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An integrated FSIWEC–FCORASO approach for organizational model selection in university economic enterprises

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Abstract

Universities often operate social facilities that provide public services while conducting commercial activities under the status of economic enterprises. Due to this dual nature, these entities possess a hybrid managerial structure. This dual character makes the determination of an appropriate organizational model for such enterprises a multidimensional and strategic decision problem. This study focuses on identifying the most suitable organizational model for university social facility economic enterprises. To address the uncertainties and subjective evaluations involved in the decision-making process, a fuzzy logic–based multi-criteria decision-making (MCDM) approach was adopted. In this framework, the fuzzy simple weight calculation (FSIWEC) method was used to determine the weights of the evaluation criteria, while the fuzzy combined compromise solution (FCORASO) method was applied to rank the alternative organizational models. Within the proposed integrated model, economic, managerial, and social criteria were considered simultaneously, and the alternative organizational structures were comparatively analyzed. The findings provide decision makers with a systematic decision-support tool that balances public interest, service quality, and financial sustainability objectives. In addition, the study contributes to the literature by representing one of the first applications that employs the integrated FSIWEC-FCORASO approach to evaluate organizational models for university social facility economic enterprises.

Keywords Social facilities, Economic enterprise, Fuzzy logic, FSIWEC, FCORASO

Jel Codes C44, D81, M10, I23

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1. Introduction

Social facilities operated by universities aim to meet the social and cultural needs of students, university staff, and their families. In addition to serving these various needs, these facilities operate as institutional structures that fulfill a public service function. These entities operate within a public legal framework, where service provision constitutes their primary objective. Their financial and accounting practices are regulated by formal provisions, most notably the "Principles and Procedures Regarding the Accounting Practices of Social Facilities Operated by Public Institutions and Organizations," which entered into force in 2006, thereby establishing the institutional and financial basis of these facilities (Akşehir, 2016).

From a tax law perspective, organizations that provide goods and/or services in return for a fee on a continuous basis are defined as economic enterprises. According to the General Communiqué on Corporate Tax No. 1, the defining characteristic of such enterprises is not necessarily profit maximization, but rather their participation in market-like activities through the provision of paid services (Ünveren, 2016). In this respect, university social facilities represent a hybrid organizational form that simultaneously embodies the characteristics of both public service providers and economic enterprises.

This dual structure creates a complex managerial environment in which multiple, and sometimes conflicting, objectives must be addressed concurrently. While these facilities are expected to prioritize public benefit and service quality, they are also required to ensure financial sustainability, efficiency, and compliance with market conditions. The coexistence of these objectives transforms organizational model selection into a multidimensional and strategic decision problem. Decisions made in this context directly influence cost control, resource allocation, service effectiveness, and long-term sustainability.

This complexity necessitates the adoption of a systematic and analytical framework in the decision-making process. However, in practice, organizational model selection is often based on intuitive judgments rather than structured evaluation processes, which may lead to inconsistencies and suboptimal outcomes. Furthermore, traditional decision-making methods are generally insufficient to capture the uncertainty and subjectivity inherent in evaluating multiple criteria with varying levels of importance. In the literature, problems involving the simultaneous evaluation of multiple and often conflicting criteria under uncertainty are conceptualized as multi-criteria decision-making (MCDM) problems (García-Alcaraz et al., 2016).

Although MCDM methods have been widely utilized in various domains, research addressing the selection of organizational models for university social facility economic enterprises remains limited. This situation underscores the need for a scientifically grounded and systematic approach capable of addressing the specific challenges posed by hybrid structures. In particular, the absence of integrated approaches that incorporate both weighting and ranking mechanisms under uncertainty indicates a significant research opportunity. In response to this gap, this study proposes an integrated decision-making framework to determine the most suitable organizational model for university social facility economic enterprises. The study employs Fuzzy Simple Weight Calculation (FSIWEC) and Fuzzy Combined Compromise Solution (FCORASO) methods to evaluate alternative models based on economic, managerial, and social criteria. The integration of fuzzy logic into the analysis enables a more realistic representation of decision-makers' judgments by considering uncertainty and differences in the relative importance of criteria.

This study primarily aims to determine the essential factors that need to be considered in the selection of an organizational model. Additionally, it aims to analyze the relative importance of these factors and to identify the most suitable alternative through a comparative evaluation of different organizational models. In addition, the study seeks to provide strategic insights into which criteria should be prioritized to enhance the performance and sustainability of these enterprises.

By addressing this decision problem within a structured MCDM framework, the study makes several contributions. First, it proposes a comprehensive evaluation model tailored to the hybrid nature of university social facility economic enterprises. Second, the integration of fuzzy logic into the proposed structure enhances the consistency and robustness of decisions made under conditions of uncertainty. Third, the model serves as a flexible and adaptable decision support tool that can be applied to other public economic entities with similar characteristics, providing practical value for university administrators and policymakers.

2. Literature Review

In this study, the literature review was conducted in two stages. The first stage focused on studies related to the FSIWEC method, and the second stage focused on studies related to the FCORASO method.

The SIWEC method for determining criterion weights was first proposed by Puška et al. (2024a). In addition to presenting its methodological foundations, the authors demonstrated its applicability through a case study addressing the prioritization of criteria related to agricultural product sales in the Semberija region. Subsequently, the method was extended to uncertain decision environments through the incorporation of linguistic variables, resulting in the FSIWEC method. In a later study, Puška et al. (2024b) integrated FSIWEC with the FCORASO method to evaluate spraying drones for an agricultural enterprise. In that application, FSIWEC was employed to determine criteria weights, while FCORASO was used to rank alternatives, with the DJI Agras T30 identified as the most suitable option.

Following these foundational contributions, the FSIWEC method has been increasingly adopted and integrated with other MCDM approaches across diverse application domains. El-Jaberi et al. (2024) combined FSIWEC with the fuzzy rough combined compromise solution (CoCoSo) method to assess renewable energy projects. Gökalp et al. (2025) utilized FSIWEC to analyze factors influencing investment strategies for green hospitals, identifying effective waste management and carbon footprint reduction as the most critical determinants. In the context of sustainable smart cities, Cao et al. (2025) applied spherical FSIWEC to determine the weights of digital twin technology criteria and subsequently employed spherical fuzzy Simple Additive Weighting (SAW) to rank innovative green digital twin alternatives.

The method has also been integrated with other MCDM methods to obtain advanced hybrid models in transportation, agriculture, logistics, and urban planning. Kaya (2025) employed FSIWEC alongside the fuzzy logarithmic methodology of additive weights (FLMAW) to design green and safe micro-mobility routes. Puška, Božanić, et al. (2025) proposed a hybrid fuzzy rough SIWEC- ranking of alternatives with weights of criterion (RAWEC) framework for tractor selection, identifying the Solectrac e25 as the optimal alternative. Similarly, Eti et al. (2025) combined FSIWEC with the evaluation based on distance from average solution (EDAS) method to identify key strategies for renewable energy adoption in regionalized supply chain-based logistics systems. Kaya & Kabakuş (2025) applied a four-stage hybrid approach that integrates FSIWEC, GIS-based spatial analysis, and correlation analysis to examine how the location of logistics centers influences the severity of heavy vehicle accidents.

Beyond sector-specific applications, the method has also been used to address broader socio-economic and performance-related issues. Puška, Bosna, et al. (2025) applied FSIWEC to evaluate criteria associated with urban youth housing challenges. Lukić (2025) integrated FSIWEC with the rough Multi-Attributive Border Approximation Area Comparison (MABAC) method to analyze trade performance dynamics in Serbia, while Nedeljković, Puška, et al. (2025) employed FSIWEC to assess criteria relevant to consumer communication processes.

