interval uncertainties. Moreover, the application of hybrid methods, like Borda-CoCoSo for supplier ranking in organ transplant networks, has been rarely explored. An integration of the Borda method, which effectively aggregates different rankings with the CoCoSo method. It provides stable and accurate multi-criteria rankings that can significantly enhance the flexibility and precision of decision-making. Nevertheless, prior studies have often relied on single methods, which are insufficient for simultaneously managing multiple criteria and group judgments in such critical environments, thereby restricting the stability of results against parameter variations. In addition, criteria weighting methods have often relied on precise data and have less frequently employed expert opinion-based approaches in the IVF environment. These gaps indicate a need for novel and integrated methods to improve group decision-making in the supplier selection problem within organ transplant networks.

This study proposes a new G-MCDM method based on the combination of Borda and CoCoSo methods in the environments of IVFSs to rank hospital resource suppliers in organ transplant networks. The innovations of this research include: 1) the use of interval-valued fuzzy Shannon entropy (IVF-Shannon entropy) based on experts opinions to calculate the weight of criteria, 2) a new development of the hybrid Borda-CoCoSo method for more accurate ranking in group decision-making environments, and 3) the presentation of an integrated IVF-framework for managing uncertain data in the organ transplant supply chain. Further, this method demonstrates its accuracy and efficiency through a sensitivity analysis in a practical example.

The structure of the article is as follows: Section 2 introduces the concepts of IVFSs. Section 3 describes the proposed method. Section 4 presents the practical example and analyses, and Section 5 states the conclusion and future suggestions.

II. CONCEPTUAL AND MATHEMATICAL FOUNDATIONS OF INTERVAL-VALUED FUZZY SETS

In dealing with complex decision-making problems characterized by uncertainty and imprecise information, linguistic values represent a fundamental advantage. These values, as introduced by pioneers, such as Zadeh (1975) and Zimmermann (1986), allow decision-makers to express subjective and qualitative uncertainties in an intuitive and effective manner. However, traditional fuzzy sets, due to the assignment of a single precise membership degree to each element, sometimes face limitations in fully capturing the subtleties of linguistic expressions.

To address this challenge, the concept of Interval-Valued Fuzzy Sets (IVFSs) was developed by researchers, such as Grattan-Guinness (1976) and Karnik & Mendel (2001). These sets assign an interval to the membership degree of each element, thereby providing significant flexibility for modeling vague and uncertain information. This feature is particularly valuable in contexts like supplier selection within the organ transplant supply chain, where decision-making often involves incomplete, subjective, and qualitative data. For example, Karami et al. (2023) demonstrated that IVFSs enhanced the accuracy of supplier selection in complex environments by more precisely handling interval uncertainties. When combined with hybrid methods, e.g., Borda-CoCoSo, they enabled the effective aggregation of group judgments and provided stable rankings, thereby delivering superior performance compared to traditional approaches. As noted by Ashtiani et al. (2009) and Barzegari et al. (2023), this approach has turned IVFSs into a powerful tool for complex decision-making domains.

According to the classical definition by Gorzałczany (1987), an interval-valued fuzzy set $\tilde{A}$ over the domain of real numbers is defined as follows:

$$\tilde{A} = \{X, [\mu_{\tilde{A}^L}(x), \mu_{\tilde{A}^U}(x)]\}, x \epsilon (-\infty, +\infty) \tag{1}$$

In this definition, $\mu_{\tilde{A}^L}(x)$ and $\mu_{\tilde{A}^U}(x)$ are the lower and upper bounds of the membership function for element x, respectively, and the condition $\mu_{\tilde{A}^L}(x) \leq \mu_{\tilde{A}^U}(x)$ must always hold.

One of the most widely used forms of IVFS is the Interval-Valued Triangular Fuzzy Number (IVTFN). Due to their simple yet powerful structure, these numbers are highly popular in MCDM modeling. An interval-valued triangular fuzzy number $\tilde{A}$, as described by Yao and Lin (2002) and shown in Figure 1, is generally represented as follows:

$$\tilde{A} = [\tilde{A}_X^L, \tilde{A}_X^U] = [(a_1^L, a_2^L, a_3^L; \widehat{w}_{\tilde{A}}^L), (a_1^U, a_2^U, a_3^U; \widehat{w}_{\tilde{A}}^U)] \tag{2}$$

In this structure, $(\tilde{A}_X^L)$ represents the interval for the lower bound, and $(\tilde{A}_X^U)$ represents the interval for the upper bound of the fuzzy number. These relationships indicate when $\tilde{A}_X^L = \tilde{A}_X^U$, the triangular fuzzy number becomes a crisp number. $\mu_{\tilde{A}^L}(X) = \widehat{w}_{\tilde{A}}^L$ and $\mu_{\tilde{A}^U}(X) = \widehat{w}_{\tilde{A}}^U$ are the lower and upper membership functions, respectively.

According to the following relationships illustrated in Figure 1, triangular fuzzy numbers have specific characteristics:

- If $\tilde{A}_X^L = \tilde{A}_X^U$, the interval-valued triangular fuzzy number becomes a regular triangular fuzzy number.
- If the relationships $\tilde{A}_X^L = a_2^L = a_3^L = a_1^U = a_2^U = a_3^U$ hold, the interval-valued triangular fuzzy number becomes a crisp number.
- If $\widehat{w}_{\tilde{A}}^L = \widehat{w}_{\tilde{A}}^U$, the interval-valued triangular fuzzy number is specifically defined.

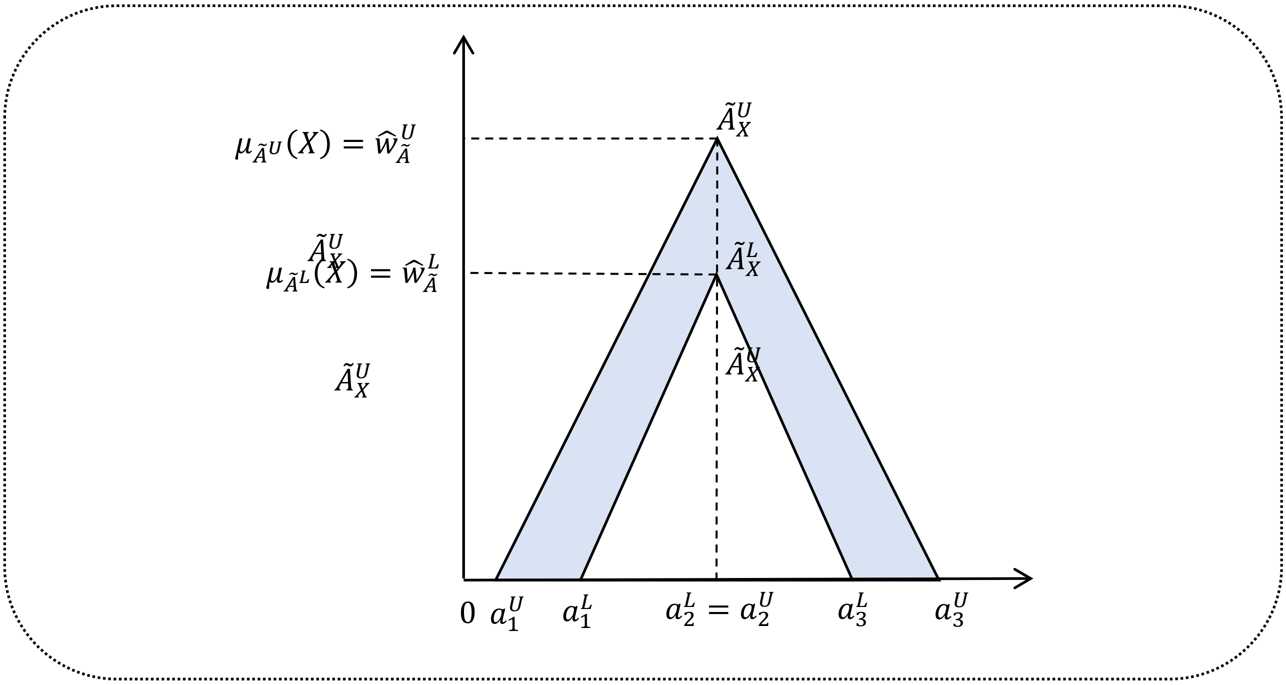

Figure 1. Interval-Valued Triangular Fuzzy Numbers

To analyze and aggregate these numbers, a set of mathematical operations has been defined. Suppose we have two interval-valued triangular fuzzy numbers as follows:

