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RESEARCH ARTICLE

A Hybrid MCDM Model for Personnel Evaluation: Integrating AHP, Fuzzy TOPSIS and VIKOR with Composite Scoring

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ABSTRACT

Personnel selection is a vital strategic function for businesses that work in knowledge-intensive and public-facing sectors, such as science centers. Traditional evaluation methodologies frequently fail to capture the inherent ambiguity and subjectivity in candidate assessments. To address these constraints, this study offers a robust hybrid fuzzy multi-criteria decision-making (MCDM) framework that incorporates the Analytic Hierarchy Process (AHP), Fuzzy TOPSIS, and Fuzzy VIKOR. Furthermore, a unique aggregation mechanism known as the Fuzzy Composite Ranking Score (FCRS) is developed to combine the outputs of Fuzzy TOPSIS and Fuzzy VIKOR into a single ranking score that balances proximity to the ideal solution with compromise among conflicting criteria.

The proposed methodology was applied to a real-world case study at the Konya Science Center (KSC), where seven full-time and seven part-time candidates were evaluated based on seven criteria. The AHP method was used to derive weights for each criterion through expert pairwise comparisons, which were validated through consistency ratio analysis. Expert linguistic evaluations of candidates were converted into triangular fuzzy numbers and processed through Fuzzy TOPSIS and VIKOR models. The final rankings produced by FCRS demonstrated a high degree of agreement with individual method results while addressing contradictions between them.

The results show that the proposed hybrid framework can allow nuanced, transparent, and robust personnel selection decisions in complicated organizational situations. The model is scalable and adaptable to a wide range of decision-making scenarios involving human judgment in uncertain environments.

Keywords: AHP-based criteria weighting, Fuzzy TOPSIS–VIKOR fusion, Fuzzy composite ranking score

1. Introduction

In today's knowledge-driven public service sector, personnel selection has transformed from a regular administrative task to a strategic undertaking with implications for organizational performance, operational stability, and long-term success. This is especially important for science centers, which require interdisciplinary knowledge, excellent science communication, and active public participation. Institutions such as the Konya Science Center (KSC) require personnel who can effectively bridge scientific knowledge and teaching, typically in engaging and dynamic settings.

Despite the strategic significance of hiring processes, numerous public organizations still depend on informal, unstructured, or overly simplified selection methods. Such practices frequently overlook the multifaceted qualifications of candidates, particularly when considering subjective qualities like adaptability, collaboration, or educational effectiveness. Additionally, linguistic imprecision and lack of expert consensus contribute to inconsistencies and biases in human resource (HR) evaluations. This challenge has prompted the growing use of Multi-Criteria Decision-Making (MCDM) techniques in hiring, allowing decision-makers to assess multiple conflicting criteria in a structured and transparent way (Vaidya & Kumar, 2006).

Among MCDM techniques, the Analytic Hierarchy Process (AHP) is commonly utilized to assess the relative importance of selection criteria due to its straightforward pairwise comparison method (Saaty, 1980). However, AHP often faces criticism for its sensitivity to inconsistencies and its limited capacity to handle linguistic uncertainty (Abdulvahitoglu & Kilic, 2022). To overcome these shortcomings, fuzzy logic has been incorporated into MCDM models, leading to methods like Fuzzy

AHP, Fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Fuzzy VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), each successfully implemented in personnel evaluations.

Despite the efficacy of these models, a significant challenge persists: the absence of a consistent mechanism to harmonize the differing rankings produced by various fuzzy MCDM approaches. Consequently, decision-makers often experience confusion or randomness in choosing one method's result over another. Although some studies have sought to bridge this gap with hybrid or ensemble strategies (Ayadi et al., 2021; Daus et al., 2023). These models often struggle with generalizability or transparency.

To address this methodological gap, this study introduces a novel hybrid fuzzy MCDM framework that combines AHP, Fuzzy TOPSIS, and Fuzzy VIKOR into a cohesive evaluation process. A key innovation of this framework is the FCRS, a synthesis-based scoring method that integrates outputs from Fuzzy TOPSIS and VIKOR into one clear ranking index. Unlike simple rank averaging, the FCRS is crafted to preserve both consistency and the distinction of competing rankings, thus enhancing the robustness of final decisions without succumbing to oversimplification.

The framework is validated through a real-world case study at the KSC, where 14 candidates were assessed for full-time and part-time positions in science education. The criteria were collaboratively developed with institutional experts and reflect practical aspects of operational, educational, and scientific performance within the center.

Consequently, this research aims to: identify and organize essential personnel selection criteria for scientific institutions; evaluate their relative significance using AHP; assess candidate performance through Fuzzy TOPSIS and Fuzzy VIKOR; and consolidate these results into a composite ranking using the proposed FCRS method.

This study not only advances the theoretical aspects of hybrid fuzzy decision-making techniques but also provides a scalable, interpretable, and validated decision-support framework for strategic personnel selection amidst uncertainty.

The paper is structured as follows: Section 2 reviews the literature on fuzzy MCDM applications in personnel selection. Section 3 describes the methodology, detailing the phases of the hybrid model. Section 4 discusses its application to the KSC case. Section 5 presents findings and comparative outcomes from each method. Section 6 concludes with suggestions for future studies.

2. Literature Review

Personnel selection is a critical decision-making process that shapes the strategic, operational, and cultural outcomes of organizations. Since HRs directly affect productivity, adaptability, and innovation, selecting the right candidates remains a high-stakes task, especially in knowledge-intensive environments such as science centers. Traditional selection methods, while still prevalent, often fail to capture the multidimensional, subjective, and uncertain nature of candidate assessment . In response, researchers are increasingly adopting MCDM models to provide more structured, transparent, and defensible evaluation frameworks (Vaidya & Kumar, 2006).

Under the classic MCDM approach, the AHP has gained significant attention for its simplicity and adaptability. It decomposes decision problems into hierarchies and derives criterion weights through expert-based pairwise comparisons (Saaty, 1980). Its applicability in personnel selection is well-established: (Kurnia et al., 2019) used AHP to select the most suitable candidates for Call Center 112 operator roles based on multi-stage evaluation criteria, (Anna Prusak et al., 2015) applied it to hire in the public sector, and (Konacoglu & Albayrak, 2018) proposed a hybrid AHP model to improve reliability in personnel evaluations.

Fuzzy AHP was developed to address language ambiguity in qualitative qualities (such as emotional intelligence). Samanlioglu et al. (2018) paired it with Fuzzy TOPSIS for IT staffing, and (Singh et al., 2023)employed a similar hybrid in manufacturing. (C.-T. Chen, 2000) created Fuzzy TOPSIS, which evaluates candidates based on their proximity to ideal/anti-ideal solutions and excels in imprecise contexts (for example, "moderate experience"). Applications include research and development staffing (Aytekin et al., 2022) and human error evaluation (Velmurugan et al., 2022).

Hybrids such as Fuzzy AHP-TOPSIS integrate standard weights and rankings. Jain et al. (2018) showed robustness in supplier selection, and Kusumawardani and Agintiara (2015) applied them to HR management choices. In contrast, Salehi (2016) addressed conflicting criteria in personnel selection evaluation with a fuzzy AHP–VIKOR framework. Krishankumar et al. (2020) used the intuitionist fuzzy extension for HR choice using Milojkovic and Prascevic (2024) applied to project teams.

Fuzzy TOPSIS ranks candidates based on their proximity to an ideal solution while considering inaccuracies in expert assessments. It is widely used for human-centric decision-making, especially when qualitative and quantitative criteria are intertwined (Chen, 2000; Liou & Tzeng, 2012). While TOPSIS seeks closeness to the ideal, Fuzzy VIKOR provides a compromise-based approach that balances group satisfaction and individual dissatisfaction. This makes it especially useful when conflicting criteria must be reconciled (Opricovic & Tzeng, 2004). Comparative studies indicate that while both methods offer value, they may produce differing rankings when employed separately (Yazdani et al., 2021; Sharma et al., 2024). In personnel selection, Krishankumar et al. (2020) demonstrated the strength of using an intuitionistic fuzzy extension. Milojkovic and Prascevic (2024) applied it in project team selection, and Sequeira et al. (2023) in facility relocation—each showing VIKOR's adaptability across domains.

Moreover, Bakioglu and Atahan (2021) introduced a hybrid AHP–TOPSIS–VIKOR model within a Pythagorean fuzzy environment to assess risk in autonomous vehicle systems. Although HRs are not specifically addressed, this study demonstrates the scalability of the integration of fuzzy MCDM models in decision environments with high operation.

The Hybrid-Fuzzy-MCDM model was developed to deal with the shortcomings of separate approaches. These combinations help manage both qualitative and quantitative data while also increasing ranking stability. Dursun and Karsak (2010) provided a fuzzy MCDM model that combines numerical and linguistic information, while Ertugrul Karsak (2001) proposed a useful method to analyze candidates using ideal and anti-aware standards.

Despite the success of these approaches, there are still problems that remain with dispute resolution. Sharma et al. (2024) and Yazdani et al. (2021) discovered a significant distinction between Fuzzy TOPSIS and VICOR output, especially among candidates at moderate levels. This variability affects the final decision and can lead to paralysis.

While previous studies have introduced various hybrid fuzzy MCDM models tailored for specific domains—ranging from sustainable logistics (Ayadi et al., 2021) to industrial robot selection (Chung et al., 2024), IT personnel evaluation (Aggarwal et al., 2025), and agricultural production analysis (Savalan & Rouyendegh, 2022), most of these approaches remain domain-specific and lack generalizability to public service contexts. For instance, Savalan and Rouyendegh (2022) proposed a fuzzy AHP–TOPSIS-based model to assess sustainable agricultural technologies by incorporating both quantitative and qualitative uncertainties through fuzzy set theory. Similarly, Hu et al. (2022) developed a fuzzy rough number-based hybrid AHP–VIKOR approach for Failure Mode and Effects Analysis (FMEA), effectively addressing uncertainty and subjectivity in risk prioritization. Additionally, models such as Fuzzy Composite Programming (Daus et al., 2023), Z-numbers-based AROMAN (Gottwald et al., 2024), and Interval Type-2 Fuzzy TOPSIS (Nalbant, 2025) offer methodological enhancements to improve decision stability. Yet, they still fall short in systematically resolving the ranking inconsistencies often produced by different fuzzy MCDM techniques such as Fuzzy TOPSIS and Fuzzy VIKOR.

To address this methodological challenge, the present study proposes a robust hybrid decision-making framework that integrates AHP-based criteria weighting with Fuzzy TOPSIS and Fuzzy VIKOR and introduces a novel Fuzzy Composite Ranking Score (FCRS) for result aggregation. Unlike conventional ensemble or averaging approaches, the FCRS ensures methodological coherence by consolidating distance-based and compromise-based evaluations into a single interpretable score. This fusion enhances decision consistency, reduces ambiguity, and provides more defensible outcomes for final candidate selection.