Recent studies have increasingly extended the FSIWEC framework through various methodological integrations and domain-specific applications. For instance, Katrancı et al. (2026) integrated the FSIWEC and FRAWEC methods to identify the most appropriate sustainable solid waste disposal technology within the framework of municipal waste management systems. Similarly, Bouraima & Badi (2026) employed an integrated FSIWEC–FRAWEC structure to assess strategic alternatives aimed at improving accessibility in cultural heritage tourism.

In the field of energy planning, Sahoo & Debnath (2026) incorporated FSIWEC with the Fuzzy Ranking Alternatives by Perimeter Similarity (FRAPS) method to support hydroelectric power plant site selection. Extending the methodological scope of SIWEC, Dereköy et al. (2026) introduced a novel decision-making model grounded in Koch snowflake-based fuzzy sets to determine strategies that enhance trust in AI-driven auditing systems.

Yalçın et al. (2026) developed a comprehensive decision support model to evaluate promotional video performance by integrating eye-tracking metrics and cognitive assessment data. Their framework combined Fermatean fuzzy Hamacher–SIWEC for subjective weighting, Fermatean fuzzy method based on the removal effects of criteria (MEREC) for objective weighting based on criterion removal effects, and the Alternative Ranking using two-step Logarithmic Normalization (ARLON) method for final ranking. The Hamacher aggregation operator was utilized to synthesize viewer evaluations, enabling a robust multi-stage assessment process.

In another innovative contribution, Kou et al. (2026) proposed an AI-supported fuzzy decision framework integrating Koch snowflake-based fuzzy structures, fractal theory, and deep learning techniques to identify financial instruments suitable for addressing energy poverty. Their model employed a Siamese neural network to derive expert weights, applied SIWEC for determining criterion importance, and used hybrid fuzzy ranking procedures to prioritize alternatives. The study emphasized the significance of risk management and governmental support mechanisms, highlighting sukuk and energy leasing as particularly effective financial solutions.

Overall, the literature indicates that SIWEC and its fuzzy extensions have evolved into flexible and integrative weighting tools, frequently embedded within hybrid MCDM frameworks to address complex decision problems characterized by uncertainty and multi-dimensional evaluation criteria.

The Fuzzy Compromise Ranking from Alternative Solutions (FCORASO) method was introduced by Puška et al. (2024b), who initially applied the approach to evaluate and identify the most suitable drone for an agricultural company. Following this initial study, the method has been increasingly employed in supplier selection problems. For example, Nedeljković, Vujić, et al. (2025) utilized FSIWEC and FCORASO methods to evaluate and select the most appropriate table egg supplier for an agribusiness firm. Similarly, Puška, Igić, et al. (2025) assessed equipment and machinery suppliers by integrating the step-wise weight assessment ratio analysis (SWARA) and CORASO methods within an intuitionistic fuzzy environment. More recently, Tufan & Ulutaş (2026) proposed an integrated MCDM approach based on the Logarithmic Decomposition of Criteria Importance (LODECI) and CORASO methods to evaluate suppliers for a milk and dairy manufacturing company, using the criteria such as cost, production capacity quality, delivery performance, and financial strength.

Unlike the aforementioned studies, this research integrates the FSIWEC and FCORASO methods to determine the most suitable organizational model for university economic enterprises. In this context, the study extends the application area of the CORASO-based approach beyond traditional supplier selection and product evaluation problems to the field of higher education management and organizational decision-making.

Furthermore, this study contributes to the literature by proposing a fuzzy MCDM framework for evaluating alternative organizational structures under uncertainty. By incorporating expert judgments through fuzzy logic, the proposed approach enables a more flexible and realistic evaluation of organizational models. In addition, the study provides a systematic decision-support tool that can assist university administrators and policymakers in selecting the most suitable governance structure for university economic enterprises.

3. Methodology

3.1. Fuzzy Number

The foundations of fuzzy logic were established by Zadeh (1965) with the aim of capturing the vagueness and imprecision embedded in natural language expressions. Unlike classical logic, which operates on crisp and binary distinctions, fuzzy logic extends traditional set theory by allowing gradual membership rather than strict inclusion or exclusion. In classical sets, an element either fully belongs to a set (assigned a value of 1) or does not belong at all (assigned a value of 0). Fuzzy set theory, however, permits elements to possess varying degrees of membership within the closed interval [0,1], thereby providing a more flexible framework for modeling uncertainty. Among the various representations of fuzzy numbers, the Triangular Fuzzy Number (TFN) is widely used due to its simplicity and computational convenience. A TFN, denoted as $\tilde{\mathrm{A}}$, is characterized by three real parameters and expressed as $\tilde{\mathrm{A}} = (l, m, u)$, where l and u represent the lower and upper bounds, respectively, and m indicates the modal value. The corresponding membership function $\mu\tilde{\mathrm{A}}(x) : E \rightarrow [0, 1]$ is defined piecewise. It increases linearly from l to m, reaches its maximum value at m, and then decreases linearly from m to u. Outside the interval $[l, u]$, the membership degree is equal to zero (Görçün et al., 2026).

Formally, the membership function is expressed as:

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-l}{m-l}\,, & l \le x \le m \\ \frac{u-x}{u-m}\,, & m \le x \le u \\ 0\,, & \text{otherwise} \end{cases} \tag{1}$$

The TFN is indicated by $\tilde{A} = (l, m, u)$. The operational rules of $\tilde{A}_1 = (l_1, m_1, u_1)$ and $\tilde{A}_2 = (l_2, m_2, u_2)$ are shown is Eq. 2-6 (Chen et al., 2011).

Addition:

$$\tilde{A}_1 \oplus \tilde{A}_2 = (l_1, m_1, u_1) + (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{2}$$

Multiplication:

$$\tilde{A}_1 \otimes \tilde{A}_2 = (l_1, m_1, u_1) \times (l_2, m_2, u_2) = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2) \tag{3}$$

Subtraction:

$$\tilde{A}_1 \ominus \tilde{A}_2 = (l_1, m_1, u_1) - (l_2, m_2, u_2) = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \tag{4}$$

Division:

$$\tilde{A}_1 \oslash \tilde{A}_2 = (l_1, m_1, u_1) \,/\, (l_2, m_2, u_2) = (l_1/u_2, m_1/m_2, u_1/l_2) \tag{5}$$

Reciprocal:

$$\tilde{A}_1^{-1} = (l_1, m_1, u_1)^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}\right) \tag{6}$$

3.2. FSIWEC Method

SIWEC method is proposed by Puška et al. (2024a) for determining the weights of the criteria in MCDM. The principal strength of the SIWEC method lies in its conceptual and computational simplicity, which enhances its practical applicability in decision-making contexts. Unlike many conventional MCDM methods, SIWEC relies solely on direct evaluations provided by decision-makers, thereby eliminating the need for pairwise comparisons or explicit ranking procedures (Puška et al., 2024a). This streamlined structure reduces cognitive burden and facilitates more efficient weight elicitation. In this context, the fundamental objectives of the SIWEC method in determining criterion weights in the decision-making process are to provide a simplified and systematic procedure for assessing the importance of criteria when direct comparison or ranking is inappropriate or impossible, and to calculate criterion weights through clear and manageable steps (Puška et al., 2024a).

Within the original SIWEC framework, both alternatives and criteria are expressed in terms of precise (crisp) numerical values. Nevertheless, given that real-world decision environments are typically characterized by ambiguity, vagueness, and incomplete information, such a deterministic structure may limit the method's capacity to adequately reflect practical complexities. To address this limitation, Puška et al. (2024a) introduced an extended version of the approach, namely the FSIWEC method, which incorporates fuzzy set theory to better capture uncertainty in expert judgments.