$$\tilde{A} = [(a_1^u, a_1^l); a_2; (a_3^l, a_3^u)] \tag{3}$$

$$\tilde{B} = [(b_1^u, b_1^l); b_2; (b_3^l, b_3^u)] \tag{4}$$

The main mathematical operations between these two numbers, based on the works of Chen and Chen (2008) and Barzegari et al. (2023), are as follows:

• Addition (⊕):

$$\begin{aligned}\tilde{A} \oplus \tilde{B} &= \left[\left(a_1^u, a_1^l\right); a_2; \left(a_3^l, a_3^u\right)\right] \oplus \left[\left(b_1^u, b_1^l\right); b_2; \left(b_3^l, b_3^u\right)\right] \\ &= \left[\left(a_1^l + b_1^l, a_1^u + b_1^u\right), (a_2 + b_2), \left(a_3^l + b_3^l, a_3^u + b_3^u\right)\right]\end{aligned} \tag{5}$$

• Subtraction (⊖):

$$\tilde{A} \ominus \tilde{B} = [(a_1^u, a_1^l); a_2; (a_3^l, a_3^u)] \ominus [(b_1^u, b_1^l); b_2; (b_3^l, b_3^u)] \\ = [(a_1^l - b_3^l, a_1^u - b_3^u), (a_2 - b_2), (a_3^l - b_1^l, a_3^u - b_1^u)] \tag{6}$$

• Multiplication (⊗):

$$\tilde{A} \otimes \tilde{B} = [(a_1^u, a_1^l); a_2; (a_3^l, a_3^u)] \otimes [(b_1^u, b_1^l); b_2; (b_3^l, b_3^u)] \\ = [(a_1^l \times b_1^l, a_1^u \times b_1^u), (a_2 \times b_2), (a_3^l \times b_3^l, a_3^u \times b_3^u)] \tag{7}$$

• Generalized Division (⊘):

$$\tilde{A} \oslash \tilde{B} = [(a_1^u, a_1^l); a_2; (a_3^l, a_3^u)] \oslash [(b_1^u, b_1^l); b_2; (b_3^l, b_3^u)] = \left[\left(\frac{a_1^l}{b_3^l}, \frac{a_1^u}{b_3^u}\right), \left(\frac{a_2}{b_2}\right), \left(\frac{a_3^l}{b_1^l}, \frac{a_3^u}{b_1^u}\right)\right] \tag{8}$$

• Multiplication by a Scalar (m):

$$m\tilde{A} = [(ma_1^u, ma_1^l); ma_2; (ma_3^l, ma_3^u)] \tag{9}$$

• Inverse of a Fuzzy Number:

$$\frac{1}{\tilde{A}} = \left[\left(\frac{1}{a_1^u}, \frac{1}{a_1^l}\right); \frac{1}{a_2}; \left(\frac{1}{a_3^l}, \frac{1}{a_3^u}\right)\right] \tag{10}$$

This precise computational framework not only enables the mathematical processing of vague information but also significantly enhances the ability to analyze, compare, and rank alternatives within an interval-valued fuzzy decision-making environment. These characteristics have made the IVF a key and essential tool in group-multiple criteria decision analysis under uncertainty.

III. PROPOSED METHODOLOGY

This study presents an integrated and novel group-multiple criteria decision-making (G-MCDM) framework for evaluating and selecting resource suppliers within member-linked networks. The proposed model is based on the integration of Shannon Entropy, CoCoSo (Combined Compromise Solution), and Borda methods, inspired by the work of Su et al. (2025). This approach is developed within the context of IVFSs to effectively handle the uncertainties and ambiguities inherent in human judgments and real-world data. In this framework, the decision alternative A_{ij} is evaluated by the decision-maker (DM) with respect to the criterion C_j. To achieve this, a linguistic term set (Table 4) is employed to transform qualitative judgments into quantitative values. For instance, if the decision-maker uses the term (*High)*, it is represented by the value [(0.55,0.75),0.9,(0.95,1)]. This procedure enables a more precise and structured expression of the decision-makers opinions, thereby enhancing the quality and reliability of the decision-making process.

The process of the model is implemented in two main phases:

- **Phase 1: Criteria Weight Calculation:** In this phase, the objective weights of the supplier evaluation criteria are determined using the Interval-Valued Fuzzy Shannon Entropy (IVF-Shannon Entropy) method. This approach extracts the significance of each criterion based on the amount of information embedded in the experts' judgments.
- **Phase 2: Ranking of Alternatives**: In this phase, the final ranking of suppliers is performed using a new hybrid method called IVF-Borda-CoCoSo. This method first employs the CoCoSo logic to calculate three separate evaluation scores for each alternative. Subsequently, these scores are aggregated into a final and robust ranking through the Borda technique.

The detailed implementation steps of this framework are explained in the following sections:

Phase 1: Criteria Weighting Using the IVF-Shannon Entropy Method

To determine the objective weights of the criteria (C_j), the IVF-Shannon Entropy method is employed. This method derives the weights based on the degree of dispersion and uncertainty present in the decision matrix. The steps are outlined as follows:

Step 1: Construct the group fuzzy decision matrix based on the opinions of K experts (Matrix 12).

Step 2: Aggregate the decision matrix using the Interval-Valued Fuzzy Weighted Averaging (IVFWA) operator.

Step 3: The aggregated decision matrix is normalized, and each normalized element is denoted as $\widetilde{p_{ij}}$. Normalization is performed by dividing each element of a column by the sum of that column.

Step 4: Calculate the entropy value $(\widetilde{E_j})$ for each criterion (the constant K keeps the value of $\widetilde{E_j}$ between 0 and 1).

$$\widetilde{E_j} = -k \sum_{i=1}^{m} \widetilde{p_{ij}}.Ln\widetilde{p_{ij}} \qquad i = 1,2,\dots,m \tag{11}$$

Step 5: Determine the degree of divergence $(\widetilde{d_j} = 1 - \widetilde{E_j})$.

Step 6: Compute the final objective weight of each criterion using the formula

$(\widetilde{w_j} = \varphi\left(\frac{\widetilde{d_j}}{\sum_{j=1}^{n}\widetilde{d_j}}\right) + (1-\varphi)(\widetilde{W'}))$.

This step represents a linear combination of the weights from the Shannon entropy method $\left(\frac{\widetilde{d_j}}{\sum_{j=1}^{n}\widetilde{d_j}}\right)$ and experts opinions $(\widetilde{W'})$. This value, combined with a coefficient φ, which ranges between 0 and 1, calculates the final weight. This approach reflects the aggregated opinions of experts and the weight of the entropy weighting method, providing a more precise criterion weight for rankings in the proposed approach compared to the base method.