Furthermore, by applying the proposed model within a resource-constrained yet socially impactful institution like the Konya Science Center (KSC), this research extends the applicability of fuzzy hybrid MCDM models beyond industrial or private-sector use cases. It addresses a significant gap in literature by offering a validated and scalable framework suitable for public, education-oriented organizations where personnel evaluation involves complex, multidimensional, and subjective criteria.

3. Materials and Methods

This study uses a hybrid MCDM framework to evaluate and rank candidates for full-time and part-time roles, using the AHP, Fuzzy TOPSIS, and Fuzzy VIKOR approaches. The hybrid evaluation model combines AHP, Fuzzy TOPSIS, and Fuzzy VIKOR before aggregating the results using FCRS. This section explains the theoretical foundations, operational steps, and reasons for integrating various strategies.

3.1 Materials

KSC, founded with the support of the Scientific and Technological Research Council of Turkey (TÜBİTAK), continues to be a pioneer in science communication in Turkey. In 2025, the center is expected to host over **365,000** visitors, based on current operational reports, highlighting its sustained public engagement.

KSC employs both full and part-time employees. To implement a fair, consistent, and analytical approach to personnel selection, this study developed a hybrid decision support model that integrates AHP, Fuzzy TOPSIS, and Fuzzy VIKOR methods.

A total of 14 candidates (7 full-time and 7 part-time) were evaluated. The selection criteria were meticulously formulated based on structured interviews with the HRs team at KSC, ensuring both institutional alignment and operational relevance. The evaluation criteria varied based on the nature of the position. For full-time positions, the decision criteria included:

- C1 – Foreign language proficiency
- C2 – Educational background
- C3 – Professional experience
- C4 – Communication skills
- C5 – Sensitivity (empathy and awareness)
- C6 – Relevant certifications

- C7 – Teamwork compatibility

For part-time positions, the criteria were slightly different, reflecting the nature of the roles:

- C1* – Foreign language proficiency
- C2* – Education level
- C3* – Grade point average (GPA)
- C4* – Communication skills
- C5* – Sensitivity (especially social responsibility engagement)
- C6* – Participation in science projects
- C7* – Teamwork suitability

The weights of these criteria were calculated using the AHP approach, and the candidates were ordered using the Fuzzy TOPSIS and Fuzzy VIKOR procedures. Finally, the data were integrated using the FCRS to get a single final score.

This hybrid model is thus uniquely positioned to address the strategic personnel needs of an institution like the KSC, where human capital plays a pivotal role in shaping public science communication and educational innovation.

The structured sequence of this decision-making process is illustrated in Figure 1, which outlines each step from the definition of personnel needs to the synthesis of results using the composite FCRS approach.

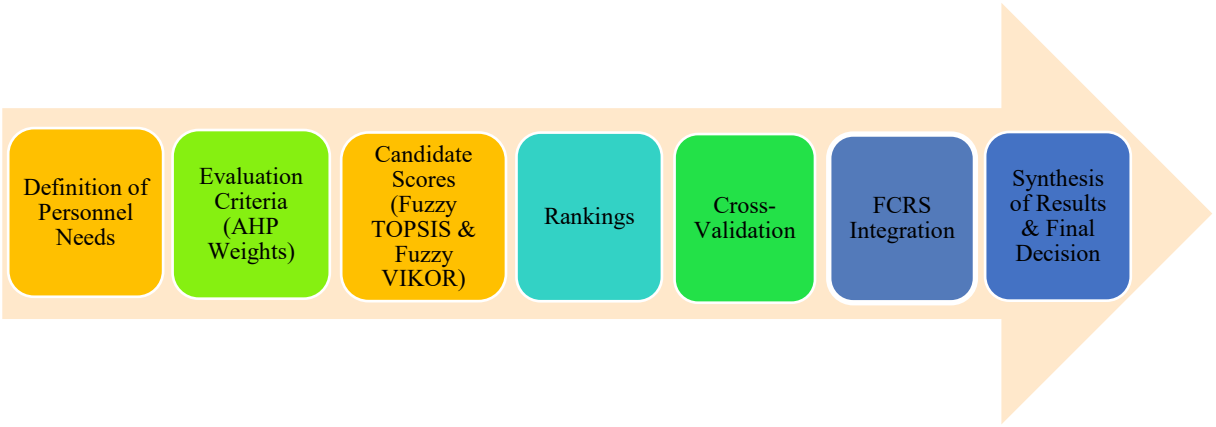

Figure 1. Structured hybrid fuzzy MCDM decision-making flow with FCRS integration for personnel selection at KSC.

This flowchart illustrates the structured decision-making process employed in the personnel selection case study at KSC. The process begins with the identification of personnel needs and the definition of role-specific evaluation criteria, established through expert consultations with HR professionals. These criteria are weighed by AHP. In other words, stakeholder priorities are recorded through pairing. In the next stage, candidate performance is evaluated in both Fuzzy TOPSIS and Fuzzy VIKOR methods.

To consolidate these outputs and enhance the interpretability of the final rankings, the FCRS is applied, generating a unified score that balances both decision perspectives. This composite logic ensures a more robust, transparent, and defensible selection outcome aligned with the strategic objectives of the KSC.

3.2 Methods

3.2.1 AHP: Deriving Criteria Weights

AHP was applied to compute the relative weights of the evaluation criteria based on expert pairwise comparisons. The AHP is a widely utilized multi-criteria decision-making method developed by Saaty (1980). It provides a structured framework for complex decision problems by decomposing them into a hierarchical structure consisting of the goal, criteria, sub-criteria (if any), and alternatives. The application of AHP in this study is consistent with the methods proposed in the literature (e.g., Russo & Camanho, 2015). The procedure involved in the AHP methodology is outlined as follows:

A pairwise comparison matrix $A = [a_{ij}]$ is constructed, where each element a_{ij} represents the relative importance of an element i over element j using a scale of 1 to 9 (Saaty, 1987). The reciprocal property holds: $a_{ji} = 1/a_{ij}$ and $a_{ii} = 1$

Normalized values are given by Equation 1:

$$a'_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad (1)$$

The weight of each criterion is the row average as shown in Equation 2:

$$w_i = \frac{1}{n}\sum_{j=1}^{n} a'_{ij} \quad (2)$$

For the consistency check, the maximum eigenvalue is calculated using Equation 3:

$$\lambda_{max} = \frac{1}{n}\sum_{i=1}^{n} \frac{(A \cdot w)_i}{w_i} \quad (3)$$

Consistency metrics are defined as in Equation 4:

$$CI = \frac{\lambda_{max} - n}{n-1}, CR = \frac{CI}{RI} \quad (4)$$

A CR value under 0.10 is considered acceptable.

3.2.2 Fuzzy TOPSIS: Ranking Based on Closeness to Ideal

Wang and Elhag (2006) developed Fuzzy TOPSIS, an enhanced version of the original TOPSIS technique that employs fuzzy set theory (Zadeh, 1964) to address the ambiguity and subjectivity inherent in human decision-making. This method is especially useful when evaluators provide language word preferences, which are then converted into triangular fuzzy numbers (TFN) for systematic quantitative analysis.

Table 1 shows the linguistic terms used in the evaluation process, their simplified codes, and the associated TFN, which together form the foundation for converting qualitative assessments into quantitative fuzzy values.

Table 1. Linguistic variables for the ratings (Gul & Guneri, 2016)

Linguistic Variable	Code	TFN
Very Poor	VP	(0, 0, 1)
Poor	PR	(0, 1, 3)
Medium Poor	MP	(1, 3, 5)
Fair	FR	(3, 5, 7)
Medium Good	MG	(5, 7, 9)
Good	GD	(7, 8, 10)
Very Good	VG	(9, 10, 10)

The application of linguistic variables is particularly suitable in MCDM contexts that involve subjective assessments, such as personnel selection. Prior research (Büyüközkan & Çifçi, 2012; Chen & Hwang, 1992; Kahraman et al., 2004) emphasizes that linguistic evaluations contribute to reducing ambiguity and enhancing interpretability in expert judgments.

Fuzzy TOPSIS ranks candidates by measuring their closeness to the fuzzy ideal and anti-ideal solutions.

Let $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ be the fuzzy score of the candidate i on criterion j.

Normalization for benefit-type criteria is computed using Equation 5:

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{m_j^+}, \frac{u_{ij}}{l_j^+}\right) \quad (5)$$

For cost-type criteria, the normalization follows Equation 6:

$$\tilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{m_j^-}{m_{ij}}, \frac{u_j^-}{l_{ij}}\right) \quad (6)$$

The weighted normalized values are indicated in Equation 7, the normalized values are weighted by the fuzzy importance weights $\tilde{w}_j$:

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j \tag{7}$$

Ideal and anti-ideal values are defined by Equations 8:

$$\tilde{A}^+ = \left(max(u_{ij})\right), \ \ \tilde{A}^- = \left(min(l_{ij})\right), \tag{8}$$

The distance $d(\tilde{a}, \tilde{b})$ between two triangular fuzzy numbers $\tilde{a} = (l_a, m_a, u_a)$ and $\tilde{b} = (l_b, m_b, u_b)$ is calculated using Equation 9:

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}[(l_a - l_b)^2 + (m_a - m_b)^2 + (u_a - u_b)^2]} \tag{9}$$

Using the vertex method, the combined distances from Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) are obtained via Equation 10:

$$D_i^+ = \sum_{j=1}^{n} \left(\tilde{v}_{ij} - \tilde{A}^+\right), \quad D_i^- = \sum_{j=1}^{n} \left(\tilde{v}_{ij} - \tilde{A}^-\right) \tag{10}$$

The closeness coefficient is then computed using Equation 11:

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{11}$$

Alternatives are ranked in descending CC_i values.

3.2.3 Fuzzy VIKOR: Compromise-Based Ranking

Fuzzy VIKOR method, developed by Opricovic (2011), identifies compromise solutions by evaluating both group utility and individual regret.

The best and worst fuzzy values per criterion are given by Equation 12:

$$\tilde{f}_j^* = max(u_{ij}), \qquad \tilde{f}_j^- = min(l_{ij}) \tag{12}$$

The group utility $\tilde{S}_i$ and individual regret $\tilde{R}_i$ for each alternative are calculated as shown in Equation 13:

$$\tilde{S}_i = \sum_{j=1}^{n} \tilde{w}_j \cdot \frac{\tilde{f}_j^* - \tilde{x}_{ij}}{\tilde{f}_j^* - \tilde{f}_j^-}, \qquad \tilde{R}_i = \max_j \left(\tilde{w}_j \cdot \frac{\tilde{f}_j^* - \tilde{x}_{ij}}{\tilde{f}_j^* - \tilde{f}_j^-} \right) \tag{13}$$

Defuzzification is performed using the centroid method, as presented in Equation 14:

$$Defuzz(\tilde{a}) = \frac{l + m + u}{3} \tag{14}$$

The VIKOR index Q_i, which combines the concepts of group utility and individual regret, is computed using Equation 15:

$$Q_i = v \cdot \frac{S_i - S^*}{S^- - S^*} + (1 - v) \cdot \frac{R_i - R^*}{R^- - R^*} \tag{15}$$

where $v = 0.5$ reflects equal importance between group satisfaction and individual regret.