According to Puška et al. (2024a) and Puška et al. (2024b), the FSIWEC methodology follows a structured sequence of procedures:

Step 1. In the first step, decision-makers assess the criteria by employing the linguistic variables provided in Table 1, thereby enabling qualitative evaluations to be systematically incorporated into the weighting process(Puška et al., 2024a).

Table 1. Linguistic variables for evaluating criteria and alternatives

Linguistic Variables	Abbreviations	Fuzzy Number
Very Low	VL	(1, 1, 2)
Low	L	(1, 2, 4)
Medium Low	ML	(2, 4, 6)
Medium	M	(3, 5, 7)
Medium High	MH	(5, 7, 9)
High	H	(7, 9, 10)
Very High	VH	(9, 10, 10)

Step 2. Subsequently, a fuzzy decision matrix is constructed by converting the linguistic assessments provided by each decision-maker into their corresponding fuzzy number representations in accordance with Eq. 7.

$$\tilde{A} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{1n} \\ \cdots & \cdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{7}$$

Eq. 7 defines the structure of the decision matrix, where the columns represent the criteria and the rows correspond to the individual decision-makers. Within this matrix, each element denotes the evaluation of a given criterion by a specific decision-maker expressed in fuzzy form. In the present study, triangular fuzzy numbers are employed to model these assessments, and their formal representation is provided in Eq. 8.

$$\tilde{x}_{ij} = \left(x_{ij}^{l}, x_{ij}^{m}, x_{ij}^{u} \right) \tag{8}$$

Here, $x_{ij}^{l} \leq x_{ij}^{m} \leq x_{ij}^{u}$ and x_{ij}^{l}, x_{ij}^{m}, and x_{ij}^{u} represent the lower, modal and upper values of the triangular fuzzy number, respectively (Shapiro & Koissi, 2017).

Step 3. Following the construction of the fuzzy decision matrix, a normalization procedure is applied in accordance with Eq. 9 to ensure comparability across criteria.

$$\tilde{n}_{ij} = \left(\frac{x_{ij}^{l}}{\max x_{ij}^{u}}, \frac{x_{ij}^{m}}{\max x_{ij}^{u}}, \frac{x_{ij}^{u}}{\max x_{ij}^{u}} \right) \tag{9}$$

Step 4. After the completion of the normalization stage, the standard deviation is computed for each decision-maker to capture the dispersion of their evaluations.

Step 5. The elements of the normalized decision matrix are then multiplied by the corresponding standard deviation values of each criterion, as specified in Eq. 10.

$$\tilde{v}_{ij} = \tilde{n}_{ij} \cdot \text{std dev}_j \tag{10}$$

Step 6. Subsequently, the aggregated values for each criterion are obtained via Eq. 11.

$$\tilde{s}_{ij} = \sum_{j=1}^{n} \tilde{v}_{ij} \tag{11}$$

Step 7. The final fuzzy weights of the criteria are determined by applying Eq. 12.

$$\tilde{w}_j = \frac{s_{ij}^l}{\sum_{j=1}^n s_{ij}^u}, \frac{s_{ij}^m}{\sum_{j=1}^n s_{ij}^m}, \frac{s_{ij}^u}{\sum_{j=1}^n s_{ij}^l} \tag{12}$$

3.3. FCORASO Method

In recent years, a number of new MCDM techniques have been proposed in order to improve the reliability and interpretability of decision-making results. One of the recently introduced approaches is the FCORASO method, which was developed by Puška et al. (2024b), as a relatively simple yet effective ranking technique. The method aims to provide a transparent decision-making framework by simultaneously considering the deviations of alternatives from both the best and worst criterion values. This characteristic distinguishes FCORASO from some classical fuzzy MCDM approaches that only focus on the distance from an ideal solution.

The steps of the FCORASO method are as given below:

Step 1: Decision-makers assess the alternatives using the linguistic variables presented in Table 1. Subsequently, these linguistic variables are transformed into triangular fuzzy numbers to obtain a fuzzy decision matrix.

Step 2: The fuzzy decision matrix is normalized using Eq. 13 for benefit criteria and Eq. 14 for cost criteria,

$$\tilde{n}_{ij} = \left(\frac{x_{ij}^l}{max\ x_{ij}^u}, \frac{x_{ij}^m}{max\ x_{ij}^u}, \frac{x_{ij}^u}{max\ x_{ij}^u} \right) \tag{13}$$

$$\tilde{n}_{ij} = \left(\frac{\min x_{ij}^l}{x_{ij}^u}, \frac{\min x_{ij}^l}{x_{ij}^m}, \frac{\min x_{ij}^l}{x_{ij}^l} \right) \tag{14}$$

Step 3: Maximum and minimum values of the alternatives for each criterion are determined.

Step 4: Weighted normalized decision matrix is obtained by multiplying normalized values of the alternatives with corresponding criteria weights via Eq. 15

$$\tilde{v}_{ij} = \tilde{w}_j \, . \, \tilde{n}_{ij} \tag{15}$$

Step 5: Total aggregated values of the alternatives are calculated by using Eq. 16.

$$\tilde{s}_{ij} = \sum_{j=1}^{n} \tilde{v}_{ij} \tag{16}$$

Step 6: Deviations from maximum and minimum values are calculated using the Eq. 17-18, respectively.

$$\tilde{R}_{ij} = \frac{\tilde{s}_{ij}}{max\ \tilde{s}_{ij}} \tag{17}$$

$$\tilde{R}'_{ij} = \frac{min\ \tilde{s}_{ij}}{\tilde{s}_{ij}} \tag{18}$$

Step 7: R_{ij} values are defuzzied. Fuzzy numbers are converted into crisp numbers via Eq. 19-20.

$$\text{Defuzzified } R_{ij} = \frac{R^l_{ij} + 4R^m_{ij} + R^u_{ij}}{6} \tag{19}$$

$$\text{Defuzzified } R'_{ij} = \frac{R'^l_{ij} + 4R'^m_{ij} + R'^u_{ij}}{6} \tag{20}$$

Step 8: The final performance values for each alternative are obtained using Eq. 21.

$$Q_i = \frac{R_{ij} - R'_{ij}}{R_{ij} + R'_{ij}} \tag{21}$$

4. Application

In today's dynamic and uncertain economic conditions, economic enterprises operating within universities play a crucial role in ensuring financial sustainability, managing resources effectively, and increasing institutional service capacity. These enterprises operating in public universities necessitate a reassessment of management and business models that will increase their performance and ensure their sustainability.

Determining the most suitable management/organizational model for university economic enterprises is a complex decision problem that requires the simultaneous consideration of multidimensional criteria such as cost efficiency, service quality, organizational flexibility, risk management, and strategic alignment. In this context, alternative models need to be assessed through a structured and analytical approach.

This study proposes a systematic decision-making approach for determining the most suitable management/organizational model for economic enterprises operating in universities. A fuzzy MCDM framework based on the FSIWEC and FCORASO methods was utilized to convert uncertainties in the decision-making process and linguistic evaluations based on expert opinions into a mathematical structure. Figure 1 shows the flowchart of the proposed method.