Phase 2: Ranking of Alternatives Using the IVF-Borda-CoCoSo Method

After determining the criteria weights, the ranking of suppliers (alternatives) is conducted using the proposed hybrid approach.

Step 1: Construction of the Initial Decision Matrix

First, the decision matrix is constructed based on the evaluation of *m* alternatives (suppliers) against *n* criteria by the experts. The experts' linguistic assessments are modeled using Interval-Valued Triangular Fuzzy Numbers (IVTFNs).

$$A = \begin{bmatrix} \tilde{A}_{11k} & \tilde{A}_{12k} & \dots & \tilde{A}_{1nk} \\ \tilde{A}_{21k} & \tilde{A}_{22k} & \dots & \tilde{A}_{2nk} \\ \dots & \dots & \ddots & \vdots \\ \tilde{A}_{m1k} & \tilde{A}_{m2k} & \dots & \tilde{A}_{mnk} \end{bmatrix}, \text{ i=1, 2, … , m , j=1, 2, … , n, k=1, 2, … , K} \tag{12}$$

To implement the experts' opinions, their assessments are aggregated. The initial decision matrix $\tilde{X}$ is constructed as follows:

$$X = \frac{\tilde{A}_{ijk}}{K} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \dots & \dots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \tilde{x}_{mn} \end{bmatrix}, \text{ i=1, 2, … , m , j=1, 2, … , n} \tag{13}$$

where each element $\tilde{x}_{ij} = \left[\left(x'^{u}_{ij}, x'^{l}_{ij}\right), x_{ij}, \left(x''^{l}_{ij}, x''^{u}_{ij}\right)\right]$ represents an interval-valued triangular fuzzy number.

Step 2: Normalization of the Decision Matrix

To eliminate the effect of different scales and make the criteria comparable, the decision matrix is normalized using the following equation:

$$\tilde{r}_{ij} = \begin{cases} \dfrac{\tilde{x}_{ij} - minx'^{u}_{ij}}{maxx''^{u}_{ij} - minx'^{u}_{ij}} & (Benefit) \\ \dfrac{maxx''^{u}_{ij} - \tilde{x}_{ij}}{maxx''^{u}_{ij} - minx'^{u}_{ij}} & (cost) \end{cases} \tag{14}$$

The normalized matrix $\tilde{R}$ and its elements ($\tilde{r}_{ij}$) are also interval-valued triangular fuzzy numbers.

Step 3: Calculation of the Weighted Sum S_i and Weighted Product P_i

In this step, the normalized decision matrix is combined with the weights obtained from Phase 1 to calculate two aggregate measures, S_i and P_i, for each alternative. These calculations are performed separately for the upper and lower bounds of the fuzzy numbers:

$$S_i^l = 1/3\left(\sum_{j=1}^{n} w_j'^{l}\, r_{ij}'^{l} + \sum_{j=1}^{n} w_j r_{ij} + \sum_{j=1}^{n} w_j''^{l}\, r_{ij}''^{l}\right) \tag{15}$$

$$P_i^l = 1/3\left(\sum_{j=1}^{n} r_{ij}'^{l\, w_j'^{l}} + \sum_{j=1}^{n} r_{ij}^{\ w_j} + \sum_{j=1}^{n} r_{ij}''^{l\, w_j''^{l}}\right) \tag{16}$$

$$S_i^u = 1/3\left(\sum_{j=1}^{n} w_j'^{u}\, r_{ij}'^{u} + \sum_{j=1}^{n} w_j r_{ij} + \sum_{j=1}^{n} w_j''^{u}\, r_{ij}''^{u}\right) \tag{17}$$

$$P_i^u = 1/3\left(\sum_{j=1}^{n} r_{ij}'^{u\, w_j'^{u}} + \sum_{j=1}^{n} r_{ij}^{\ w_j} + \sum_{j=1}^{n} r_{ij}''^{u\, w_j''^{u}}\right) \tag{18}$$

Step 4: Calculation of Relative Assessment Scores (K_{ia}, K_{ib}, K_{ic})

Three aggregation strategies are employed to calculate the assessment scores for each alternative. These scores are also computed for the upper and lower bounds of the IVF numbers (with $\lambda = 0.5$ considered):

$$K_{ia}^l = \frac{S_i^l + P_i^l}{\sum_{i=1}^{m}(S_i^l + P_i^l)} \quad ; K_{ia}^u = \frac{S_i^u + P_i^u}{\sum_{i=1}^{m}(S_i^u + P_i^u)} \tag{19}$$

$$K_{ib}^l = \frac{S_i^l}{minS_i^l} + \frac{P_i^l}{minP_i^l} \ ; \ K_{ib}^u = \frac{S_i^u}{minS_i^u} + \frac{P_i^u}{minP_i^u} \tag{20}$$

$$K_{ic}^l = \frac{\lambda S_i^l + (1-\lambda)P_i^l}{\lambda maxS_i^l + (1-\lambda)maxP_i^l} \ ; \ K_{ic}^u = \frac{\lambda S_i^u + (1-\lambda)P_i^u}{\lambda maxS_i^u + (1-\lambda)maxP_i^u} \qquad , 0 \le \lambda \le 1 \tag{21}$$

Step 5: Normalization and Aggregation of Assessment Scores

To establish a common and balanced basis for the Borda stage, the assessment scores obtained in the previous step are normalized using vector normalization. Subsequently, the upper and lower bound values are aggregated:

$$K_{ia}^{l} = \frac{K_{ia}^{l}}{\sqrt{\sum_{i=1}^{m}(K_{ia}^{u})^2}} \; ;K_{ib}^{l} = \frac{K_{ib}^{l}}{\sqrt{\sum_{i=1}^{m}(K_{ib}^{u})^2}} \; ; \; K_{ic}^{l} = \frac{K_{ic}^{l}}{\sqrt{\sum_{i=1}^{m}(K_{ic}^{u})^2}} \tag{22}$$

$$K_{ia}^{u} = \frac{K_{ia}^{u}}{\sqrt{\sum_{i=1}^{m}(K_{ia}^{l})^2}} \; ; \; K_{ib}^{u} = \frac{K_{ib}^{u}}{\sqrt{\sum_{i=1}^{m}(K_{ib}^{l})^2}} \; ;K_{ic}^{u} = \frac{K_{ic}^{u}}{\sqrt{\sum_{i=1}^{m}(K_{ic}^{l})^2}} \tag{23}$$

Then, the final score for each strategy is obtained by averaging the normalized upper and lower bounds values.

$$K_{ia} = 1/2\left(K_{ia}^{l} + K_{ia}^{u}\right) \; ; \; K_{ib} = 1/2\left(K_{ib}^{l} + K_{ib}^{u}\right) \; ; K_{ic} = 1/2\left(K_{ic}^{l} + K_{ic}^{u}\right) \tag{24}$$