Ranking is based on ascending Q_i values.

3.2.4 Hybridization Strategy

The hybrid methodology combines the advantages of each approach by integrating AHP for criterion weighting, Fuzzy TOPSIS for similarity-based ranking, and Fuzzy VIKOR for compromise-based ranking AHP guarantees that the weights are determined consistently and methodically. Fuzzy VIKOR ensures balance by taking into account both group utility and

individual regret, whereas fuzzy TOPSIS offers a distance-based perspective of preference, emphasizing candidates who are closest to an ideal profile.

When combined, these techniques provide triangulation of decision outcomes, which facilitates cross-validation of findings and increases the final people selections' robustness. In industries like manufacturing (Mathew et al., 2020; Tran et al., 2024), logistics (Soner et al., 2017), energy planning (Taylan et al., 2020), and healthcare (Agrawal et al., 2020), this hybrid approach has been successfully validated. However, its application to personnel selection in medium-sized enterprises is still new, which makes this case study unique.

3.3 Fuzzy Composite Ranking Score (FCRS): Integrating Fuzzy TOPSIS and Fuzzy VIKOR Results

To improve the robustness and interpretability of the hybrid decision-making model, this study presents a fusion-based metric called the FCRS, which aggregates the results of Fuzzy TOPSIS and Fuzzy VIKOR into a single composite score. Fuzzy TOPSIS assesses alternatives based on their geometric proximity to the ideal solution, whereas Fuzzy VIKOR focuses on the balance of collective utility and individual regret. The FCRS reconciles various viewpoints using a weighted aggregate approach.

Let:

- CC_i^{TOPSIS}: The closeness coefficient of the candidate i from Fuzzy TOPSIS,
- Q_i^{VIKOR}: The compromise index of the candidate i from Fuzzy VIKOR.

The FCRS is defined as seen in Equation 16:

$$FCRS_i = \beta CC_i^{TOPSIS} + (1-\beta) \cdot (1 - Q_i^{VIKOR}) \quad (16)$$

where:

- $\beta \in [0,1]$ is a tunable parameter that adjusts the relative importance of the two methods,
- $(1 - Q_i^{VIKOR})$ converts the VIKOR index so that higher values indicate better performance.

In this study, we adopt $\beta = 0.5$ to assign equal importance to both methods.

This formulation enables a balanced integration of proximity-based and compromise-based evaluation strategies, supporting more stable and interpretable final rankings.

4. Implementation

This section presents the practical application of the hybrid fuzzy MCDM framework to a real-world personnel selection case at the Konya Science Center (KSC). The implementation process is organized into a series of methodical steps: deriving criteria weights through AHP, evaluating candidate performance using Fuzzy TOPSIS and Fuzzy VIKOR, and ultimately synthesizing the results via the Fuzzy Composite Ranking Score (FCRS). Each sub-section reflects a corresponding stage of the integrated decision-making framework and illustrates how theoretical constructs were translated into actionable decision support. By following this structured sequence, the study ensures that both subjective expert judgments and objective prioritizations are rigorously incorporated into the candidate evaluation process.

4.1 AHP Analysis: Determining Criteria Weights

A panel of four HR specialists identified relevant selection criteria for each position through structured interviews. These criteria were evaluated by 4 experts in their fields between 0 (lowest importance) and 10 (highest importance). The evaluation results of the criteria determined in the recruitment of full-time and part-time employees are given in Tables 2 and 3, respectively.

Table 2. Survey results for full-time recruits

Criterion	Participant			
	P-1	P-2	P-3	P-4
C1	6	3	6	5
C2	8	9	8	7
C3	10	9	7	10
C4	5	6	7	6
C5	6	4	4	2
C6	3	5	3	5
C7	5	6	10	7

Table 3. Survey results for part-time recruits

Criterion	Participant			
	P-1	P-2	P-3	P-4
C1*	9	7	5	7
C2*	7	8	3	6
C3*	5	4	7	8
C4*	8	6	8	10
C5*	6	5	5	8
C6*	7	2	2	5
C7*	9	3	5	3

Based on expert opinions, a pairwise comparison matrix was created. To construct the pairwise comparison matrices, the criteria were first rated by the experts on a scale of 0 to 10. These ratings were then averaged across the panel of experts. Table 4 presents the average importance ratings of the criteria for both full-time and part-time personnel evaluations. This integration into a unified format improves readability and highlights the contextual differences between the two employment types. The importance of contextual and role-based differentiation in criteria weighting is emphasized in the literature (Saaty, 1987; Govindan et al., 2020; Keshavarz-Ghorabaee et al., 2021), as it allows for tailored decision frameworks that reflect operational priorities.

Table 4. Average importance ratings of criteria for full-time and part-time candidates

Criterion	Full-Time Avg.	Part-Time Avg.
Language Skills	5	7
Educational Background	8	6
Professional Experience / GPA	9	6
Professional Experience	6	8
Communication Skills	4	6
Social Sensitivity (Volunteering)	4	4
Certification / Project Experience	7	5
Teamwork Compatibility / Suitability	5	7

The criteria were compared in pairs using the average values in Table 3. By adding 1 to the absolute difference between the averages of the criteria, the pairwise comparison matrices for full-time and part-time personnel were constructed and used in AHP calculations (see Tables 5 and 6). Experts rated each criterion on a scale of 1–9. These ratings were aggregated to compute pairwise comparison matrices.

Table 5. Pairwise comparison matrix for full-time recruits

Criterion	C1	C2	C3	C4	C5	C6	C7
C1	1	1/4	1/5	1/2	2	2	1/3
C2	4	1	1/2	3	5	5	2
C3	5	2	1	4	6	6	3
C4	2	1/3	1/4	1	3	3	1/2
C5	1/2	1/5	1/6	1/3	1	1	1/4
C6	1/2	1/5	1/6	1/3	1	1	1/4
C7	3	1/2	1/3	2	4	4	1

Table 6. Pairwise comparison matrix for part-time recruits

Criterion	C1*	C2*	C3*	C4*	C5*	C6*	C7*
C1*	1	2	2	1/2	2	4	3
C2*	1/2	1	1	1/3	1	3	2
C3*	1/2	1	1	1/3	1	3	2
C4*	2	3	3	1	3	5	4
C5*	1/2	1	1	1/3	1	3	2
C6*	1/4	1/3	1/3	1/5	1/3	1	1/2
C7*	1/3	1/2	1/2	1/4	1/2	2	1

Normalization was applied to the comparison matrices in Tables 5 and 6. As a result of the normalization process, normalized pairwise comparison matrices shown in Tables 7 and 8, respectively, were obtained for full-time and part-time employees.

Table 7. Normalized pairwise comparison matrix for full-time recruits

Criterion	C1	C2	C3	C4	C5	C6	C7
C1	0.063	0.056	0.076	0.045	0.091	0.091	0.045
C2	0.250	0.223	0.191	0.269	0.227	0.227	0.273
C3	0.313	0.446	0.382	0.358	0.273	0.273	0.409
C4	0.125	0.074	0.096	0.090	0.136	0.136	0.068
C5	0.031	0.045	0.064	0.030	0.045	0.045	0.034
C6	0.031	0.045	0.064	0.030	0.045	0.045	0.034
C7	0.188	0.112	0.127	0.179	0.182	0.182	0.136

Table 8. Normalized pairwise comparison matrix for part-time recruits

Criterion	C1*	C2*	C3*	C4*	C5*	C6*	C7*
C1*	0.198	0.231	0.231	0.173	0.23	0.189	0.214
C2*	0.104	0.111	0.111	0.111	0.11	0.142	0.142
C3*	0.104	0.111	0.111	0.111	0.11	0.142	0.142
C4*	0.389	0.342	0.342	0.342	0.34	0.243	0.278
C5*	0.104	0.111	0.111	0.111	0.11	0.142	0.142
C6*	0.051	0.042	0.042	0.069	0.04	0.049	0.029
C7*	0.072	0.063	0.063	0.078	0.06	0.103	0.069

The weights of the criteria used in the recruitment process for full-time and part-time employees were determined using normalized pairwise comparison decision matrices. These weights are presented in Tables 9 and 10, respectively.

Table 9. The weights of the criteria for full-time recruits

Criteria	Weight
C1	0.067
C2	0.237
C3	0.351
C4	0.104

Criteria	Weight
C5	0.042
C6	0.042
C7	0.158

Table 10. The weights of the criteria for part-time recruits

Criteria	Weight
C1*	0.206
C2*	0.119
C3*	0.119
C4*	0.324
C5*	0.119
C6*	0.045
C7*	0.069

AHP Consistency Ratio Calculation and Evaluation

The pairwise comparison matrices for the full-time and part-time criteria (Tables 5 and 6) were used to compute the AHP weights and consistency ratios. As is standard, each column of the matrix was summed, and the matrix was normalized by dividing each entry by its column sum. The criteria weights were then obtained as the row-average of the normalized matrix. Finally, the maximum eigenvalue λ_{max} was estimated by multiplying the original pairwise matrix by the weight vector and averaging the elementwise ratios (or equivalently by eigen analysis), and the Consistency Index CI was computed. The Consistency Ratio CR = CI/RI was then formed, where RI is Saaty's random index (for n=7, RI≈1.32). The results are shown in the tables below. All CR values are well below 0.10, indicating acceptable consistency.

From these normalized values, the full-time weights (row averages) are **w = [0.0667, 0.2372, 0.3505, 0.1036, 0.0421, 0.0421, 0.1580]**. Multiplying the original matrix by this weight vector and averaging yields $\lambda_{max} \approx 7.145$; hence CI=(7.145–7)/6=0.0242 and CR=0.0242/1.32≈0.0183.

The part-time weights are **w = [0.2071, 0.1197, 0.1220, 0.3197, 0.1186, 0.0437, 0.0693]**. The dominant eigenvalue was found to be $\lambda_{max} \approx 7.314$, giving CI=(7.314–7)/6=0.0523 and CR≈0.0396. Both full- and part-time CR values (0.018 and 0.040) are well below the 0.10 threshold, confirming that the judgments are acceptably consistent.

4.2 Fuzzy TOPSIS Evaluation

Three decision makers who are specialists in their fields reviewed the CVs of seven individuals applying for full-time roles and seven candidates applying for part-time positions. Table 11 shows the evaluations of the candidates applying for full-time positions, whereas Table 12 shows the ratings of the candidates looking for part-time jobs.