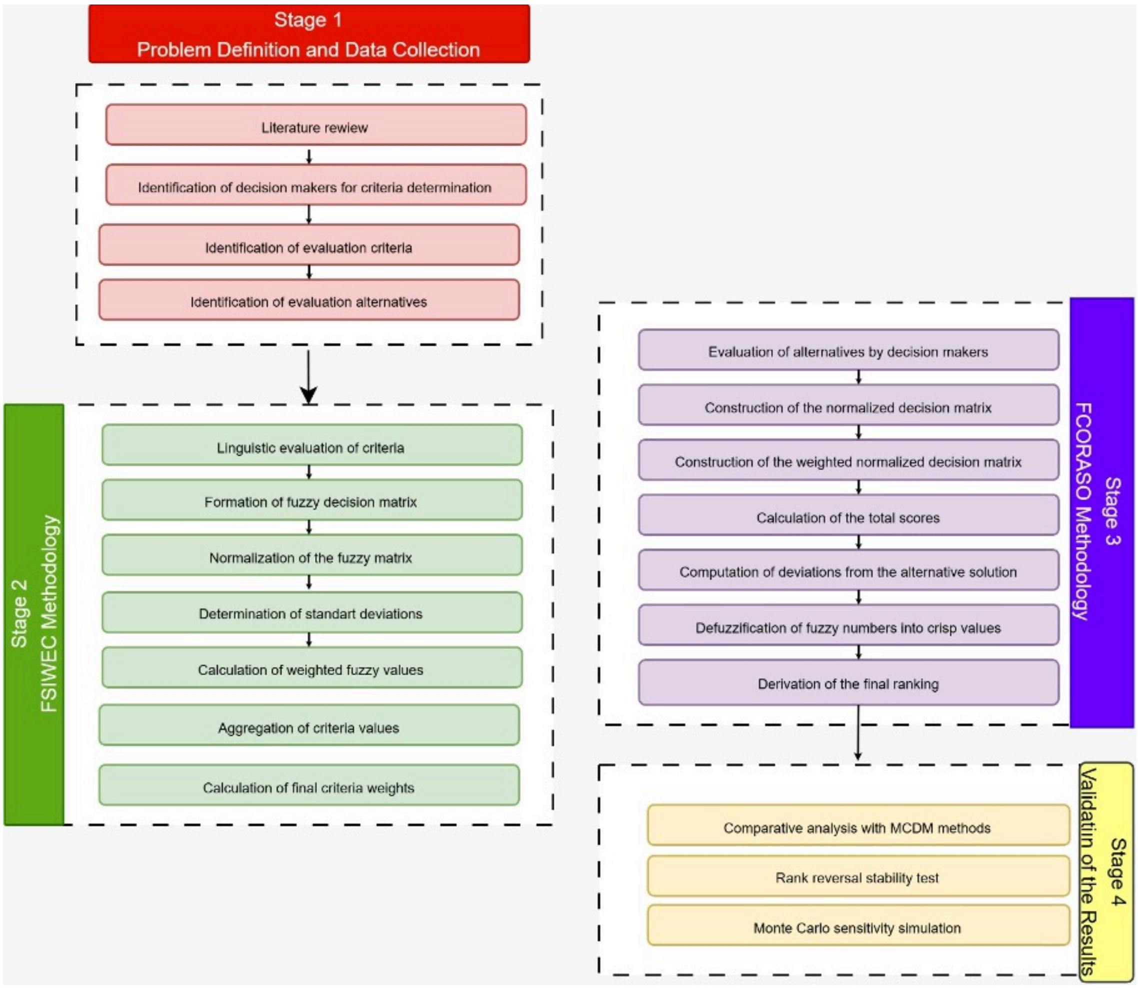

Figure 1. Steps of the proposed integrated MCDM method

The evaluation process was carried out by a group of four experts consisting of economic enterprise managers from four distinct public universities in Türkiye. The evaluation criteria were established through a combination of an extensive literature review and the sectoral expertise of the decision-makers. The set of criteria employed in the evaluation is illustrated in Figure 2.

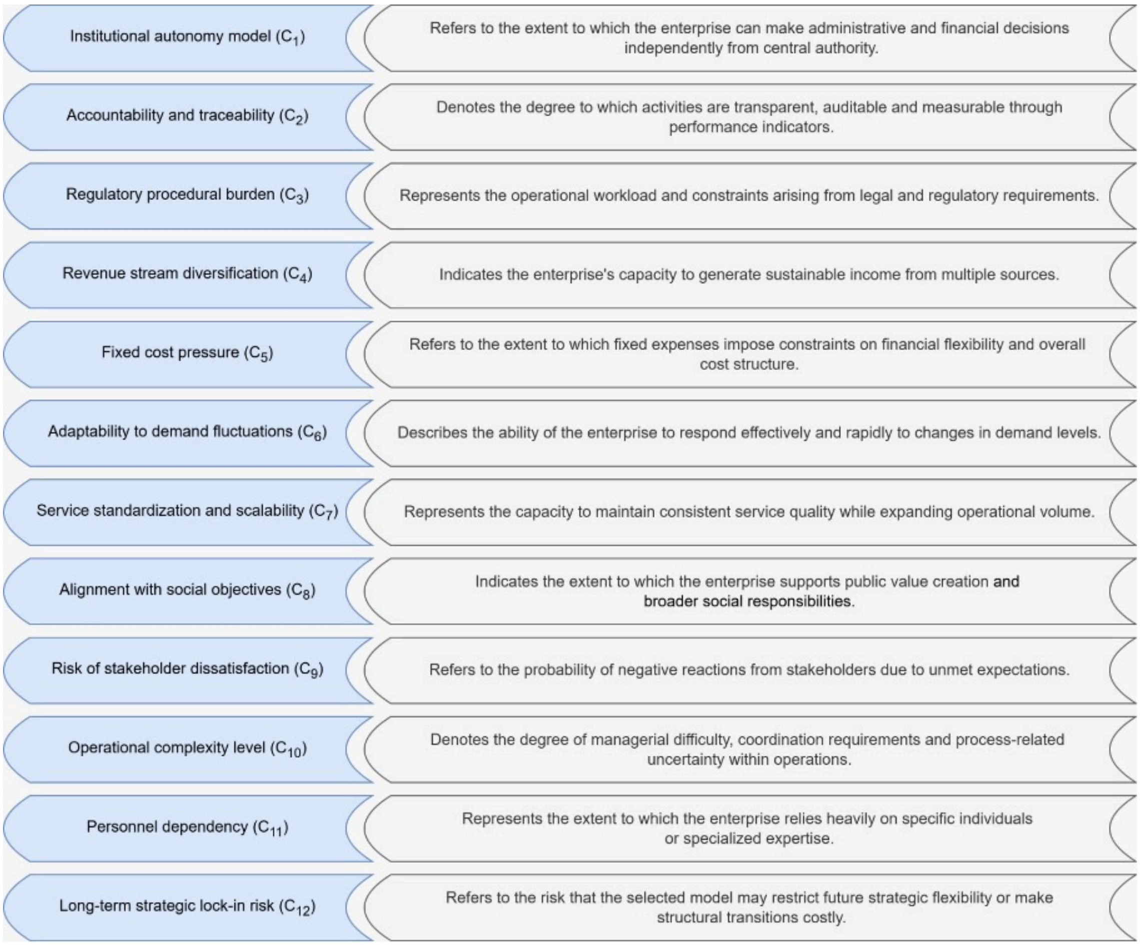

Figure 2. Criteria for the proposed MCDM model

After the criteria to be used in the evaluation process were determined, the criterion weights were calculated using the FSIWEC method, one of the weighting methods recommended in the literature. Subsequently, six alternatives; direct public sector model (A_1), leasing to the private sector model (A_2), public-private partnership model (A_3), cooperative/staff-focused model (A_4), hybrid model(A_5), and privatization model (A_6) were evaluated using the FCORASO method. The alternatives are briefly described below:

Direct public sector model A_1: This refers to a model in which both the ownership and full operation of the facilities are managed by the public sector. In this model, the primary objective is to operate in public interest rather than to generate profit.

Leasing to the private sector model A_2: This model refers to a system in which the facilities are publicly owned, but the right to operate them is transferred to the private sector for a specific period in exchange for a certain fee.