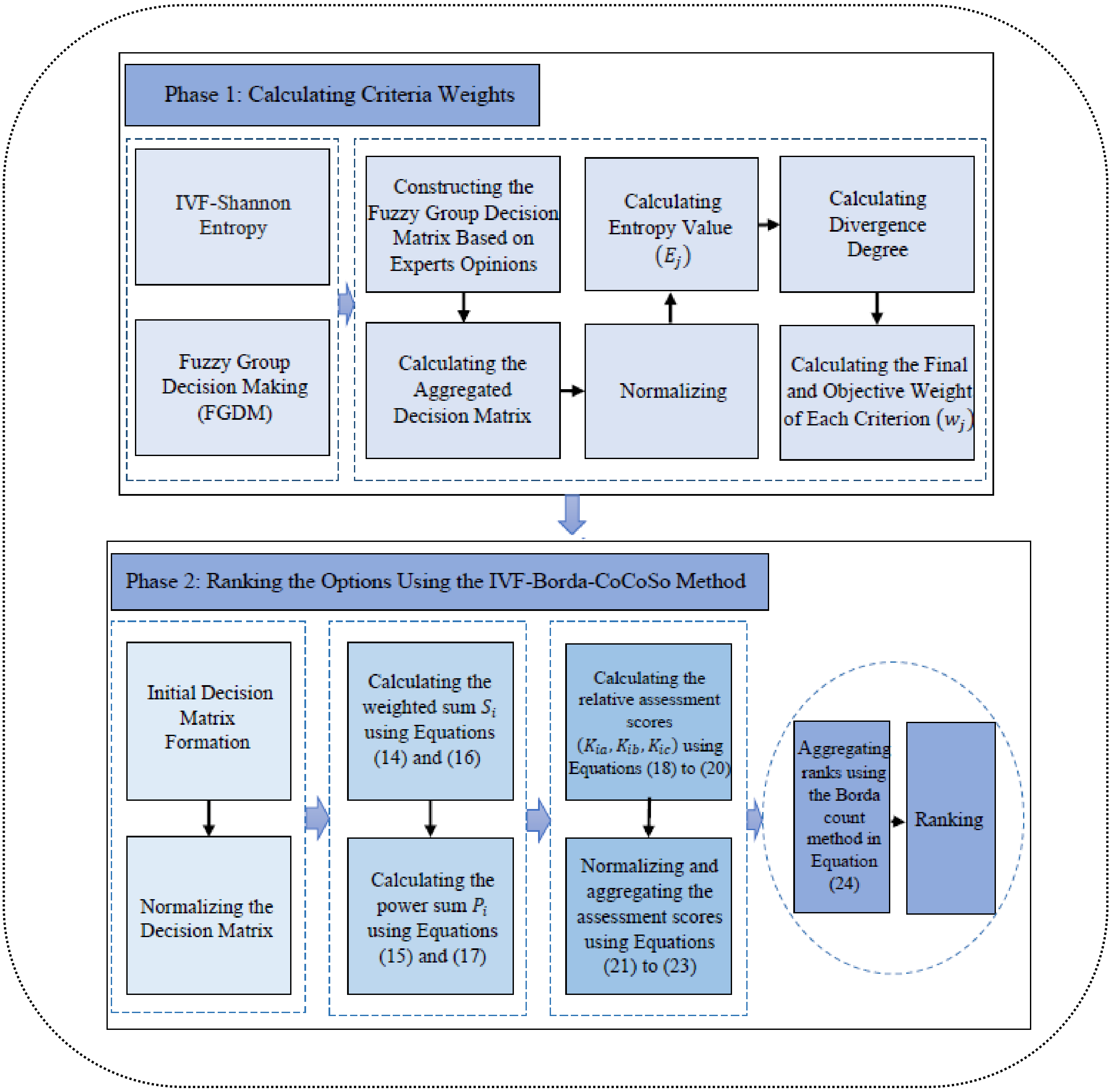

Figure 2. Flowchart of the proposed method

Step 6: Rank Aggregation Using the Borda Count

In the final step, the Borda count method is used to aggregate the rankings obtained from the three strategies, K_{ia}, K_{ib} and K_{ic}. This method assigns a score to each alternative based on its position in each of the three lists. The final score for each alternative BR_i is calculated by summing its scores across the three lists:

$$BR(i) = K_{ia}\frac{m - rank(K_{ia}) + 1}{m(m+1)/2} + K_{ib}\frac{m - rank(K_{ib}) + 1}{m(m+1)/2} + K_{ic}\frac{m - rank(K_{ic}) + 1}{m(m+1)/2} \quad (25)$$

The alternatives are ranked in descending order based on their BR_i values. The alternative with the highest BR_i score is selected as the best and most suitable supplier. This hybrid approach, by aggregating three different evaluation perspectives, achieves a robust and reliable compromise solution.

IV. PRACTICAL EXAMPLE: SUPPLIER SELECTION FOR SURGICAL EQUIPMENT

In this section, to evaluate the performance and validate the proposed model, a practical example is presented. A leading university hospital specializing in organ transplantation intends to select a primary supplier for critical operating room equipment to update its surgical technologies. Due to its direct impact on patient safety and the success of transplant surgeries, the selection process is highly sensitive. The hospital's decision-making committee consists of three key decision makers (DMs): the Head of the Transplant Surgery Department (DM_1), the Supply Chain and Procurement Manager (DM_2), and the Senior Medical Equipment Engineer (DM_3).

After preliminary evaluations, four supplier companies (A) were shortlisted as final candidates: an internationally reputable company with a broad product portfolio (A_1), a domestic manufacturer specializing in advanced surgical equipment (A_2), an experienced distributor with a strong logistics network in the country (A_3), and a startup knowledge-based company offering innovative technologies (A_4). Based on prior studies and the hospital's strategic requirements, the decision-making committee finalized a set of ten key criteria categorized into three main dimensions: economic, technical, and final service quality, which are presented in Table 2.

Table 2. Supplier Evaluation Criteria

Main Dimension	Symbol	Criteria
Economic	C_1	Competitive Price
	C_2	Flexible Payment Terms
	C_3	Product Life Cycle Costs
Technical	C_4	Quality and Technical Standards
	C_5	Innovation and Technology Level
	C_6	Compatibility with Existing Equipment
Service Quality	C_7	Delivery Time and Reliability
	C_8	After-Sales Service and Technical Support
	C_9	Personnel Training
	C_{10}	Supplier's Credibility and Track Record

The proposed IVF-Borda-CoCoSo model was applied to calculate the criteria weights and rank the suppliers. Initially, the criteria weights were computed using the IVF-Shannon Entropy method, followed by ranking the suppliers using the IVF-Borda-CoCoSo approach. The results of this process are presented below.

Phase 0: Design of the Decision Matrix

A decision matrix was designed based on the linguistic evaluations of the three key decision-makers (DM_1, DM_2, DM_3) for four suppliers (A_1, A_2, A_3, A_4) with respect to 10 main criteria. These assessments were converted into IVTFNs using a linguistic scale to accurately model the inherent uncertainty in human judgments. The linguistic scale used is presented in Table 3, and the aggregated decision matrix is shown in Table 4.

Table 3. Linguistic Scale and Interval-Valued Triangular Fuzzy Numbers

Linguistic variables	Triangular interval-valued fuzzy numbers
Very low (VL)	[(0,0),0, (0.1,0.15)]
Low (L)	[(0,0.05),0.1, (0.25,0.35)]
Medium low (ML)	[(0,0.15),0.3, (0.45,0.55)]
Equal (E)	[(0.25,0.35),0.5, (0.65,0.75)]
Medium high (MH)	[(0.45,0.55),0.7, (0.8,0.95)]
High (H)	[(0.55,0.75),0.9, (0.95,1)]
Very high (VH)	[(0.85,0.95),1, (1,1)]

Table 4. Aggregated Decision Matrix

Symbol Suppliers	DMs	Criteria									
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	DM_1	E	MH	ML	E	MH	MH	MH	E	MH	VH
	DM_2	VH	VH	MH	VH	VH	E	VH	VH	MH	VH
	DM_3	MH	MH	MH	VH	VH	ML	MH	VH	MH	VH
A_2	DM_1	MH	MH	E	MH	VH	ML	MH	MH	MH	MH
	DM_2	E	VH	VH	MH	VH	VH	MH	VH	VH	ML
	DM_3	ML	MH	VH	MH	VH	ML	MH	MH	MH	H
A_3	DM_1	VH	ML	MH	MH	MH	MH	MH	VH	VH	ML
	DM_2	VH	VH	MH	VH	VH	ML	E	VH	VH	VH
	DM_3	VH	ML	MH	MH	MH	H	MH	VH	VH	ML
A_4	DM_1	VH	MH	E	MH	VH	ML	VH	MH	MH	MH
	DM_2	MH	H	H	MH	VH	E	VH	VH	MH	VH
	DM_3	E	ML	MH	H	MH	ML	VH	MH	MH	MH

Phase 1: Criteria Weight Calculation

The objective weights of the criteria were calculated using the IVF-Shannon Entropy method. After computing the entropy weights, these were aggregated with the experts' subjective weights (Table 5) to derive the final criteria weights. The entropy weights, experts' subjective weights, and the final aggregated weights are presented in Table 6.