Table 11. Expert evaluations for candidates applying for full-time positions

Decision Maker	Candidate	C1	C2	C3	C4	C5	C6	C7
DM-1	A-1	FR	GD	MG	MG	MG	MP	VG
	A-2	MG	MG	GD	FR	MG	FR	GD
	A-3	MP	MG	VG	VG	GD	GD	VG
	A-4	MP	GD	MG	MG	MG	FR	MG
	A-5	MP	FR	FR	MG	GD	FR	GD
	A-6	FR	MG	VG	GD	VG	MG	GD
	A-7	MP	MP	MP	MG	FR	FR	MG
DM-2	A-1	MP	GD	MG	MG	MG	MP	VG
	A-2	MG	GD	GD	FR	MG	FR	GD
	A-3	MP	MG	VG	GD	GD	GD	VG
	A-4	MP	GD	MG	MG	MG	FR	MG

	A-5	MP	FR	MG	FR	GD	FR	GD
	A-6	FR	MG	VG	GD	VG	MG	GD
	A-7	MP	MP	MP	MG	FR	FR	MG
DM-3	A-1	FR	GD	MG	MG	MG	MP	GD
	A-2	GD	GD	GD	FR	MG	FR	GD
	A-3	MP	MG	VG	VG	GD	MG	VG
	A-4	MP	GD	MG	MG	MG	FR	MG
	A-5	MP	MG	FR	FR	GD	FR	GD
	A-6	FR	MG	VG	GD	VG	MG	VG
	A-7	MP	MP	MP	GD	MG	FR	MG

The selection procedure for part-time jobs involves a careful examination of both academic and soft abilities such as GPA, project experience, and teamwork. To assist in the decision-making process, three domain experts graded the candidates using linguistic phrases that represent qualitative judgment. These assessments served as the foundation for the fuzzy conversion and MCDM analysis that followed.

Table 12. Expert evaluations for candidates applying for part-time positions

Decision Maker	**Candidate**	**C1***	**C2***	**C3***	**C4***	**C5***	**C6***	**C7***
	A-1*	MP	MG	FR	GD	FR	PR	GD
	A-2*	PR	FR	FR	MG	MP	PR	MP
	A-3*	MG	VG	GD	VG	FR	GD	GD
DM-1	A-4*	FR	MG	MP	VG	MG	PR	VG
	A-5*	PR	MG	MG	VG	FR	VG	VG
	A-6*	MG	VG	VG	GD	FR	VG	VG
	A-7*	MP	MG	FR	GD	FR	PR	GD
	A-1*	FR	FR	MG	GD	FR	PR	MG
	A-2*	PR	FR	FR	FR	MP	PR	MP
	A-3*	MG	VG	GD	VG	MP	GD	GD
DM-2	A-4*	FR	MG	FR	GD	MG	PR	VG
	A-5*	PR	MG	MG	VG	FR	VG	GD
	A-6*	MG	VG	GD	GD	FR	VG	VG
	A-7*	MP	GD	VG	VG	VG	MG	GD
	A-1*	MP	GD	MG	GD	MP	MP	GD
	A-2*	PR	MP	FR	MG	MP	PR	MP
	A-3*	MG	VG	GD	MG	FR	GD	GD
DM-3	A-4*	FR	MG	MG	VG	MG	PR	VG
	A-5*	PR	MG	GD	GD	MG	VG	GD
	A-6*	GD	VG	VG	VG	FR	VG	VG
	A-7*	PR	GD	VG	VG	VG	MG	VG

The linguistic evaluations mentioned in Tables 11 and 12 were transformed into fuzzy numbers using the preset linguistic variable scale shown in Table 1. Tables 13 and 14 illustrate the fuzzy values obtained for each decision maker and candidate for full-time and part-time applicants, respectively.

Table 13. Fuzzy numbers for full-time candidates (DM-wise)

Decision Maker	Candidate	C1	C2	C3	C4	C5	C6	C7
DM-1	A-1	(3,5,7)	(7,9,10)	(5,7,9)	(5,7,9)	(5,7,9)	(1,3,5)	(9,10,10)
	A-2	(5,7,9)	(5,7,9)	(7,9,10)	(3,5,7)	(5,7,9)	(3,5,7)	(7,9,10)
	A-3	(1,3,5)	(5,7,9)	(9,10,10)	(9,10,10)	(7,9,10)	(7,9,10)	(9,10,10)
	A-4	(1,3,5)	(7,9,10)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)
	A-5	(1,3,5)	(3,5,7)	(3,5,7)	(5,7,9)	(7,9,10)	(3,5,7)	(7,9,10)
	A-6	(3,5,7)	(5,7,9)	(9,10,10)	(7,9,10)	(9,10,10)	(5,7,9)	(7,9,10)
	A-7	(1,3,5)	(1,3,5)	(1,3,5)	(5,7,9)	(3,5,7)	(3,5,7)	(5,7,9)
DM-2	A-1	(1,3,5)	(7,9,10)	(5,7,9)	(5,7,9)	(5,7,9)	(1,3,5)	(9,10,10)
	A-2	(5,7,9)	(7,9,10)	(7,9,10)	(3,5,7)	(5,7,9)	(3,5,7)	(7,9,10)
	A-3	(1,3,5)	(5,7,9)	(9,10,10)	(7,9,10)	(7,9,10)	(7,9,10)	(9,10,10)
	A-4	(1,3,5)	(7,9,10)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)
	A-5	(1,3,5)	(3,5,7)	(5,7,9)	(3,5,7)	(7,9,10)	(3,5,7)	(7,9,10)
	A-6	(3,5,7)	(5,7,9)	(9,10,10)	(7,9,10)	(9,10,10)	(5,7,9)	(7,9,10)
	A-7	(1,3,5)	(1,3,5)	(1,3,5)	(5,7,9)	(3,5,7)	(3,5,7)	(5,7,9)
DM-3	A-1	(3,5,7)	(7,9,10)	(5,7,9)	(5,7,9)	(5,7,9)	(1,3,5)	(7,9,10)
	A-2	(7,9,10)	(7,9,10)	(7,9,10)	(3,5,7)	(5,7,9)	(3,5,7)	(7,9,10)
	A-3	(1,3,5)	(5,7,9)	(9,10,10)	(9,10,10)	(7,9,10)	(5,7,9)	(9,10,10)
	A-4	(1,3,5)	(7,9,10)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)
	A-5	(1,3,5)	(5,7,9)	(3,5,7)	(3,5,7)	(7,9,10)	(3,5,7)	(7,9,10)
	A-6	(3,5,7)	(5,7,9)	(9,10,10)	(7,9,10)	(9,10,10)	(5,7,9)	(9,10,10)
	A-7	(1,3,5)	(1,3,5)	(1,3,5)	(7,9,10)	(5,7,9)	(3,5,7)	(5,7,9)

Table 14. Fuzzy numbers for part-time candidates (DM-wise)

Decision Maker	Candidate	C1*	C2*	C3*	C4*	C5*	C6*	C7*
DM-1	A-1*	(1,3,5)	(5,7,9)	(3,5,7)	(7,9,10)	(3,5,7)	(0,1,3)	(7,9,10)
	A-2*	(0,1,3)	(3,5,7)	(3,5,7)	(5,7,9)	(1,3,5)	(0,1,3)	(1,3,5)
	A-3*	(5,7,9)	(9,10,10)	(7,9,10)	(9,10,10)	(3,5,7)	(7,9,10)	(7,9,10)
	A-4*	(3,5,7)	(5,7,9)	(1,3,5)	(9,10,10)	(5,7,9)	(0,1,3)	(9,10,10)
	A-5*	(0,1,3)	(5,7,9)	(5,7,9)	(9,10,10)	(3,5,7)	(9,10,10)	(9,10,10)
	A-6*	(5,7,9)	(9,10,10)	(9,10,10)	(7,9,10)	(3,5,7)	(9,10,10)	(9,10,10)
	A-7*	(1,3,5)	(5,7,9)	(3,5,7)	(7,9,10)	(3,5,7)	(0,1,3)	(7,9,10)
DM-2	A-1*	(3,5,7)	(3,5,7)	(5,7,9)	(7,9,10)	(3,5,7)	(0,1,3)	(5,7,9)
	A-2*	(0,1,3)	(3,5,7)	(3,5,7)	(3,5,7)	(1,3,5)	(0,1,3)	(1,3,5)
	A-3*	(5,7,9)	(9,10,10)	(7,9,10)	(9,10,10)	(1,3,5)	(7,9,10)	(7,9,10)
	A-4*	(3,5,7)	(5,7,9)	(3,5,7)	(7,9,10)	(5,7,9)	(0,1,3)	(9,10,10)
	A-5*	(0,1,3)	(5,7,9)	(5,7,9)	(9,10,10)	(3,5,7)	(9,10,10)	(7,9,10)
	A-6*	(5,7,9)	(9,10,10)	(7,9,10)	(7,9,10)	(3,5,7)	(9,10,10)	(9,10,10)
	A-7*	(1,3,5)	(7,9,10)	(9,10,10)	(9,10,10)	(9,10,10)	(5,7,9)	(7,9,10)
DM-3	A-1*	(1,3,5)	(7,9,10)	(5,7,9)	(7,9,10)	(1,3,5)	(1,3,5)	(7,9,10)
	A-2*	(0,1,3)	(1,3,5)	(3,5,7)	(5,7,9)	(1,3,5)	(0,1,3)	(1,3,5)
	A-3*	(5,7,9)	(9,10,10)	(7,9,10)	(5,7,9)	(3,5,7)	(7,9,10)	(7,9,10)
	A-4*	(3,5,7)	(5,7,9)	(5,7,9)	(9,10,10)	(5,7,9)	(0,1,3)	(9,10,10)

	A-5*	(0,1,3)	(5,7,9)	(7,9,10)	(7,9,10)	(5,7,9)	(9,10,10)	(7,9,10)
	A-6*	(7,9,10)	(9,10,10)	(9,10,10)	(9,10,10)	(3,5,7)	(9,10,10)	(9,10,10)
	A-7*	(0,1,3)	(7,9,10)	(9,10,10)	(9,10,10)	(9,10,10)	(5,7,9)	(9,10,10)

After transforming the linguistic evaluations into triangular fuzzy numbers, the individual opinions of decision makers were combined to create a single fuzzy decision matrix for each candidate. Tables 15 and 16 indicate the aggregated fuzzy scores for both full-time and part-time applicants.