Public-private partnership model A_3: A model that refers to long-term partnerships in which investments, risks, and returns are shared between the public and private.

Cooperative/staff-focused model A_4: This is a model in which facilities are managed by the staff working at the organization or by stakeholders who benefit from the services. Employees participate directly in decision-making processes and receive a share of the facility's profits.

Hybrid model A_5: This refers to a flexible model in which the public and private sectors operate together. Under this model, some facilities are operated by the public sector, while others are operated by the private sector.

Privatization model A_6: This refers to a model in which both ownership and operating rights of the facilities are permanently transferred to the private sector. In the final phase of the analysis, comparative and validation procedures were conducted to assess the reliability and robustness of the findings.

4.1. Weighting of Criteria Using the FSIWEC Method

In the first stage of the FSIWEC method, decision makers evaluated the criteria shown in Figure 2 using the linguistic variables given in Table 1 and obtained the initial decision matrix in Table 2. The evaluations obtained from the decision makers were expressed as triangular fuzzy numbers, and the results are presented in Table 3.

Table 2. Initial decision matrix for criteria

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
D_1	H	VH	L	H	ML	MH	H	VH	ML	ML	ML	L
D_2	MH	H	ML	VH	L	MH	MH	H	ML	ML	ML	ML
D_3	MH	VH	L	MH	ML	M	M	VH	ML	ML	M	L
D_4	H	MH	ML	H	ML	H	VH	MH	L	L	ML	ML

Table 3. Initial fuzzy decision matrix for criteria

	C_1	C_2	C_3	...	C_{10}	C_{11}	C_{12}
D_1	(7, 9, 10)	(9, 10, 10)	(1, 2, 4)	...	(2, 4, 6)	(2, 4, 6)	(1, 2, 4)
D_2	(5, 7, 9)	(7, 9, 10)	(2, 4, 6)	...	(2, 4, 6)	(2, 4, 6)	(2, 4, 6)
D_3	(5, 7, 9)	(9, 10, 10)	(1, 2, 4)	...	(2, 4, 6)	(3, 5, 7)	(1, 2, 4)
D_4	(7 ,9, 10)	(5, 7, 9)	(2, 4, 6)	...	(1, 2, 4)	(2, 4, 6)	(2, 4, 6)

Following the construction of fuzzy decision matrix, the normalized fuzzy decision matrix was obtained in accordance with Eq. 9. Subsequently, the standard deviation values were calculated for each decision-maker, and the results are given in Table 4.

Table 4. Normalized fuzzy decision matrix

	C_1	C_2	C_3	...	C_{10}	C_{11}	C_{12}	std. dev_j
D_1	(0.7,0.9,1.0)	(0.9,1.0,1.0)	(0.1,0.2,0.4)	...	(0.2,0.4,0.6)	(0.2,0.4,0.6)	(0.1,0.2,0.4)	0.312
D_2	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.2,0.4,0.6)	...	(0.2,0.4,0.6)	(0.2,0.4,0.6)	(0.2,0.4,0.6)	0.278
D_3	(0.5,0.7,0.9)	(0.9,1.0,1.0)	(0.1,0.2,0.4)	...	(0.2,0.4,0.6)	(0.3,0.5,0.7)	(0.1,0.2,0.4)	0.280
D_4	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.2,0.4,0.6)	...	(0.1,0.2,0.4)	(0.2,0.4,0.6)	(0.2,0.4,0.6)	0.298

The normalized values were multiplied by their standard deviations using Eq. 10, and the individual total weights were calculated using Eq. 11. The final weights of the criteria were calculated using Eq. 12 and are shown in Table 5.

Table 5. Normalized fuzzy decision matrix

	$\tilde{s}_{ij}$	$\tilde{w}_{ij}$
C_1	(0.71,0.94,1.11)	(0.07,0.11,0.19)
C_2	(0.88,1.05,1.14)	(0.08,0.13,0.20)
C_3	(0.17,0.35,0.58)	(0.02,0.04,0.10)
C_4	(0.82,1.02,1.14)	(0.08,0.12,0.20)
C_5	(0.21,0.41,0.65)	(0.02,0.05,0.11)
C_6	(0.59,0.82,1.02)	(0.06,0.10,0.18)
C_7	(0.71,0.91,1.06)	(0.07,0.11,0.18)
C_8	(0.88,1.05,1.14)	(0.08,0.13,0.20)
C_9	(0.20,0.41,0.64)	(0.02,0.05,0.11)
C_{10}	(0,20,0.41,0.64)	(0.02,0.05,0.11)
C_{11}	(0.26,0.50,0.73)	(0.03,0.06,0.13)
C_{12}	(0.17,0.35,0.58)	(0.02,0.04,0.10)

4.2. Evaluation of Alternatives Using the FCORASO Method

After determining the criterion weights using the FSIWEC method, the application steps of the FCORASO method were followed to select the most suitable model alternative. In the first stage of the application process, decision makers evaluated the alternatives with the help of linguistic variables in Table 1. The obtained evaluation results are given in Table 6. Subsequently, the fuzzy evaluations belonging to the decision makers were combined to obtain the average fuzzy decision matrix, which is given in Table 7.

Table 6. Initial decision matrix for alternatives

DM_1	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
A_1	L	MH	H	ML	MH	ML	M	H	M	M	MH	MH
A_2	MH	M	ML	MH	ML	MH	MH	M	M	ML	ML	M
A_3	M	M	H	MH	M	M	MH	M	M	MH	M	MH
A_4	M	M	MH	ML	M	ML	ML	H	ML	M	MH	M
A_5	MH	M	MH	MH	M	MH	MH	MH	M	M	M	M
A_6	H	M	L	MH	ML	H	H	ML	MH	ML	ML	ML
DM_2	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
A_1	ML	M	H	ML	MH	ML	M	H	M	M	MH	MH
A_2	MH	M	ML	MH	ML	MH	MH	M	M	ML	ML	M
A_3	M	M	MH	MH	M	M	MH	M	M	MH	M	MH
A_4	M	ML	M	ML	M	ML	L	H	ML	M	H	M
A_5	MH	M	M	H	M	MH	MH	MH	M	M	M	M
A_6	VH	M	L	MH	ML	VH	H	ML	MH	ML	L	ML
DM_3	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
A_1	ML	MH	H	ML	MH	ML	M	VH	M	M	MH	MH
A_1	MH	M	ML	MH	ML	MH	MH	M	M	ML	ML	M
A_1	M	M	MH	MH	M	M	MH	M	M	MH	M	MH
A_1	M	M	M	ML	M	ML	ML	VH	ML	M	H	MH

A_1	MH	M	M	MH	M	MH	MH	MH	M	M	M	M
A_1	H	ML	L	MH	ML	VH	H	VL	H	ML	L	ML
DM_4	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
A_1	ML	MH	H	ML	MH	ML	M	H	M	M	MH	MH
A_1	MH	M	ML	MH	ML	MH	MH	M	M	ML	ML	M
A_1	M	M	MH	MH	M	M	MH	M	M	MH	M	H
A_1	M	M	M	ML	M	ML	ML	H	ML	M	MH	M
A_1	MH	M	M	H	M	MH	MH	MH	M	M	M	M
A_1	H	M	L	MH	ML	H	H	ML	MH	ML	ML	ML