Table 5. Experts' Subjective Weights for the Criteria

Criteria Symbol	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Expert Opinion Weight	ML	H	VH	E	E	H	ML	E	MH	ML

Table 6. Entropy and Aggregated Weights of the Criteria

Criteria Symbol		Aggregated Weight	Entropy Weight
C_1	C_{11}	0.010746	0.021493
	C_{12}	0.098958	0.047916
	C_{13}	0.199491	0.098982
	C_{14}	0.335965	0.221929
	C_{15}	0.532301	0.514603
C_2	C_{21}	0.276612	0.003225
	C_{22}	0.384593	0.019187
	C_{23}	0.48425	0.0685
	C_{24}	0.565009	0.180019
	C_{25}	0.741106	0.482212
C_3	C_{31}	0.425997	0.001994
	C_{32}	0.484492	0.018983
	C_{33}	0.534963	0.069927
	C_{34}	0.595507	0.191015
	C_{35}	0.761682	0.523365
C_4	C_{41}	0.128854	0.007709
	C_{42}	0.19316	0.03632
	C_{43}	0.300984	0.101967
	C_{44}	0.446075	0.24215
	C_{45}	0.687749	0.625498
C_5	C_{51}	0.146673	0.043346
	C_{52}	0.222837	0.095675
	C_{53}	0.336159	0.172318
	C_{54}	0.489152	0.328303
	C_{55}	0.72138	0.692759

Continue Table 6. Entropy and Aggregated Weights of the Criteria

Criteria Symbol		Aggregated Weight	Entropy Weight
C_6	C_{61}	0.280517	0.011033
	C_{62}	0.373161	-0.00368
	C_{63}	0.454003	0.008006
	C_{64}	0.509627	0.069254
	C_{65}	0.623502	0.247003
C_7	C_{71}	0.009826	0.019653
	C_{72}	0.100448	0.050895
	C_{73}	0.206599	0.113198
	C_{74}	0.350703	0.251407
	C_{75}	0.588524	0.627047
C_8	C_{81}	0.141119	0.032238
	C_{82}	0.213536	0.077072
	C_{83}	0.324244	0.148487
	C_{84}	0.473973	0.297945
	C_{85}	0.700531	0.651063
C_9	C_{91}	0.235217	0.020435
	C_{92}	0.301896	0.053791
	C_{93}	0.409951	0.119902
	C_{94}	0.531098	0.262195
	C_{95}	0.804486	0.658971
C_{10}	C_{101}	0.009986	0.019972
	C_{102}	0.098143	0.046286
	C_{103}	0.199357	0.098713
	C_{104}	0.33297	0.21594
	C_{105}	0.524702	0.499405

Phase 2: Supplier Ranking Using the IVF-Borda-CoCoSo Method

In this phase, the hybrid IVF-Borda-CoCoSo method was applied to the normalized decision matrix to rank the suppliers. First, the decision matrix was normalized using Equation (14) to eliminate the effects of differing scales among criteria. Then, the weighted sum (S_i) and weighted product (P_i) values for the upper and lower bounds of the IVF numbers were calculated using Equations (15) to (18). Subsequently, three relative assessment scores (K_{ia}, K_{ib}, K_{ic}) for each supplier were obtained based on Equations (19) to (21). These scores were normalized and aggregated using Equations (22) to (24) to establish a common basis for the final aggregation. Finally, by applying the Borda count method and Equation (25), the final score BR_i for each supplier was performed, resulting in a consistent and integrated final ranking. The results of this process are presented in Table 7.

Table 7. Final Ranking of Suppliers

Alternative	Final Score	Final Ranking
A_1	0.304162	3
A_2	0.447745	2
A_3	0.468783	1
A_4	0.294925	4

The results indicate that supplier A_3 (the distributor with a strong logistics network) was selected as the best supplier with the highest BR_i score. This outcome aligns perfectly with the hospital's strategic priorities, particularly emphasizing the technical quality criterion (C_4) and after-sales service (C_8), and confirms the effectiveness of the hybrid IVF-Borda-CoCoSo method in providing robust compromise solutions.

V. RESULTS ANALYSIS AND VALIDATION

A. Results Analysis

The evaluation and ranking of suppliers using the proposed IVF-Borda-CoCoSo method, as presented in Table 7, provide a comprehensive insight into the performance of each supplier within the organ transplant networks. Supplier A_3 was selected as the best option with the highest score (BR_i = 0.468783). This superiority stems from its strong performance in key and effective evaluation components. Supplier A_2 ranked second with a score of 0.447745, demonstrating relatively balanced performance across various aspects. Supplier A_1, with a score of 0.304162, ranked third and exhibited weaker performance in some specialized areas. Supplier A_4 ranked last with a score of 0.294925, showing limitations in effectively meeting the demands of the organ transplant supply chain.

To validate the results of the proposed method, supplier rankings were performed using three existing MCDM approaches from the literature: TOPSIS (Mokhtarian et al., 2014), COPRAS (Ashouri et al., 2023), and CoCoSo (Karami et al., 2023), with the results presented in Table 8. Supplier A_3 was consistently ranked as the top option across all methods, demonstrating the robustness and reliability of the proposed IVF-Borda-CoCoSo approach. Furthermore, the consistent identification of A_3 as the best supplier and A_4 as the weakest supplier confirm the high accuracy of the proposed method in managing uncertainties and the complexities of the decision-making environment.

Table 8. Comparison of Supplier Rankings Across Different MCDM Methods

Supplier Symbol	IVF-Borda-CoCoSo method		IVF-TOPSIS method		IVF-COPRAS method		IVF-CoCoSo method	
	rank	Score	rank	Score	rank	Score	rank	Score
A_1	3	0.304162	3	0.683638	3	0.959939	3	0.49735
A_2	2	0.447745	2	0.700564	2	0.976207	2	0.497494
A_3	1	0.468783	1	0.721911	1	1	1	0.513348
A_4	4	0.294925	4	0.606201	4	0.927742	4	0.491542

The IVF-Borda-CoCoSo method, due to its use of IVFSs and the combination of three evaluation strategies (K_{ia}, K_{ib}, K_{ic}), demonstrates a significant capability in providing balanced and stable rankings. By leveraging the Borda count, this method integrates diverse evaluation perspectives into a unified framework and prevents biases caused by overemphasis on any single criterion. Comparison with the CoCoSo method reveals a notable similarity in outputs, attributed to their shared use of compromise logic. However, the methods, e.g., TOPSIS and COPRAS, which emphasize more on quantitative criteria, e.g., competitive price (C_1), highlight the superiority of the proposed approach in managing qualitative and subjective judgments within complex environments, like organ transplant networks.