Table 15. Combined fuzzy decision matrix – full-time

Candidate	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
A-1	(1,4.333,7)	(7,9,10)	(5,7,9)	(5,7,9)	(5,7,9)	(1,3,5)	(7,9.666,10)
A-2	(5,7.666,10)	(5,8.333,10)	(7,9,10)	(3,5,7)	(5,7,9)	(3,5,7)	(7,9,10)
A-3	(1,3,5)	(5,7,9)	(9,10,10)	(7,9.666,10)	(7,9,10)	(5,8.333,10)	(9,10,10)
A-4	(1,3,5)	(7,9,10)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)
A-5	(1,3,5)	(3,5.666,9)	(3,5.666,9)	(3,5.666,9)	(7,9,10)	(3,5,7)	(7,9,10)
A-6	(3,5,7)	(5,7,9)	(9,10,10)	(7,9,10)	(9,10,10)	(5,7,9)	(7,9.333,10)
A-7	(1,3,5)	(1,3,5)	(1,3,5)	(5,7.666,10)	(3,5.666,9)	(3,5,7)	(5,7,9)

Table 16. Combined fuzzy decision matrix – part-time

Candidate	**C1***	**C2***	**C3***	**C4***	**C5***	**C6***	**C7***
A-1*	(1,3.666,7)	(3,7,10)	(3,6.333,9)	(7,9,10)	(1,4.333,7)	(0,1.666,5)	(5,8.333,10)
A-2*	(0,1,3)	(1,4.333,7)	(3,5,7)	(3,6.333,9)	(1,3,5)	(0,1,3)	(1,3,5)
A-3*	(5,7,9)	(9,10,10)	(7,9,10)	(5,9,10)	(1,4.333,7)	(7,9,10)	(7,9,10)
A-4*	(3,5,7)	(5,7,9)	(1,5,9)	(7,9.666,10)	(5,7,9)	(0,1,3)	(9,10,10)
A-5*	(0,1,3)	(5,7,9)	(5,7.666,10)	(7,9.666,10)	(3,5.666,9)	(9,10,10)	(7,9.333,10)
A-6*	(5,7.666,10)	(9,10,10)	(7,9.666,10)	(7,9.333,10)	(3,5,7)	(9,10,10)	(9,10,10)
A-7*	(0,1.666,5)	(7,9.333,10)	(9,10,10)	(9,10,10)	(9,10,10)	(5,7,9)	(7,9.333,10)

The fuzzy decision matrices were normalized to remove the effects of varying measurement scales and allow for uniform comparison across all criteria. Tables 17 and 18 show the normalized fuzzy values for each applicant based on full-time and part-time positions, respectively.

Table 17. Normalized fuzzy decision matrix – full-time

Candidate	C1	C2	C3	C4	C5	C6	C7
A-1	(0.1,0.433,0.7)	(0.7,0.9,1)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.7,0.967,1)
A-2	(0.5,0.767,1)	(0.5,0.833,1)	(0.7,0.9,1)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.7,0.9,1)
A-3	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0.9,1,1)	(0.7,0.967,1)	(0.7,0.9,1)	(0.5,0.833,1)	(0.9,1,1)
A-4	(0.1,0.3,0.5)	(0.7,0.9,1)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)
A-5	(0.1,0.3,0.5)	(0.3,0.567,0.9)	(0.3,0.567,0.9)	(0.3,0.567,0.9)	(0.7,0.9,1)	(0.3,0.5,0.7)	(0.7,0.9,1)
A-6	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.9,1,1)	(0.7,0.9,1)	(0.9,1,1)	(0.5,0.7,0.9)	(0.7,0.933,1)
A-7	(0.1,0.3,0.5)	(0.1,0.3,0.5)	(0.1,0.3,0.5)	(0.5,0.767,1)	(0.3,0.567,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)

Table 18. Normalized fuzzy decision matrix – part-time

Candidate	C1*	C2*	C3*	C4*	C5*	C6*	C7*
A-1*	(0.1,0.367,0.7)	(0.3,0.7,1)	(0.3,0.633,0.9)	(0.7,0.9,1)	(0.1,0.433,0.7)	(0,0.167,0.5)	(0.5,0.833,1)
A-2*	(0,0.1,0.3)	(0.1,0.433,0.7)	(0.3,0.5,0.7)	(0.3,0.633,0.9)	(0.1,0.3,0.5)	(0,0.1,0.3)	(0.1,0.3,0.5)
A-3*	(0.5,0.7,0.9)	(0.9,1,1)	(0.7,0.9,1)	(0.5,0.9,1)	(0.1,0.433,0.7)	(0.7,0.9,1)	(0.7,0.9,1)
A-4*	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.1,0.5,0.9)	(0.7,0.967,1)	(0.5,0.7,0.9)	(0,0.1,0.3)	(0.9,1,1)
A-5*	(0,0.1,0.3)	(0.5,0.7,0.9)	(0.5,0.767,1)	(0.7,0.967,1)	(0.3,0.567,0.9)	(0.9,1,1)	(0.7,0.933,1)
A-6*	(0.5,0.767,1)	(0.9,1,1)	(0.7,0.967,1)	(0.7,0.933,1)	(0.3,0.5,0.7)	(0.9,1,1)	(0.9,1,1)
A-7*	(0,0.167,0.5)	(0.7,0.933,1)	(0.9,1,1)	(0.9,1,1)	(0.9,1,1)	(0.5,0.7,0.9)	(0.7,0.933,1)

The normalized fuzzy decision matrices were multiplied by their corresponding AHP-derived weights to account for both normalized candidate evaluations and the relative importance of criterion. Tables 19 and 20 show the weighted normalized fuzzy decision matrices generated for full-time and part-time positions, respectively.

Table 19. Weighted normalized fuzzy decision matrix – full-time

Candidate	C1	C2	C3	C4	C5	C6	C7
A-1	(0.007, 0.029, 0.047)	(0.166, 0.213, 0.237)	(0.176, 0.246, 0.316)	(0.052, 0.073, 0.094)	(0.021, 0.029, 0.038)	(0.005, 0.013, 0.021)	(0.111, 0.153, 0.158)
A-2	(0.034, 0.051, 0.067)	(0.119, 0.197, 0.237)	(0.246, 0.316, 0.351)	(0.032, 0.052, 0.073)	(0.021, 0.029, 0.038)	(0.013, 0.021, 0.030)	(0.111, 0.143, 0.158)
A-3	(0.007, 0.021, 0.034)	(0.119, 0.166, 0.213)	(0.316, 0.351, 0.351)	(0.073, 0.101, 0.104)	(0.029, 0.038, 0.042)	(0.021, 0.035, 0.042)	(0.143, 0.158, 0.158)
A-4	(0.007, 0.021, 0.034)	(0.166, 0.213, 0.237)	(0.176, 0.246, 0.316)	(0.052, 0.073, 0.094)	(0.021, 0.029, 0.038)	(0.013, 0.021, 0.030)	(0.079, 0.111, 0.143)
A-5	(0.007, 0.021, 0.034)	(0.072, 0.134, 0.213)	(0.106, 0.199, 0.316)	(0.032, 0.059, 0.094)	(0.029, 0.038, 0.042)	(0.013, 0.021, 0.030)	(0.111, 0.143, 0.158)
A-6	(0.021, 0.034, 0.047)	(0.119, 0.166, 0.213)	(0.316, 0.351, 0.351)	(0.073, 0.094, 0.104)	(0.038, 0.042, 0.042)	(0.021, 0.030, 0.038)	(0.111, 0.148, 0.158)
A-7	(0.007, 0.021, 0.034)	(0.024, 0.072, 0.119)	(0.036, 0.106, 0.176)	(0.052, 0.080, 0.104)	(0.013, 0.024, 0.038)	(0.013, 0.021, 0.030)	(0.079, 0.111, 0.143)

Table 20. Weighted normalized fuzzy decision matrix – part-time

Candidate	C1*	C2*	C3*	C4*	C5*	C6*	C7*
A-1*	(0.021, 0.076, 0.145)	(0.036, 0.083, 0.119)	(0.036, 0.076, 0.108)	(0.227, 0.292, 0.324)	(0.012, 0.052, 0.083)	(0.000, 0.008, 0.023)	(0.035, 0.058, 0.069)
A-2*	(0.000, 0.021, 0.062)	(0.012, 0.052, 0.083)	(0.036, 0.060, 0.083)	(0.098, 0.206, 0.292)	(0.012, 0.036, 0.060)	(0.000, 0.005, 0.014)	(0.007, 0.021, 0.035)
A-3*	(0.103, 0.145, 0.186)	(0.108, 0.119, 0.119)	(0.083, 0.108, 0.119)	(0.162, 0.292, 0.324)	(0.012, 0.052, 0.083)	(0.032, 0.041, 0.045)	(0.049, 0.063, 0.069)
A-4*	(0.062, 0.103, 0.145)	(0.060, 0.083, 0.108)	(0.012, 0.060, 0.108)	(0.227, 0.314, 0.324)	(0.060, 0.083, 0.108)	(0.000, 0.005, 0.014)	(0.063, 0.069, 0.069)
A-5*	(0.000, 0.021, 0.062)	(0.060, 0.083, 0.108)	(0.060, 0.092, 0.119)	(0.227, 0.314, 0.324)	(0.036, 0.068, 0.108)	(0.041, 0.045, 0.045)	(0.049, 0.065, 0.069)
A-6*	(0.103, 0.158, 0.206)	(0.108, 0.119, 0.119)	(0.083, 0.115, 0.119)	(0.227, 0.303, 0.324)	(0.036, 0.060, 0.083)	(0.041, 0.045, 0.045)	(0.063, 0.069, 0.069)
A-7*	(0.000, 0.035, 0.103)	(0.083, 0.111, 0.119)	(0.108, 0.119, 0.119)	(0.292, 0.324, 0.324)	(0.108, 0.119, 0.119)	(0.023, 0.032, 0.041)	(0.049, 0.065, 0.069)

Weighted fuzzy decision matrices were used to identify the FPIS-A* and FNIS-A^- for each criterion. These reference points serve as standards for comparing applicant performance to ideal and least acceptable values, as shown in Tables 21 and 22 for full-time and part-time candidates, respectively.

Table 21. Fuzzy positive and negative ideal solutions – full-time

Criterion	A* (FPIS)	A^- (FNIS)
C1	(0.0335,0.0513,0.067)	(0.0067,0.0201,0.0335)
C2	(0.1659,0.2133,0.237)	(0.0237,0.0711,0.1185)
C3	(0.3159,0.351,0.351)	(0.0351,0.1053,0.1755)
C4	(0.0728,0.1005,0.104)	(0.0312,0.052,0.0728)
C5	(0.0378,0.042,0.042)	(0.0126,0.0237,0.0378)
C6	(0.021,0.0349,0.042)	(0.0042,0.0126,0.021)
C7	(0.1422,0.158,0.158)	(0.079,0.1106,0.1422)

Table 22. Fuzzy positive and negative ideal solutions – part-time

Criterion	A* (FPIS)	A^- (FNIS)
C1*	(0.103,0.1579,0.206)	(0,0.0206,0.0618)
C2*	(0.1071,0.119,0.119)	(0.0119,0.0515,0.0833)
C3*	(0.1071,0.119,0.119)	(0.0357,0.0595,0.0833)
C4*	(0.2916,0.324,0.324)	(0.0972,0.2051,0.2916)
C5*	(0.1071,0.119,0.119)	(0.0119,0.0357,0.0595)
C6*	(0.0405,0.045,0.045)	(0,0.0045,0.0135)
C7*	(0.0621,0.069,0.069)	(0.0069,0.0207,0.0345)

After constructing the weighted normalized fuzzy decision matrices, the distance between each alternative and the FPIS and FNIS was calculated. These distances form the basis for determining each candidate's relative proximity to the best solution, as illustrated in Tables 23 and 24 for full-time and part-time roles, respectively.