Table 7. Average decision matrix

	C_1	C_2	C_3	...	C_{10}	C_{11}	C_{12}
A_1	(1.68,3.36,5.42)	(4.40,6.44,8.45)	(7.00,9.00,10.0)	...	(3.00,5.00,7.00)	(5.00,7.00,9.00)	(5.00,7.00,9.00)
A_2	(5.00,7.00,9.00)	(3.00,5.00,7.00)	(2.00,4.00,6.00)	...	(2.00,4.00,6.00)	(2.00,4.00,6.00)	(3.00,5.00,7.00)
A_3	(3.00,5.00,7.00)	(3.00,5.00,7.00)	(5.00,7.00,9.00)	...	(5.00,7.00,9.00)	(3.00,5.00,7.00)	(5.44,7.45,9.24)
A_4	(3.00,5.00,7.00)	(2.71,4.73,6.74)	(3.00,5.00,7.00)	...	(3.00,5.00,7.00)	(5.92,7.64,9.49)	(3.00,5.00,7.00)
A_5	(5.00,7.00,9.00)	(3.00,5.00,7.00)	(3.00,5.00,7.00)	...	(3.00,5.00,7.00)	(3.00,5.00,7.00)	(3.00,5.00,7.00)
A_6	(7.45,9.24,10.0)	(2.71,4.73,6.74)	(1.00,2.00,4.00)	...	(2.00,4.00,6.00)	(1.41,2.83,4.90)	(2.00,4.00,6.00)

Using the average fuzzy decision matrix shown in Table 7, normalized fuzzy decision matrices were created for the benefit and cost criteria using Eq. 13 and Eq. 14, respectively. The obtained results are presented in Table 8.

Table 8. Normalized fuzzy decision matrix

	C_1	C_2	C_3	...	C_{10}	C_{11}	C_{12}
A_1	(0.17,0.34,0.54)	(0.52,0.76,1.00)	(0.10,0.11,0.14)	...	(0.29,0.40,0.67)	(0.16,0.20,0.28)	(0.22,0.29,0.40)
A_2	(0.50,0.70,0.90)	(0.35,0.59,0.83)	(0.17,0.25,0.50)	...	(0.33,0.50,1.00)	(0.24,0.35,0.71)	(0.29,0.40,0.67)
A_3	(0.30,0.50,0.70)	(0.35,0.59,0.83)	(0.11,0.14,0.20)	...	(0.22,0.29,0.40)	(0.20,0.28,0.47)	(0.22,0.27,0.37)
A_4	(0.30,0.50,0.70)	(0.32,0.56,0.80)	(0.14,0.20,0.33)	...	(0.29,0.40,0.67)	(0.15,0.18,0.24)	(0.29,0.40,0.67)
A_5	(0.50,0.70,0.90)	(0.35,0.59,0.83)	(0.14,0.20,0.33)	...	(0.29,0.40,0.67)	(0.20,0.28,0.47)	(0.29,0.40,0.67)
A_6	(0.75,0.92,1.00)	(0.32,0.56,0.80)	(0.25,0.50,1.00)	...	(0.33,0.50,1.00)	(0.29,050,1.00)	(0.33,0.50,1.00)
max AS	(0.75,0.92,1.00)	(0.52,0.76,1.00	(0.25,0.50,1.00)	...	(0.33,0.50,1.00)	(0.29,0.50,1.00)	(0.33,0.50,1.00)
min AS	(0.17,0.34,0.54)	(0.32,0.56,0.80	(0.10,0.11,0.14)	...	(0.22,0.29,0.40)	(0.15,0.18,0.24)	(0.22,0.27,0.37)

Using the normalized fuzzy decision matrix values in Table 8, a weighted normalized decision matrix was created via Eq. 15 and the results are given in Table 9.

Table 9. Weighted normalized fuzzy decision matrix

	C_1	C_2	C_3	...	C_{10}	C_{11}	C_{12}
A_1	(0.01,0.04,0.10)	(0.04,0.10,0.20)	(0.00,0.00,0.01)	...	(0.01,0.02,0.07)	(0.00,0.01,0.04)	(0.00,0.01,0.04)
A_2	(0.03,0.08,0.17)	(0.03,0.08,0.16)	(0.00,0.01,0.05)	...	(0.01,0.02,0.07)	(0.01,0.02,0.09)	(0.00,0.02,0.07)
A_3	(0.02,0.06,0.13)	(0.03,0.08,0.16)	(0.00,0.01,0.02)	...	(0.00,0.01,0.07)	(0.01,0.02,0.06)	(0.00,0.01,0.04)
A_4	(0.02,0.06,0.13)	(0.03,0.07,0.16)	(0.00,0.01,0.03)	...	(0.01,0.02,0.11)	(0.00,0.01,0.03)	(0.00,0.02,0.07)
A_5	(0.03,0.08,0.17)	(0.03,0.08,0.16)	(0.00,0.01,0.03)	...	(0.01,0.02,0.07)	(0.01,0.02,0.06)	(0.00,0.02,0.07)

A_6	(0.05,0.11,0.19)	(0.03,0.07,0.16)	(0.00,0.02,0.10)	...	(0.01,0.02,0.04)	(0.01,0.03,0.13)	(0.01,0.02,0.10)
max AS	(0.05,0.11,0.19)	(0.04,0.10,0.20)	(0.00,0.02,0.10)	...	(0.01,0.02,0.11)	(0.01,0.03,0.13)	(0.01,0.02,0.10)
min AS	(0.01,0.04,0.10)	(0.03,0.07,0.16)	(0.00,0.00,0.01)	...	(0.00,0.01,0.04)	(0.00,0.01,0.03)	(0.00,0.01,0.04)

After obtaining the weighted normalized decision matrix, the total aggregated values for the alternatives were calculated using Eq. 16. The deviation values for the alternative solutions were calculated using Eq. 17-18, and the defuzzied values were obtained using Eq. 19-20. The final performance values obtained using the FCORASO method were calculated using Eq. 21, and the results are shown in Table 10.

Table 10. Ranking results using the FCORASO method

	$\tilde{S}_j$	$\tilde{R}_j$	$\widetilde{R'}_j$	$R_{j\ \mathrm{def}}$	$R'_{j\ \mathrm{def}}$	Q_i	**Rank**
A_1	(0.19,0.48,1.14)	(0.11,0.63,3.40)	(0.10,0.71,4.66)	1.01	1.27	−0.12	5
A_2	(0.22,0.58,1.48)	(0.12,0.75,4.44)	(0.08,0.60,3.96)	1.26	1.07	0.08	3
A_3	(0.19,0.50,1.22)	(0.11,0.66,3.64)	(0.09,0.68,4.60)	1.06	1.24	−0.08	4
A_4	(0.18,0.48,1.21)	(0.10,0.62,3.60)	(0.09,0.72,5.01)	1.03	1.33	−0.13	6
A_5	(0.25,0.60,1.41)	(0.14,0.78,4.22)	(0.08,0.58,3.62)	1.25	1	0.11	2
A_6	(0.26,0.64,1.57)	(0.14,0.83,4.70)	(0.07,0.54,3.43)	1.36	0.95	0.18	1
max AS	(0.33,0.77,1.80)						
min AS	(0.11,0.34,0.89)						

According to the results of the FCORASO method presented in Table 10 ($A_6 > A_5 > A_2 > A_3 > A_1 > A_4$), alternatives A_6 (privatization model) and A_4 (cooperative/staff-focused model) were identified as the best and worst options, respectively.

4.3. Validation and Sensitivity Analysis

In this section, a three-stage validation process was applied to assess the methodological robustness of the results obtained using the FCORASO method.

4.3.1. Comparison of results obtained using FCORASO and other methods

In the first stage, the consistency and comparability of the ranking results obtained using the FCORASO method were evaluated through comparative analysis with the FRAWEC, FSAW, Fuzzy Weighted Aggregated Sum Product Assessment (FWASPAS), and Fuzzy Technique for Order Performance by Similarity to Ideal Solution (FTOPSIS) methods, which are widely used in the literature. The ranking results of the alternatives are presented in Figure 3.