The analysis of the confidence intervals of the calculated scores reveals that supplier A_3 has a narrower confidence interval compared to the other options, indicating high accuracy and low variability in the evaluation of this supplier. This feature assures decision-makers that the selection of A_3 remains stable and reliable under different conditions. In contrast, supplier A_4 exhibits a wider confidence interval, which likely results from fluctuations in expert judgments or structural weaknesses in technical and service criteria.

From an external factors perspective, elements such as supplier resource limitations, market conditions, or delivery scheduling may influence the results. To enhance the comprehensiveness of the model, it is recommended to consider additional criteria, such as environmental sustainability or supply chain flexibility. Furthermore, examining input data for anomalies and preventing result distortion is advised.

Overall, the IVF-Borda-CoCoSo method, by providing accurate and stable rankings, demonstrates a strong capability in managing uncertainties and complexities in decision-making within organ transplant networks. This method not only aids in identifying the best supplier but also, by offering clear insights into the strengths and weaknesses of each option, supports decision-makers in optimal resource allocation and improving supply chain performance.

B. Sensitivity Analysis

Sensitivity analysis is an essential tool for evaluating the robustness and reliability of decision-making models. In this study, to examine the impact of changes in criteria weights on the supplier ranking results, a random weight substitution approach was employed. In this method, the weights of the criteria were randomly reassigned in each run based on a continuous uniform distribution within a specified range. The analysis process was designed and executed over 100 independent trials to assess the stability and sensitivity of the model against potential fluctuations in weighting. These tests have aimed to identify the degree of rank deviation and validate the results of the proposed method. The outcomes are presented in Table 9, and the distribution of rankings is visually illustrated in Figure 3.

Table 9. Supplier Rankings in 100 Sensitivity Analysis Trials

Test	Rank			
	Supplier 1	Supplier 2	Supplier 3	Supplier 4
Test 1	3	2	1	4
Test 2	4	3	2	1
Test 3	3	4	1	2
Test 4	3	4	1	2
Test 5	4	3	2	1
Test 6	4	3	2	1
Test 7	4	3	1	2
Test 8	4	3	1	2

Continue Table 9. Supplier Rankings in 100 Sensitivity Analysis Trials

Test	Rank			
	Supplier 1	Supplier 2	Supplier 3	Supplier 4
Test 9	4	2	1	3
Test 10	4	1	2	3
Test 11	3	2	1	4
Test 12	3	4	1	2
Test 13	3	4	1	2
Test 14	3	4	1	2
Test 15	3	4	1	2
Test 16	3	2	1	4
Test 17	4	3	2	1
Test 18	4	1	2	3
Test 19	4	2	1	3
Test 20	3	2	1	4
Test 21	4	1	2	3
Test 22	3	2	1	4
Test 23	3	4	1	2
Test 24	4	2	1	3
Test 25	3	2	1	4
Test 26	3	2	1	4
Test 27	3	4	1	2
Test 28	4	2	1	3
Test 29	3	4	2	1
Test 30	4	2	1	3
Test 31	3	2	1	4
Test 32	4	3	2	1
Test 33	4	1	2	3
Test 34	4	3	2	1
Test 35	3	4	1	2
Test 36	3	4	2	1
Test 37	3	4	1	2

Continue Table 9. Supplier Rankings in 100 Sensitivity Analysis Trials

Test	Rank			
	Supplier 1	Supplier 2	Supplier 3	Supplier 4
Test 38	4	1	2	3
Test 39	2	4	1	3
Test 40	3	4	1	2
Test 41	3	2	1	4
Test 42	4	3	1	2
Test 43	3	4	1	2
Test 44	3	2	1	4
Test 45	4	3	1	2
Test 46	2	3	1	4
Test 47	3	2	1	4
Test 48	3	2	1	4
Test 49	4	2	1	3
Test 50	4	2	1	3
Test 51	4	3	2	1
Test 52	4	3	2	1
Test 53	3	4	1	2
Test 54	3	4	1	2
Test 55	4	1	2	3
Test 56	4	3	2	1
Test 57	3	2	1	4
Test 58	4	2	1	3
Test 59	3	4	1	2
Test 60	3	1	2	4
Test 61	4	1	2	3
Test 62	4	3	2	1
Test 63	4	1	2	3
Test 64	3	2	1	4
Test 65	4	2	1	3
Test 66	4	3	2	1

Continue Table 9. Supplier Rankings in 100 Sensitivity Analysis Trials

Test	Rank			
	Supplier 1	Supplier 2	Supplier 3	Supplier 4
Test 67	4	2	1	3
Test 68	4	3	2	1
Test 69	4	1	3	2
Test 70	3	4	1	2
Test 71	4	2	1	3
Test 72	4	1	2	3
Test 73	4	1	2	3
Test 74	4	3	1	2
Test 75	4	3	2	1
Test 76	3	4	2	1
Test 77	3	4	1	2
Test 78	2	3	1	4
Test 79	3	1	2	4
Test 80	4	2	1	3
Test 81	4	2	1	3
Test 82	4	1	2	3
Test 83	4	2	1	3
Test 84	4	2	1	3
Test 85	3	4	1	2
Test 86	4	2	1	3
Test 87	4	2	1	3
Test 88	3	4	1	2
Test 89	4	2	1	3
Test 90	3	4	1	2
Test 91	3	4	1	2
Test 92	4	3	1	2
Test 93	4	3	1	2
Test 94	3	1	4	2
Test 95	4	2	3	1

Continue Table 9. Supplier Rankings in 100 Sensitivity Analysis Trials

Test	Rank			
	Supplier 1	**Supplier 2**	**Supplier 3**	**Supplier 4**
Test 96	2	3	1	4
Test 97	3	4	1	2
Test 98	3	2	4	1
Test 99	4	1	2	3
Test 100	3	2	1	4

The results of the sensitivity analysis indicate that supplier A_3 secured the first rank in 66 out of 100 trials, demonstrating its high stability against changes in criteria weights. Even in scenarios where the weights of key criteria, such as Technical Quality (C_4) or After-Sales Service (C_8), were reduced, A_3 mostly remained in the first or second positions. In contrast, supplier A_1 ranked last (fourth place) in 52 trials and never ranked better than third in any test, reflecting a consistently poor performance across the evaluated criteria. Suppliers A_2 and A_4 fluctuated in the middle ranks (second and third). For instance, A_2 achieved the second rank in 35 trials but dropped to third or fourth place in some scenarios, such as trials 2, 5, 6, and 17. Similarly, A_4 ranked second in 31 trials and third in another 31 trials. These fluctuations indicate the sensitivity of these suppliers to changes in criteria weights, particularly economic criteria, such as Competitive Price (C_1) and Life Cycle Costs (C_3).

Figure 3 clearly illustrates the distribution of supplier rankings. In this chart, A_3 is prominently positioned at the top, demonstrating its consistent stability in the higher ranks. Conversely, A_1 consistently appears at the bottom of the chart, exhibiting a pattern of weak and low-variance performance. Suppliers A_2 and A_4 show greater dispersion in the middle ranks, indicating a relative instability of their rankings across different scenarios.