Table 23. Distances to FPIS/FNIS – full-time

Candidate	d* (Distance to FPIS)	d^- (Distance to FNIS)
A-1	0.1985	0.3428
A-2	0.1599	0.3858
A-3	0.0771	0.4535
A-4	0.2256	0.3102
A-5	0.3268	0.2380
A-6	0.0856	0.4491
A-7	0.4970	0.0452

Table 24. Distances to FPIS/FNIS – part-time

Candidate	d* (Distance to FPIS)	d^- (Distance to FNIS)
A-1*	0.3350	0.2528
A-2*	0.5555	0.0000
A-3*	0.1919	0.3856
A-4*	0.2642	0.3250
A-5*	0.2940	0.2793
A-6*	0.1109	0.4506
A-7*	0.1465	0.4192

In the last stage of the fuzzy TOPSIS technique, each candidate's closeness coefficient (CCi) was obtained by comparing their relative distances from the ideal and anti-ideal solutions. These factors were then applied to rank the candidates, as shown in Tables 25 and 26 for full-time and part-time roles, respectively.

Table 25. Closeness coefficients and rankings – full-time

Candidate	CCi	Rank
A-1	0.6333	4

A-2	0.7070	3
A-3	0.8547	1
A-4	0.5790	5
A-5	0.4214	6
A-6	0.8399	2
A-7	0.0834	7

Table 26. Closeness coefficients and rankings – part-time

Candidate	CCi	Rank
A-1*	0.4301	6
A-2*	0.0000	7
A-3*	0.6677	3
A-4*	0.5516	4
A-5*	0.4872	5
A-6*	0.8025	1
A-7*	0.7411	2

4.3 Fuzzy VIKOR Evaluation

The fuzzy evaluations provided by decision makers (see Tables 13 and 14) have been converted to numerical expressions for use in the VIKOR approach. Based on these evaluations, the fuzzy importance values for each candidate across all criteria were determined individually for full-time and part-time roles, as shown in Tables 27 and 28.

Table 27. Importance weights by criterion – full-time (VIKOR)

Candidate	C1	C2	C3	C4	C5	C6	C7
A-1	(2.33,4.33,6.33)	(7.00,9.00,10.00)	(5.00,7.00,9.00)	(5.00,7.00,9.00)	(5.00,7.00,9.00)	(1.00,3.00,5.00)	(8.33,9.67,10.00)
A-2	(5.67,7.67,9.33)	(6.33,8.33,9.67)	(7.00,9.00,10.00)	(3.00,5.00,7.00)	(5.00,7.00,9.00)	(3.00,5.00,7.00)	(7.00,9.00,10.00)
A-3	(1.00,3.00,5.00)	(5.00,7.00,9.00)	(9.00,10.00,10.00)	(8.33,9.67,10.00)	(7.00,9.00,10.00)	(6.33,8.33,9.67)	(9.00,10.00,10.00)
A-4	(1.00,3.00,5.00)	(7.00,9.00,10.00)	(5.00,7.00,9.00)	(5.00,7.00,9.00)	(5.00,7.00,9.00)	(3.00,5.00,7.00)	(5.00,7.00,9.00)
A-5	(1.00,3.00,5.00)	(3.67,5.67,7.67)	(3.67,5.67,7.67)	(3.67,5.67,7.67)	(7.00,9.00,10.00)	(3.00,5.00,7.00)	(7.00,9.00,10.00)
A-6	(3.00,5.00,7.00)	(5.00,7.00,9.00)	(9.00,10.00,10.00)	(7.00,9.00,10.00)	(9.00,10.00,10.00)	(5.00,7.00,9.00)	(7.67,9.33,10.00)
A-7	(1.00,3.00,5.00)	(1.00,3.00,5.00)	(1.00,3.00,5.00)	(5.67,7.67,9.33)	(3.67,5.67,7.67)	(3.00,5.00,7.00)	(5.00,7.00,9.00)

Table 28. Importance weights by criterion – part-time (VIKOR)

Candidate	C1*	C2*	C3*	C4*	C5*	C6*	C7*
A-1*	(1.67,3.67,5.67)	(5.00,7.00,8.67)	(4.33,6.33,8.33)	(7.00,9.00,10.00)	(2.33,4.33,6.33)	(0.33,1.67,3.67)	(6.33,8.33,9.67)
A-2*	(0.00,1.00,3.00)	(2.33,4.33,6.33)	(3.00,5.00,7.00)	(4.33,6.33,8.33)	(1.00,3.00,5.00)	(0.00,1.00,3.00)	(1.00,3.00,5.00)
A-3*	(5.00,7.00,9.00)	(9.00,10.00,10.00)	(7.00,9.00,10.00)	(7.67,9.00,9.67)	(2.33,4.33,6.33)	(7.00,9.00,10.00)	(7.00,9.00,10.00)
A-4*	(3.00,5.00,7.00)	(5.00,7.00,9.00)	(3.00,5.00,7.00)	(8.33,9.67,10.00)	(5.00,7.00,9.00)	(0.00,1.00,3.00)	(9.00,10.00,10.00)
A-5*	(0.00,1.00,3.00)	(5.00,7.00,9.00)	(5.67,7.67,9.33)	(8.33,9.67,10.00)	(3.67,5.67,7.67)	(9.00,10.00,10.00)	(7.67,9.33,10.00)
A-6*	(5.67,7.67,9.33)	(9.00,10.00,10.00)	(8.33,9.67,10.00)	(7.67,9.33,10.00)	(3.00,5.00,7.00)	(9.00,10.00,10.00)	(9.00,10.00,10.00)
A-7*	(0.33,1.67,3.67)	(7.67,9.33,10.00)	(9.00,10.00,10.00)	(9.00,10.00,10.00)	(9.00,10.00,10.00)	(5.00,7.00,9.00)	(7.67,9.33,10.00)

The fuzzy VIKOR procedure determined the optimal (f*j) and worst (f⁻j) fuzzy performance values for each criterion. These values serve as reference points for determining the distance between each alternative and the ideal and anti-ideal solutions, as illustrated in Tables 29 and 30 for full-time and part-time candidates.

Table 29. Best/worst fuzzy values per criterion – full-time (VIKOR)

Criterion	Best (f*)	Worst (f⁻)
C1	(5.67,7.67,9.33)	(1.00,3.00,5.00)
C2	(7.00,9.00,10.00)	(1.00,3.00,5.00)
C3	(9.00,10.00,10.00)	(1.00,3.00,5.00)
C4	(8.33,9.67,10.00)	(3.00,5.00,7.00)
C5	(9.00,10.00,10.00)	(3.00,5.00,7.00)
C6	(6.33,8.33,9.67)	(1.00,3.00,5.00)
C7	(9.00,10.00,10.00)	(5.00,7.00,9.00)

Table 30. Best/worst fuzzy values per criterion – part-time (VIKOR)

Criterion	Best (f*)	Worst (f⁻)
C1*	(5.67,7.67,9.33)	(0.00,1.00,3.00)
C2*	(9.00,10.00,10.00)	(2.33,4.33,6.33)
C3*	(9.00,10.00,10.00)	(3.00,5.00,7.00)
C4*	(9.00,10.00,10.00)	(4.33,6.33,8.33)
C5*	(9.00,10.00,10.00)	(1.00,3.00,5.00)
C6*	(9.00,10.00,10.00)	(0.00,1.00,3.00)
C7*	(9.00,10.00,10.00)	(1.00,3.00,5.00)

In the VIKOR methodology, the Si and Ri values represent the overall group utility and individual regret for each candidate, respectively. These values, which reflect the candidate's proximity to the ideal and worst solutions, are summarized in Tables 31 and 32 for full-time and part-time applicants.

Table 31. Si and Ri values – full-time

Candidate	Si	Ri
A-1	0.552	0.206
A-2	0.496	0.205
A-3	0.161	0.102
A-4	0.572	0.215
A-5	0.659	0.250
A-6	0.175	0.102
A-7	0.977	0.351

Table 32. Si and Ri values – part-time

Candidate	Si	Ri
A-1*	0.615	0.233
A-2*	0.933	0.506
A-3*	0.457	0.207
A-4*	0.502	0.240
A-5*	0.553	0.278
A-6*	0.181	0.102
A-7*	0.226	0.129

To proceed with the calculation of the Qi compromise index in the VIKOR method, the best (S*, R*) and worst (S^-, R^-) values of group utility and individual regret were identified. These reference values are presented in Tables 33 and 34 for full-time and part-time candidates, respectively.

Table 33. S, S-, R, R- – full-time**

Metric	Value
S*	0.161
S-	0.977
R*	0.102
R-	0.351

Table 34. S, S-, R, R- – part-time**

Metric	Value
S*	0.181
S-	0.933
R*	0.102
R-	0.506

Based on the previously calculated Si and Ri values, the Qi compromise index was computed for each candidate. The resulting Qi scores were then used to generate a final ranking, as shown in Tables 35 and 36 for full-time and part-time applicants, respectively.

Table 35. Qi index and rankings – full-time

Candidate	Qi	Rank
A-3	0.0089	1
A-6	0.0099	2
A-2	0.4057	3
A-1	0.4796	4
A-4	0.5130	5
A-5	0.6760	6
A-7	0.9998	7

Table 36. Qi index and rankings – part-time

Candidate	Qi	Rank
A-6*	0.0000	1
A-7*	0.0694	2
A-3*	0.3198	3
A-4*	0.3861	4
A-5*	0.5113	5
A-1*	0.6712	6
A-2*	1.0003	7

4.4 Cross-Method Comparison

To assess the consistency and robustness of the hybrid decision-making framework, the final rankings obtained from both Fuzzy TOPSIS and Fuzzy VIKOR methods were compared for full-time and part-time candidates. The following tables present a side-by-side comparison of these rankings, highlighting the degree of alignment between the two methodologies, as shown in Tables 37 and 38 for full-time and part-time applicants, respectively.

Table 37. Comparison of rankings – full-time

Candidate	TOPSIS Rank	VIKOR Rank
A-3	1	1
A-6	2	2
A-2	3	3
A-1	4	4
A-4	5	5
A-5	6	6
A-7	7	7

Table 38. Comparison of rankings – part-time

Candidate	TOPSIS Rank	VIKOR Rank
A-6*	1	1
A-7*	2	2
A-3*	3	3
A-4*	4	4
A-5*	5	5
A-1*	6	6
A-2*	7	7

The strong agreement in results demonstrates methodological robustness across both fuzzy TOPSIS and VIKOR methods.

4.5 Hybrid Ranking Fusion: Integrating Fuzzy TOPSIS and Fuzzy VIKOR Results

To assess the effectiveness of the hybrid ranking method described in Section 3, the candidate evaluation problem was solved using the FCRS. This method combines the results of Fuzzy TOPSIS and Fuzzy VIKOR into a single, unified score to improve the resilience and interpretability of the decision-making process. Fuzzy TOPSIS measures each alternative's

proximity to an ideal solution, whereas Fuzzy VIKOR considers a trade-off between group gain and individual displeasure. The FCRS, as formally stated in Equation (16), operates this integration by taking a weighted average of both metrics. In this study, the weight parameter β was set to 0.5, equal importance is given to both methods, resulting in a more balanced and interpretable ranking.

The integrated FCRS for full-time candidates, along with individual Fuzzy TOPSIS and Fuzzy VIKOR values, are presented in Table 39, highlighting that candidates A-3 and A-6 emerged as top performers based on both closeness and compromise metrics.