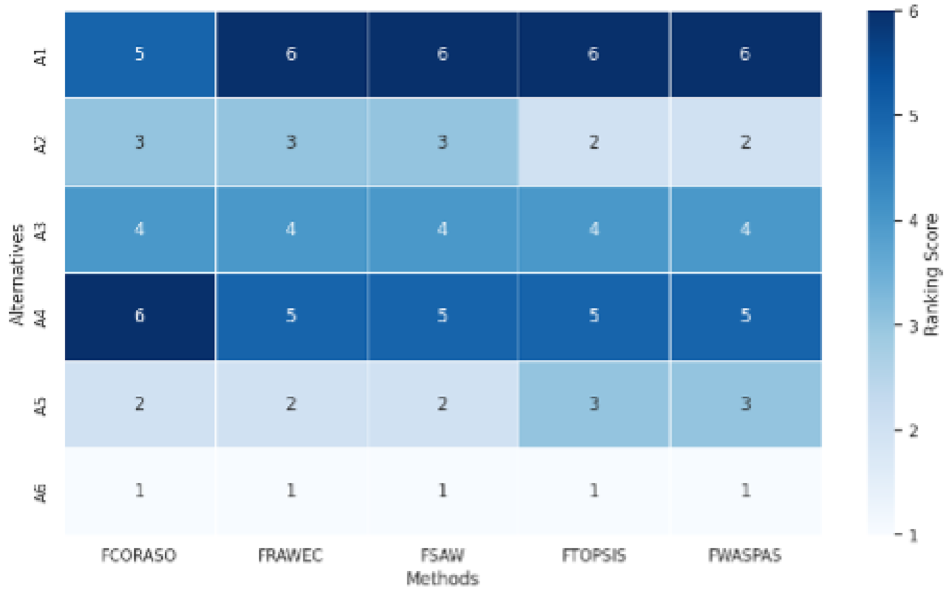

Figure 3. Ranking of alternatives using different MCDM methods

The results of the comparative analysis indicate that the differences between the alternatives are quite limited. These limited differences stem from the specific implementation steps of each method.

The rankings obtained using the FCORASO method were compared with the ranking results obtained using other MCDM methods using the Spearman rank correlation coefficient (SCC), and the results are presented in Figure 4.

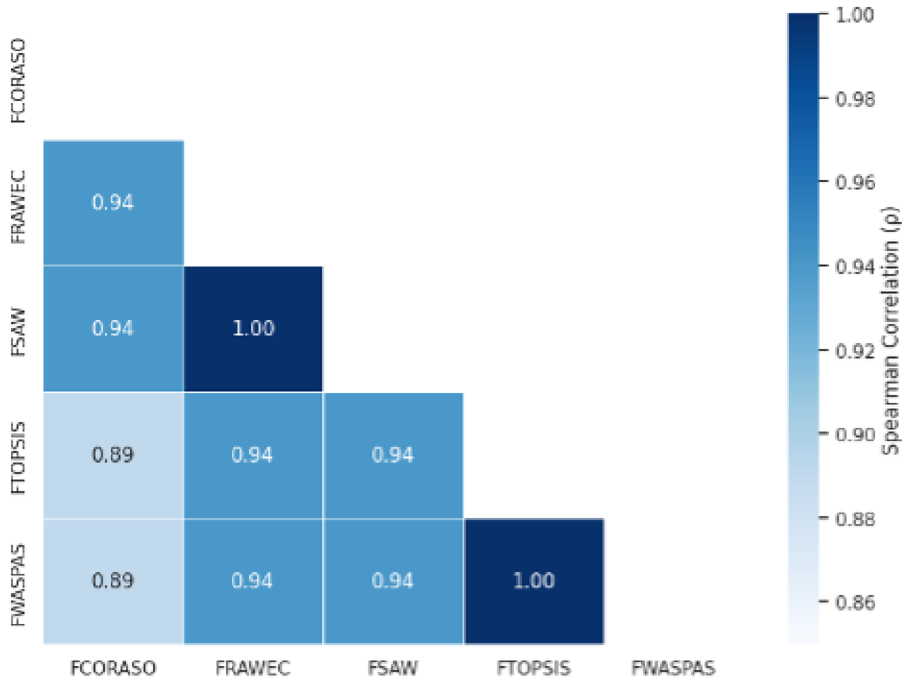

Figure 4. SCC values for alternative ranks obtained by different MCDM methods

When examining Figure 4, SCC varies between 0.89 and 1. This confirms that there is a strong and positive correlation between the FCORASO method and other methods.

The findings strongly demonstrate that the ranking obtained using the FCORASO method is consistent with the rankings obtained using other MCDM methods. In conclusion, the findings obtained using the FCORASO method and the success of this study in identifying the most suitable organizational model alternative for university social facility economic enterprises can be considered reliable.

4.3.2. Assessment of model stability under rank reversal

In MCDM methods, the reverse ranking effect refers to the examination of whether the final ranking changes when a new alternative is added to the decision matrix or when one of the existing alternatives is removed. This situation is considered one of the most important limitations in MCDM methods (Bakır & Atalık, 2021). The ranking results for management and operation model alternatives for economic operations conducted within universities using the FCORASO method were determined as follows: $A_6 > A_5 > A_2 > A_3 > A_1 > A_4$. Based on these findings, A_4 was identified as the lowest-performing alternative and was initially excluded from the decision matrix. Subsequently, to analyze how the rankings of the remaining alternatives evolved, the lowest-performing alternative at each stage was systematically removed, and dynamic decision matrices were generated until only one alternative remained (Bakır & Atalık, 2021). The corresponding results are presented in Figure 5.

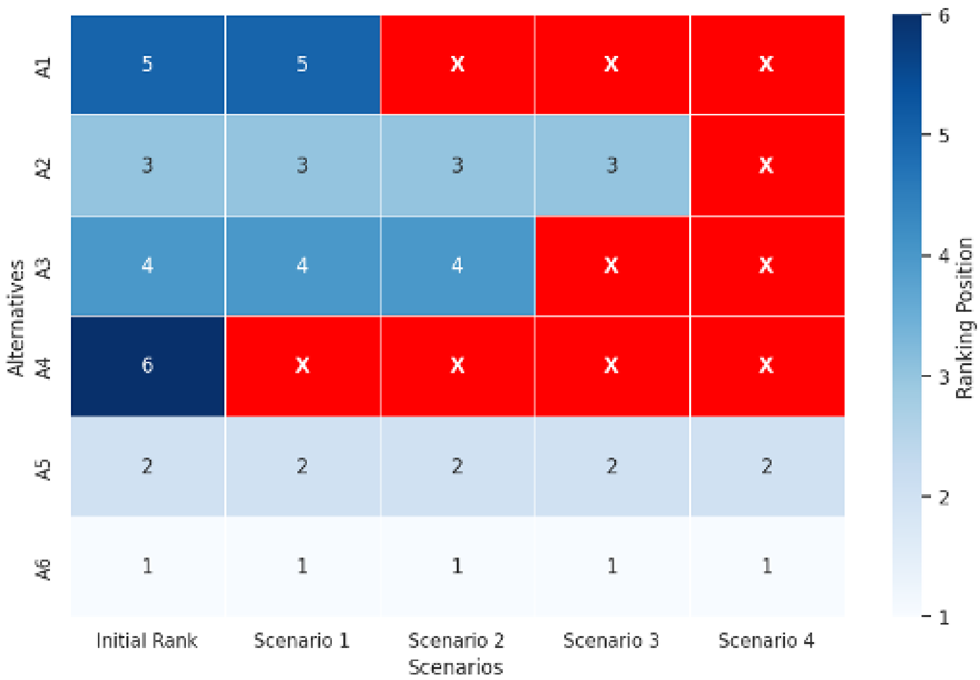

Figure 5. Rank reversal effect in the application

As illustrated in Figure 5, the A_4 alternative, which exhibited the lowest performance, was initially eliminated from the decision matrix, and the ranking of the remaining alternatives is presented in Scenario 1. In the following stages, the lowest-performing alternative in each scenario was successively removed from the matrix. Across all scenarios, A_6 consistently maintained its top-ranking position even after the exclusion of the weakest alternatives.