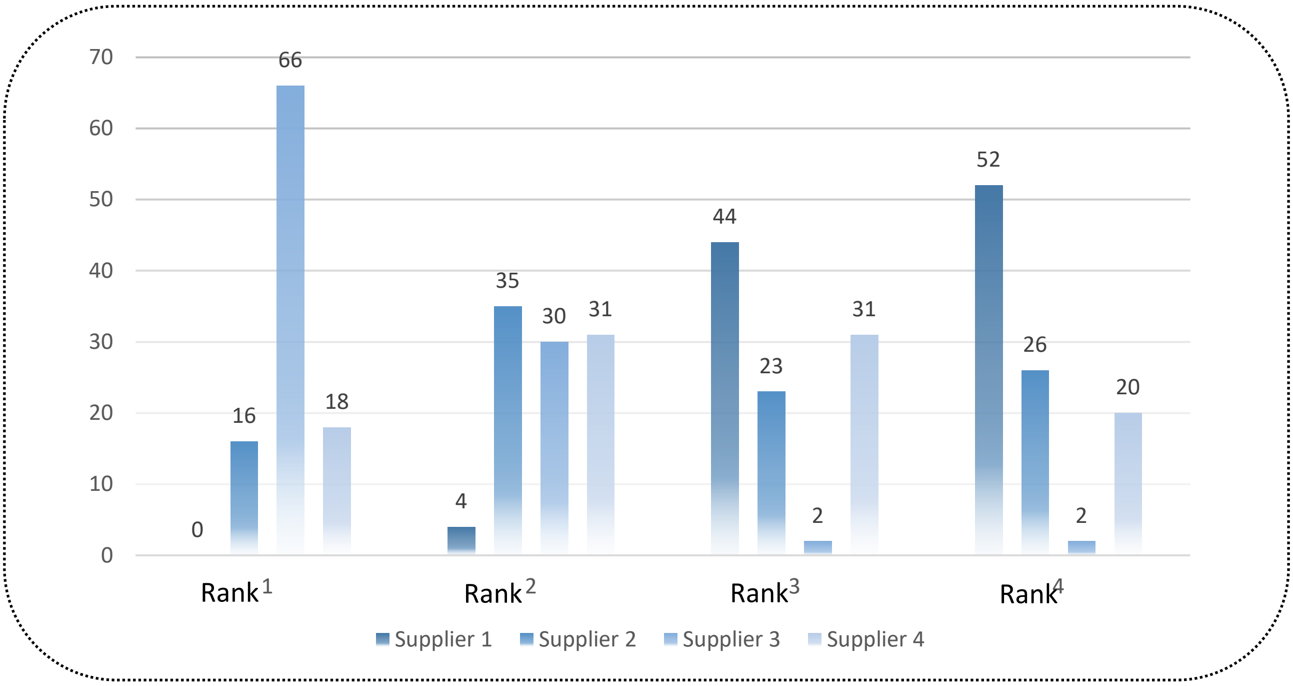

Figure 3. Distribution of Supplier Rankings in 100 Sensitivity Tests

A more detailed analysis reveals that in 60 out of the 66 scenarios where A_3 ranked first, the technical quality criterion (C_4) was among the two criteria with the highest weight. This confirms that A_3's strong performance in this criterion played a decisive role in its success. In scenarios where the weights of criteria C_4 or C_8 significantly decreased, A_2 occasionally achieved a better ranking, indicating its relative strength in economic criteria.

A notable point in this analysis is that A_3 never ranked last in any of the 100 tests. This consistent performance demonstrates the high reliability of supplier A_3 under varying decision-making conditions. Conversely, the persistently low ranking of A_1 stems from weaknesses in technical and service-related criteria, which were clearly reflected across all scenarios.

To gain a better understanding of the model's performance, the effect of the parameter λ in the CoCoSo method's formulas was also examined. This parameter, which plays a crucial role in adjusting the emphasis placed on different criteria, was varied within the range of 0.1 to 0.9. The results indicated that, in most cases, the supplier rankings remained stable, and changes in λ had no significant impact on the positions of the alternatives. However, at lower values of λ, such as 0.1, greater weight was assigned to the power-sum criteria, which led to a relative improvement in the ranking of supplier A_2 in certain scenarios. This finding suggests that tuning this parameter can influence the model's output, and selecting an appropriate value is essential for achieving accurate and balanced results.

Overall, sensitivity analysis and comparisons with established methods indicate that the IVF-Borda-CoCoSo approach delivers accurate and reliable performance under uncertainty conditions. The method exhibits robustness against changes in criteria weights, as Supplier A_3 consistently ranked first while Supplier A_1 remained steady in the last position. This stability provides decision-makers with confidence in the reliability of the model's outputs across different scenarios. However, fluctuations in the rankings of intermediate suppliers (A_2 and A_4) underscore the importance of precise criteria selection and appropriate weighting in the decision-making process.

Moreover, the comparisons with TOPSIS, COPRAS, and CoCoSo indicate that the IVF-Borda-CoCoSo method excels in managing uncertainties and providing balanced rankings, due to its use of interval-valued fuzzy logic and integrated scoring approach. Its key features under uncertain conditions ensure the reliability of the model in complex environments, including advanced uncertainty modeling using IVFSs for precise handling of subjective judgments and ambiguous data, multi-faceted integration through the combination of evaluation strategies and Borda count to aggregate diverse perspectives and reduce bias, and stability of results against changes in criteria weights. Ultimately, this analysis not only confirms the accuracy and efficiency of the proposed method but also assists decision-makers in precisely identifying suppliers' strengths and weaknesses, allocating resources more effectively, and making informed decisions to enhance supply chain performance in the complex domain of organ transplantation.

VI. CONCLUSION

This study introduces an innovative IVF-Borda-CoCoSo method for evaluating and selecting suppliers in organ transplant networks. By integrating Interval-Valued Fuzzy Sets (IVFSs), objective weighting based on fuzzy Shannon entropy, and the Borda-CoCoSo aggregation approach, the method provides a precise and flexible framework for decision-making in complex and ambiguous environments. This method demonstrated a strong capability in handling uncertainties by integrating multiple perspectives and reducing biases in the evaluation process. Additionally, by delivering stable and reliable rankings, the approach aids decision-makers in optimal resource allocation and enhances supply chain performance in the important domain of organ transplantation. The results obtained from this model indicate that supplier A_3 demonstrated the best performance among the evaluated alternatives. This superiority was primarily attributed to its strong performance in key criteria, such as technical quality (C_4) and after-sales service (C_8). In contrast, supplier A_1 received the lowest score, reflecting its weaker ability to meet the supply chain's requirements. The other two suppliers, A_4 and A_2, achieved moderate rankings with some fluctuations in performance. To ensure the model's reliability, its results were validated using three alternative methods: TOPSIS, COPRAS, and CoCoSo. Notably, in all these methods, A_3 was consistently ranked as the top-performing option, demonstrating the proposed model's robustness and high level of reliability. To assess the model's sensitivity to changes in criteria weights, 100 different analyses were conducted. These analyses revealed that the top ranking of A3 was maintained even with variations in weight assignments, particularly due to the pivotal role of criterion C4 in preserving this position. Leveraging interval-valued fuzzy logic, the IVF-Borda-CoCoSo method has proven effective in handling the uncertainties and complexities inherent in supplier evaluation processes, especially in the highly complex context of organ transplantation. This approach not only delivers accurate supplier rankings but also provides decision-makers with a clear understanding of each supplier's strengths and weaknesses, enabling more targeted resource allocation and more precise selection.

From a practical perspective, the application of this method can contribute to improving supply chain performance, enhancing patient safety, and increasing the reliability of organ transplant networks. However, it should be noted that the approach is partially dependent on expert judgments and external conditions, such as market dynamics or resource availability. Therefore, future studies are recommended to incorporate additional criteria, such as environmental sustainability or supply chain flexibility, and to test the model on a larger scale with real-world data. Moreover, the development of software tools to automate the evaluation process could simplify and accelerate the practical implementation of this method. Additionally, it is suggested that the model be tested with dynamic data and under critical conditions to assess its adaptability in unexpected scenarios and evaluate its generalizability to other supply chain contexts. Overall, the IVF-Borda-CoCoSo method can be considered a powerful tool for decision-making under uncertain conditions. It has the potential to play a significant role in improving supply chain management in critical domains, including organ transplantation.