Table 39. FCRS application to full-time candidates

Candidate	CC_i^{TOPSIS}	Q_i^{VIKOR}	$1 - Q_i^{VIKOR}$	$FCRS_i$	Rank
A-1	0.6333	0.4796	0.5204	0.5768	4
A-2	0.7070	0.4057	0.5943	0.6507	3
A-3	0.8547	0.0089	0.9911	0.9229	1
A-4	0.5790	0.5130	0.4870	0.5330	5
A-5	0.4214	0.6760	0.3240	0.3727	6
A-6	0.8399	0.0099	0.9901	0.9150	2
A-7	0.0834	0.9998	0.0002	0.0418	7

A similar analysis for part-time candidates is shown in Table 40, where A-6* and A-7* achieved the highest composite scores, validating the model's ability to handle part-time selection with consistent ranking logic.

Table 40. FCRS application to part-time candidates

Candidate	CC_i^{TOPSIS}	Q_i^{VIKOR}	$1 - Q_i^{VIKOR}$	$FCRS_i$	Rank
A-1*	0.4301	0.6712	0.3288	0.3794	6
A-2*	0.0000	1.0003	-0.0003	-0.0002	7
A-3*	0.6677	0.3198	0.6802	0.6740	3
A-4*	0.5516	0.3861	0.6139	0.5828	4
A-5*	0.4872	0.5113	0.4887	0.4879	5
A-6*	0.8025	0.0000	1.0000	0.9012	1
A-7*	0.7411	0.0694	0.9306	0.8358	2

The ranking results show that candidates A-3 and A-6 (full-time), as well as A-6* and A-7* (part-time), regularly beat others in both Fuzzy TOPSIS and Fuzzy VIKOR. The suggested FCRS score not only confirms the agreement between the two methodologies but also quantifies it as a single interpretable statistic that can be used to make final decisions.

This hybrid fusion method provides a scalable and adaptable framework for aggregating fuzzy multi-criteria rankings. It improves stability, robustness, and discriminatory power by incorporating various ranking logics into a single value.

This methodology is easily extended to additional MCDM combinations (e.g., Fuzzy TOPSIS-EDAS, AHP-MARCOS), as well as decision-making scenarios in education, public administration, and HRs.

5. Discussion and Findings

This section provides a complete analysis of the findings achieved by using the suggested hybrid AHP-Fuzzy TOPSIS-Fuzzy VIKOR model to evaluate candidates for both full-time and part-time roles. The findings aim to improve interpretability, evaluate the framework's resilience, and provide practical decision support by combining visual representations and theoretical components. The rankings provided by Fuzzy TOPSIS and Fuzzy VIKOR are compared in order to assess technique consistency and establish the hybrid approach's reliability.

For full-time positions, Candidate A-3 ranked first in both ways, closely followed by A-6. These findings emphasize the importance of professional expertise and teamwork, which had the highest AHP-derived weights. For part-time positions,

Candidate A-6* was consistently ranked first, followed by A-7*. This shows that communication skills and language competency, which are the most important factors for part-time evaluations, were well captured in the decision-making process.

The proximity coefficients (Fuzzy TOPSIS) and Qi indices (Fuzzy VIKOR) indicate a high level of concordance between approaches, with no inconsistencies in the top or bottom ranks. This cross-method consistency improves the hybrid framework's reliability, particularly in the presence of language uncertainty and subjective assessment. The findings also show that the methodology is appropriate for medium-sized institutions, with a replicable and scalable strategy for organized people selection.

The following sub-sections cover empirical consistency checks, criterion prioritizing, decision modeling, and sensitivity analysis.

5.1 Consistency Between Fuzzy TOPSIS and Fuzzy VIKOR

The scatter plot in Figure 2 illustrates the correlation between Fuzzy TOPSIS closeness coefficients and Fuzzy VIKOR compromise indices. Candidates cluster along a near-linear trajectory, confirming a strong monotonic relationship. This empirical consistency supports the robustness of the dual-method model.

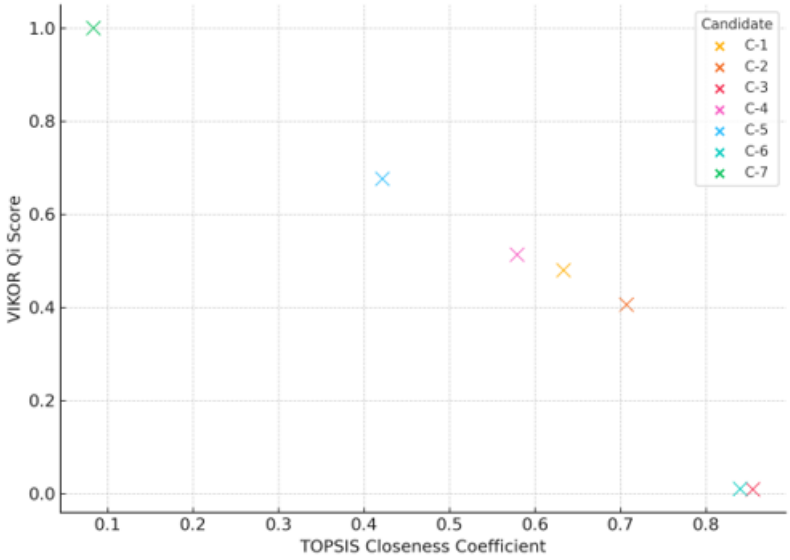

Figure 2. Correlation between Fuzzy TOPSIS and Fuzzy VIKOR rankings

This scatter plot depicts the linear relationship between the Fuzzy TOPSIS closeness coefficients and the complementary VIKOR indices (1 - Qi). The near-perfect alignment shows a high level of methodological agreement, particularly among the top and bottom-ranked candidates. The figure empirically confirms the hybrid framework's robustness, demonstrating that both methods provide consistent and convergent rankings in the presence of uncertainty.

5.2 Prioritization of Criteria via AHP

The weight distribution in Figure 3 shows role-specific prioritization: 'Experience' and 'Education' emerged as dominant characteristics for full-time roles, but 'Communication' and 'Language' were most significant for part-time candidates. These different priorities are consistent with the KSC's institutional goals, demonstrating the contextual adaptability of the AHP technique.

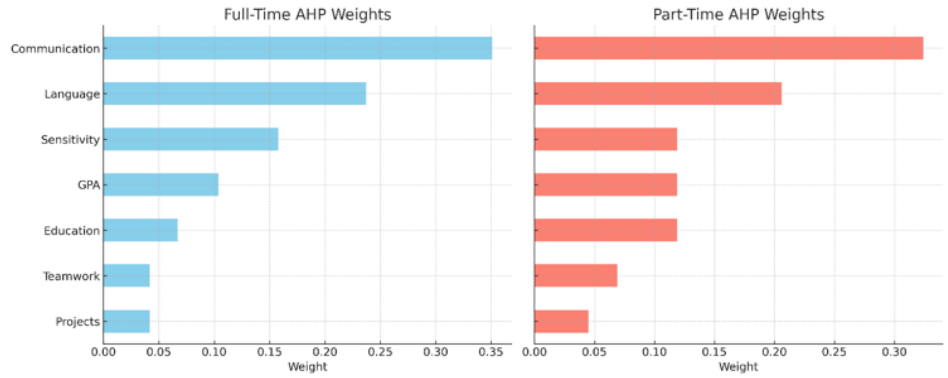

Figure 3. AHP-derived criteria weights for full-time and part-time positions

This bar chart shows the distribution of AHP-calculated weights for each criterion by employment type. Experience and Education are the most important weighted factors for full-time work, whereas Communication Skills and Language Proficiency are more important in part-time roles. These findings reflect context-specific institutional priorities at KSC and demonstrate the AHP method's applicability to a variety of role requirements.

5.3 Criteria-Based Candidate Profiling

Radar charts in Figure 4 visualize the contribution patterns of candidates across all evaluation criteria. Top-performing individuals (A-3, A-6, A-6*) display balanced excellence across core and supplementary criteria, while lower-ranked candidates show sharp deficiencies, particularly in foundational competencies. These profiles reveal distinct performance patterns such as:

- A-3 and A-6: Strong in *Experience*, *Teamwork*, and *Communication* — aligns with their top rankings.
- A-7: Weak across all dimensions, particularly in *Experience* and *Education*.
- A-5: Higher scores in secondary criteria (*Sensitivity*, *Certificate*), but weaker in core competencies.

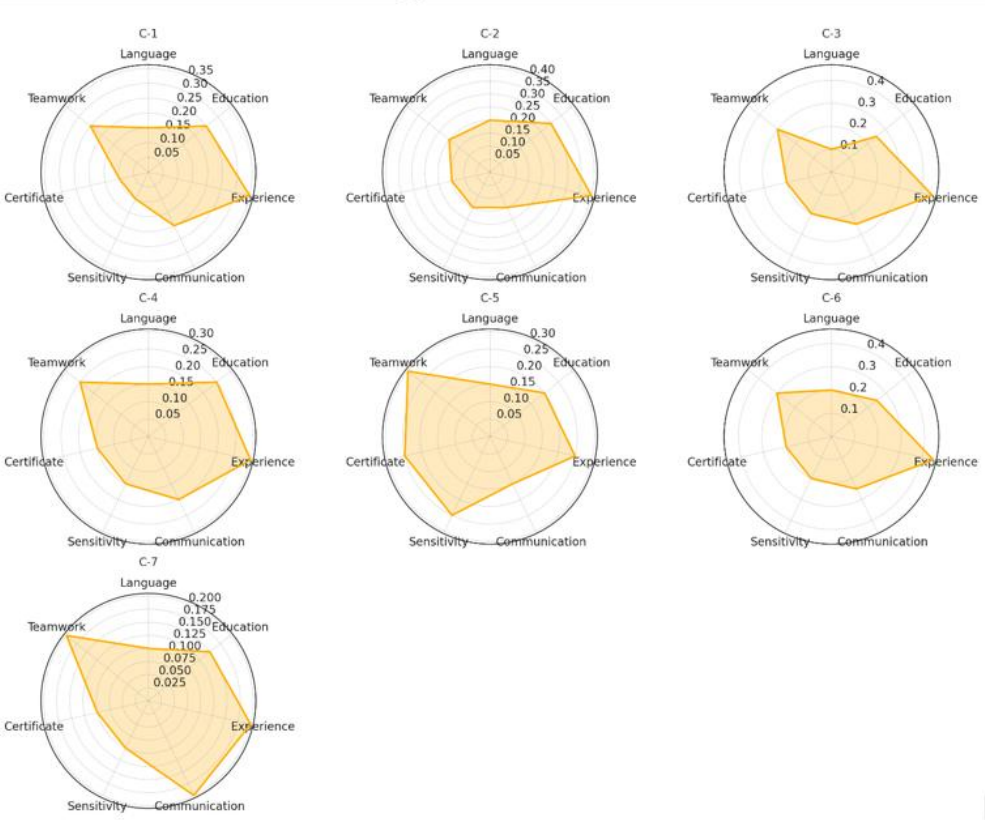

Figure 4. Criteria-based contribution profiles of candidates (radar chart)

Figure 4 shows radar maps that depict the performance distribution of applicants across all evaluation criteria. The goal of these visualizations is to present a multidimensional picture of candidate strengths and weaknesses, allowing for criterion-specific interpretation. Top-ranked full-time candidates (A-3 and A-6) demonstrate balanced and elevated scores across high-weighted criteria such as Professional Experience and Teamwork Compatibility, whereas lower-ranked candidates (e.g., A-7) have weaker profiles, particularly in foundational dimensions including Education and Communication Skills. Similarly, part-time candidates A-6* and A-7* outperform in criteria such as Language Proficiency and Communication, nearly matching the highest AHP-derived weights. These radar profiles visually corroborate the numerical results, enabling decision-makers to understand performance disparities that extend beyond aggregate ratings.