These findings demonstrate that the FCORASO method is highly resistant to the reversal effect. In particular, the fact that the highest-performing alternatives maintain their rankings when other alternatives are removed supports the consistency of the method.

4.3.3. Sensitivity analysis Monte Carlo simulation

Sensitivity analysis was conducted to evaluate the robustness and validity of the decision-making process for selecting the most suitable organizational model alternative. This analysis utilized Monte Carlo simulation to systematically examine the effect of possible changes in criterion weights on the ranking of the alternatives.

In accordance with the methodology proposed by Soltani & Imani (2024), the weights were determined using a Dirichlet distribution, subject to the condition that the sum of the weights equals 1. The reliability and validity of the model were tested through 10,000 simulations across various weight scenarios.

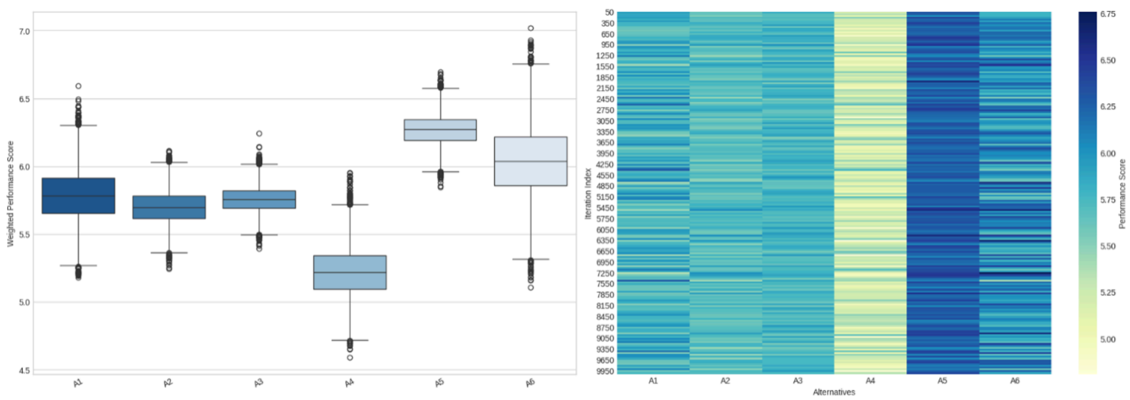

Figure 6. Comparative analysis of Monte Carlo simulation outcomes

Figure 6 shows the score distributions obtained from 10,000 simulation runs for each alternative. The boxplot highlights the central tendency and distribution of the performance scores, while the heatmap displays the average performance values across all iterations (Soltani & Imani, 2024).

When examining the box plot, it is observed that alternative A_6 has the highest median performance score and is concentrated in the upper quartile region of the distribution. This indicates that alternative A_6 has the highest performance even at different weight values. Alternatives A_5, A_2, and A_3 follow alternative A_6 in that order. In particular, the relatively narrow interquartile range (IQR) observed for alternative A5 suggests that it maintains a more stable performance under varying criterion weights.

In contrast, it is observed that the median values of alternatives A_1 and especially A4 are lower and the interquartile range is relatively wider. This situation indicates that these alternatives are more sensitive to changes in criterion weights and exhibit more volatile performance.

The heat map findings support the box plot results. It shows that the columns for alternatives A_6 and A_5 produced high performance values in most simulations. In contrast, the concentration of lighter tones in the A4 column confirms that this alternative performed less effectively.

As a result, considering the uncertainty in the criterion weights, alternatives A_6 and A_5 stand out in terms of both high performance and stability. Alternatives A_2 and A_3 exhibit a moderate level of structure, while alternatives A_{14} ∧A_4 are seen to be more sensitive to weight changes. Consequently, if decision-makers prefer a more resilient and high-performance option under uncertainty, alternatives A_6 and A_5 can be prioritized.

5. Conclusions and Recommendations

This study addressed the problem of selecting the most appropriate organizational model for university social facility economic enterprises, which inherently operate under a hybrid structure combining public service responsibilities with economic activities. Given the complex and multifaceted nature of this decision-making problem, an integrated fuzzy MCDM framework based on the FSIWEC and FCORASO methods has been proposed.

The findings clearly demonstrate that organizational model selection cannot be effectively handled through intuitive or single-dimensional approaches. Instead, it requires a structured evaluation process that simultaneously considers economic efficiency, managerial effectiveness, and social responsibility. Within this framework, the integration of fuzzy logic enabled the incorporation of expert judgments in a more realistic manner by reflecting uncertainty and subjective evaluations.

According to the results, the privatization-based model A_6 emerged as the most suitable alternative, while the cooperative/staff-focused model A_4 showed the lowest performance. This indicates that models emphasizing operational efficiency, financial sustainability, and adaptability to market conditions tend to outperform more internally focused or less flexible structures. Also, the relatively strong performance of the hybrid model A_5 suggests that balanced approaches combining public oversight with private sector efficiency may offer viable and stable solutions.

The robustness analyses further strengthen the reliability of these findings. The high correlation between FCORASO results and other MCDM methods confirms methodological consistency, while the rank reversal and Monte Carlo simulation analyses demonstrate that the results remain stable under different conditions and weight variations. In particular, the consistent top ranking of A6 across scenarios highlights its resilience as a preferred option.

From a practical perspective, the study provides several important implications. First, university administrators and policymakers should adopt systematic decision-support tools when evaluating organizational alternatives, rather than relying solely on experience-based judgments. Second, decision-makers should prioritize criteria related to financial sustainability, service quality, and operational flexibility, as these factors significantly influence overall performance. Third, while privatization appears to be the most effective model in this study, institutional context, regulatory constraints, and stakeholder expectations should also be carefully considered before implementation. In addition, the findings suggest that hybrid organizational structures may be a balanced option in situations where full privatization is not appropriate or desirable. Such models can help maintain public service objectives while benefiting from private sector efficiency and innovation.

Although this study makes significant contributions to the literature, it has certain limitations. The evaluation process was based on a limited number of experts, and the results may vary with a broader or more diverse decision-making group. In addition, the study focuses on specific criteria and alternatives; this scope may be expanded in future studies. Future studies may extend this research by incorporating different fuzzy environments, integrating additional MCDM techniques, and applying the proposed framework to various types of public economic enterprises. Furthermore, combining real performance data with expert evaluations may improve the reliability and practical applicability of the decision-making process. Future research may also focus on developing dynamic and multi-stakeholder decision-making frameworks for university economic enterprises. In particular, integrating longitudinal performance indicators, stakeholder-based preference structures, and artificial intelligence-supported analytical tools may significantly improve the robustness and applicability of organizational model selection processes. In addition, comparative cross-country studies may provide valuable insights into how institutional, cultural, and regulatory differences shape organizational preferences in higher education-related economic enterprises. Such extensions would contribute to both the theoretical development of fuzzy MCDM literature and the practical design of sustainable governance models in public-oriented economic organizations.

In conclusion, this study offers a structured, flexible, and reliable decision-support framework for organizational model selection in university economic enterprises. By combining methodological rigor with practical relevance, it contributes both to academic literature and to real-life decision-making processes.

Declarations

Conflict of interest The author(s) have no competing interests to declare that are relevant to the content of this article.

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