REFERENCES

Abdalla, M. E. M., Uzair, A., Ishtiaq, A., Tahir, M., & Kamran, M. (2025). Algebraic Structures and Practical Implications of Interval-Valued Fermatean Neutrosophic Super HyperSoft Sets in Healthcare. *Spectrum of Operational Research*, *2*(1), 199-218.

Alabool, H. M. (2025). Large language model evaluation criteria framework in healthcare: fuzzy MCDM approach. *SN Computer Science*, *6*(1), 57.

Alghawli, A. S. A., Nasser, A. A., & Aljober, M. N. (2021). A fuzzy MCDM approach for structured comparison of the health literacy level of hospitals. *International Journal of Advanced Computer Science and Applications*, *12*(7).

Alsalem, M. A., Albahri, O. S., Zaidan, A. A., Al-Obaidi, J. R., Alnoor, A., Alamoodi, A. H., ... & Jumaah, F. M. (2022). Rescuing emergency cases of COVID-19 patients: an intelligent real-time MSC transfusion framework based on multicriteria decision-making methods. *Applied Intelligence*, 1-25.

Ashouri, M., Hadi-Vencheh, A., & Jamshidi, A. (2023). An interval valued fuzzy complex proportional assessment (IVF-COPRAS) method to solve MCDM problem with an application. *J. Decis. Operat. Res*, *8*, 861-871.

Ashtiani, B., Haghighirad, F., Makui, A., & ali Montazer, G. (2009). Extension of fuzzy TOPSIS method based on interval-valued fuzzy sets. *Applied soft computing*, *9*(2), 457-461.

Barzegari, M. J., Mousavi, S. M., & Karami, S. (2023). An interval-valued fuzzy MULTIMOOSRAL method for supplier evaluation in oil production projects. *Journal of Quality Engineering and Production Optimization*, *8*(1), 217-241.

Bouraima, M. B., Jovčić, S., Dobrodolac, M., Pamucar, D., Badi, I., & Maraka, N. D. (2024). Sustainable healthcare system devolution strategy selection using the AROMAN MCDM approach. *Spectrum of Decision Making and Applications*, *1*(1), 46-63.

Chakraborty, S., Raut, R. D., Rofin, T. M., Chatterjee, S., & Chakraborty, S. (2023). A comparative analysis of Multi-Attributive Border Approximation Area Comparison (MABAC) model for healthcare supplier selection in fuzzy environments. *Decision Analytics Journal*, *8*, 100290.

Chen, S. J., & Chen, S. M. (2008). Fuzzy risk analysis based on measures of similarity between interval-valued fuzzy numbers. *Computers & Mathematics with Applications*, *55*(8), 1670-1685.

Chen, T. C. T., & Lin, C. W. (2022). An FGM decomposition-based fuzzy MCDM method for selecting smart technology applications to support mobile health care during and after the COVID-19 pandemic. *Applied soft computing*, *121*, 108758.

Gorzałczany, M. B. (1987). A method of inference in approximate reasoning based on interval-valued fuzzy sets. *Fuzzy sets and systems*, *21*(1), 1-17.

Grattan-Guinness, I. (1976). Fuzzy membership mapped onto intervals and many-valued quantities. *Mathematical Logic Quarterly*, *22*(1), 149-160.

Hashemkhani Zolfani, S., Yazdani, M., Ebadi Torkayesh, A., & Derakhti, A. (2020). Application of a gray-based decision support framework for location selection of a temporary hospital during COVID-19 pandemic. *Symmetry*, *12*(6), 886.

Jalilvand, S., Heidari, S., Mohammadnazari, Z., Aghsami, A., Rabbani, E., & Rabbani, M. (2023). A bi-objective organ transplant supply chain network with recipient priority considering carbon emission under uncertainty, a case study. *Process Integration and Optimization for Sustainability*, *7*(4), 709-727.

Karami, S., Mousavi, S. M., & Antucheviciene, J. (2023). Enhancing contractor selection process by a new interval-valued fuzzy decision-making model based on SWARA and cocoso methods. *Axioms*, *12*(8), 729.

Karnik, N. N., & Mendel, J. M. (2001). Operations on type-2 fuzzy sets. *Fuzzy sets and systems*, *122*(2), 327-348.

Liu, Y., Yang, Y., Liu, Y., & Tzeng, G. H. (2019). Improving sustainable mobile health care promotion: a novel hybrid MCDM method. *Sustainability*, *11*(3), 752.

Lo, C. L., Chang, H. Y., & Lee, G. M. (2022). Evaluating Organ Donation Decision in ICU Patients' Families by Analytic Network Process Approach. *Journal of Healthcare Engineering*, *2022*(1), 9969604.

Mokhtarian, M. N., Sadi-Nezhad, S., & Makui, A. (2014). A new flexible and reliable IVF-TOPSIS method based on uncertainty risk reduction in decision making process. Applied Soft Computing, 23, 509-520.

Pamucar, D., Torkayesh, A. E., & Biswas, S. (2023). Supplier selection in healthcare supply chain management during the COVID-19 pandemic: a novel fuzzy rough decision-making approach. Annals of Operations Research, 328(1), 977-1019.

Rishabh, R., & Das, K. N. (2025). Selection of a Suitable Healthcare Supplier Using AHP and TOPSIS Methods Hybridized in Metaheuristic Environment. *SN Computer Science*, *6*(2), 1-17.

Sabripoor, A., Ghousi, R., Najafi, M., Barzinpour, F., & Makui, A. (2024). Risk assessment of organ transplant operation: A fuzzy hybrid MCDM approach based on fuzzy FMEA. *Plos one*, *19*(5), e0299655.

Salehi, V., Moradi, G., Omidi, L., & Rahimi, E. (2023). An MCDM approach to assessing influential factors on healthcare providers' safe performance during the COVID-19 pandemic: Probing into demographic variables. *Journal of Safety Science and Resilience*, *4*(3), 274-283.

Salimian, S., Mousavi, S. M., & Antucheviciene, J. (2022). An interval-valued intuitionistic fuzzy model based on extended VIKOR and MARCOS for sustainable supplier selection in organ transplantation networks for healthcare devices. *Sustainability*, *14*(7), 3795.

Salimian, S., Mousavi, S. M., & Turskis, Z. (2023). Transportation mode selection for organ transplant networks by a new multi-criteria group decision model under interval-valued intuitionistic fuzzy uncertainty. *Informatica*, *34*(2), 337-355.

Stević, Ž., Pamučar, D., Puška, A., & Chatterjee, P. (2020). Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS). *Computers & industrial engineering*, *140*, 106231.

Su, J., Xu, B., Liu, H., Chen, Y., & Zhang, X. (2025). A Probabilistic Hesitant Fuzzy Multi-Criteria Decision-Making Method Based on CSOGRMILP and Borda-CoCoSo. *International Journal of Fuzzy Systems*, 1-18.

Yao, J. S., & Lin, F. T. (2002). Constructing a fuzzy flow-shop sequencing model based on statistical data. *International journal of approximate reasoning*, *29*(3), 215-234.

Yılmaz, B. Ö., Tozan, H., & Karadayı, M. A. (2020). Multi-criteria decision making (MCDM) applications in military healthcare field. *Journal of Health Systems and Policies*, *2*(2), 149-181.

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning—I. *Information sciences*, *8*(3), 199-249.

Zimmermann, H. J. (1986). Fuzzy set theory and mathematical programming. *Fuzzy sets theory and applications*, 99-114.