5.4 Sensitivity Analysis: Impact of AHP Weight Variations

To assess model robustness, each AHP weight was increased by 20%, and the resulting FCRS scores were recorded. As illustrated in Figure 5, 'Experience' and 'Teamwork' had the greatest impact on ranks, emphasizing their importance in the grading scheme. In contrast, 'Certificate' and 'Sensitivity' produced just marginal changes, indicating that they had little influence on final results. The heatmap shows that:

- The most influential characteristics are *Experience* and *Teamwork*, with little weight changes causing significant ranking variations.
- *Sensitivity* and *Certificate* have less influence on final selections.

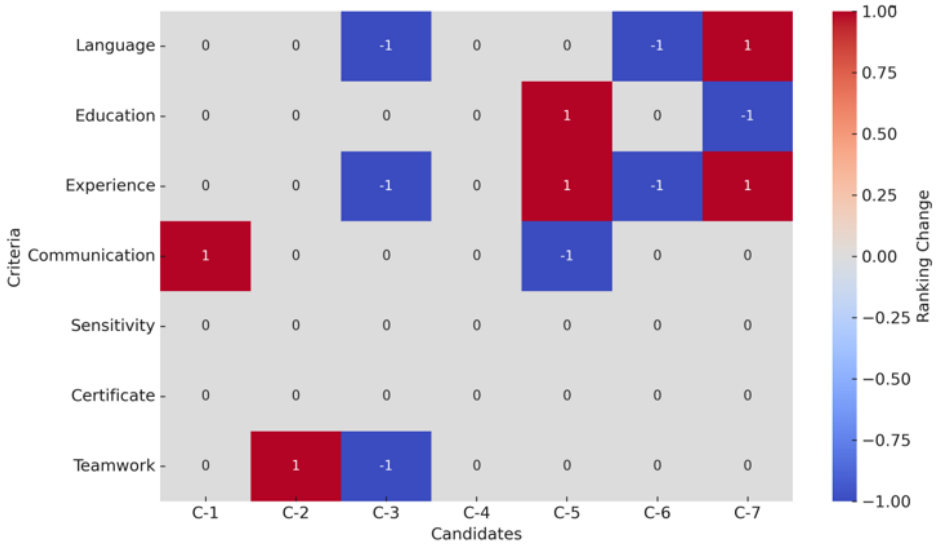

Figure 5. Sensitivity of rankings to AHP weight variations

This heatmap illustrates how changes in individual AHP criterion weights affect candidate rankings. Criteria such as Professional Experience and Teamwork Compatibility have a high leverage—small weight adjustments result in significant rank swings. In contrast, characteristics such as sensitivity and certificates have little impact. This research improves the model's interpretability and defensibility by identifying which dimensions have the most influence on decision-making.

This sensitivity analysis helps decision-makers evaluate the model's robustness by illustrating how changes in criterion weights affect final rankings. The resulting sensitivity map shows that the model responds logically to weight fluctuations and highlights which criteria have the largest influence on selection results, improving interpretability and providing HR managers with more decision control.

Before entering the FCRS synthesis, the preceding analyses must be defined. Sections 5.1-5.4 analyzed the alignment of decision-making procedures, the distribution of criteria importance, candidate-specific performance dynamics, and the sensitivity of findings to input changes. These first data now provide a consistent platform for assessing the integrated power of the FCRS metric.

5.5 Integrated Ranking Validation via FCRS

Tables 39-40 aggregate the Fuzzy TOPSIS and Fuzzy VIKOR ranks using the FCRS metric. This fusion score's reliability and simplicity improves decision interpretability, especially in the presence of expert uncertainty and language fuzziness. The model's performance confirms its practical usefulness in assisting with HR decisions in structured, mid-scale institutions. To visualize and validate the performance of FCRS, the following figures are presented:

As shown in Figure 6, the bar chart presentation of FCRS scores reveals distinct performance differences across candidates, allowing for straightforward comparison and rank confirmation.

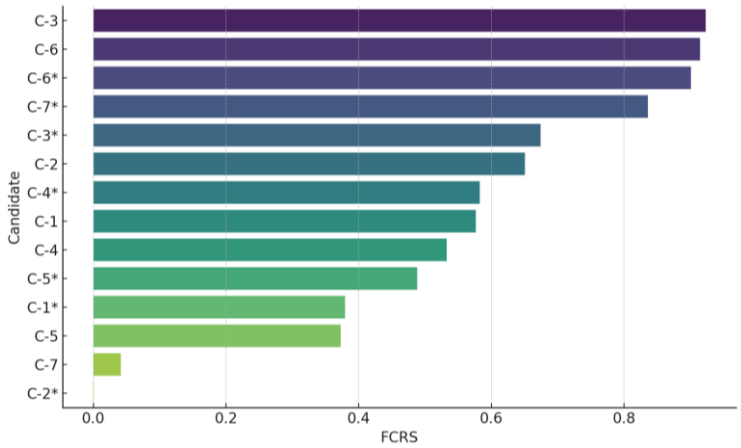

Figure 6. Bar chart of FCRS scores for all candidates

The bar chart displays the final FCRS scores, providing a clear snapshot of performance distribution among all candidates. Candidates A-3, A-6 (full-time), and A-6*, A-7* (part-time) had superior scores, demonstrating their selection robustness using the hybrid approach. The steep reduction in score following the top applicants indicates strong score discrimination, which is required for clear personnel decisions.

Figure 7 shows a line graph comparing TOPSIS, 1-VIKOR, and FCRS results, highlighting the consistency of individual approaches and the composite score.

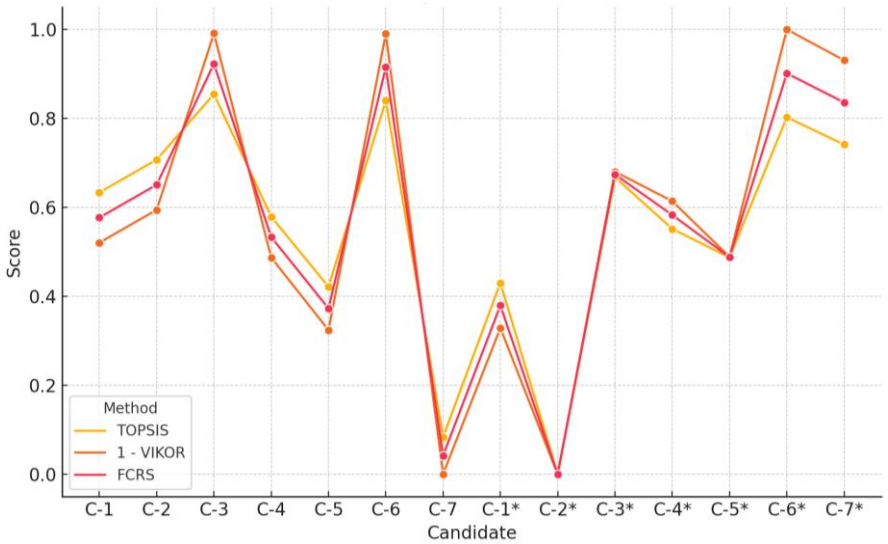

Figure 7. Comparison of TOPSIS, 1–VIKOR, and FCRS scores

Figure 8 depicts a correlation matrix that quantifies the statistical alignment between the three scoring dimensions, hence validating the hybrid model's internal validity.

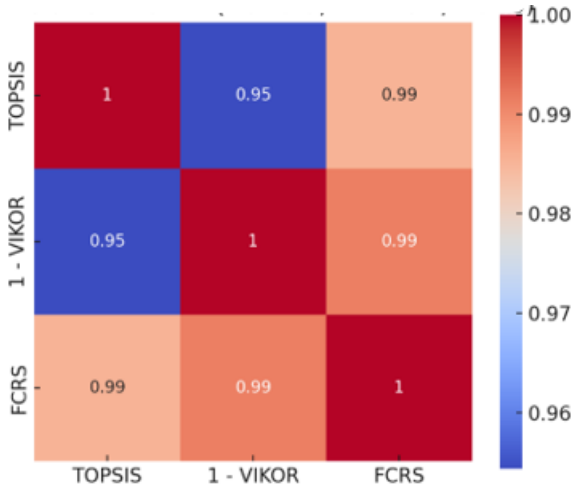

Figure 8. Correlation matrix of TOPSIS, 1–VIKOR, and FCRS

This matrix quantifies the statistical correlations between the three ranking approaches. The high positive correlations between FCRS and both individual approaches demonstrate that FCRS accurately integrates input measurements without distortion. The matrix maintains the hybrid framework's internal consistency while also experimentally supporting the composite ranking strategy's reliability.

Figure 9 depicts the distribution of FCRS scores by employment type, emphasizing the relative scoring patterns and potential selection bias across full-time and part-time candidates.

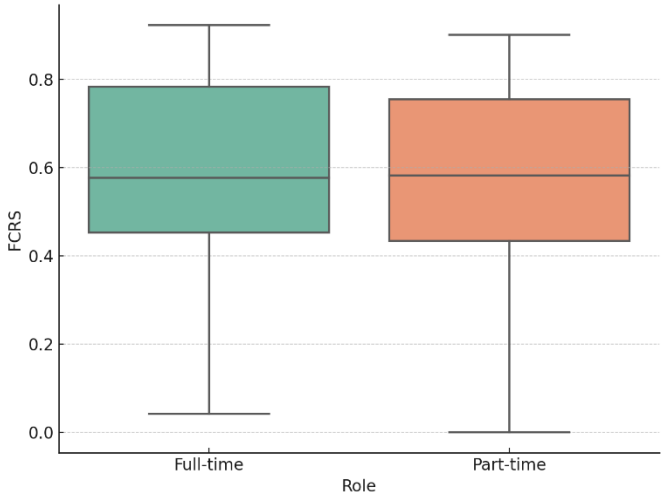

Figure 9. FCRS distribution by employment type (full-time vs part-time)

This comparison plot divides FCRS scores by employment type, indicating distinct performance patterns for full-time and part-time candidates. The steeper gradient in full-time roles indicates greater variety in candidate quality, whereas part-time candidates have more grouped scores. These findings can help guide role-specific selection tactics and resource allocation decisions.

The results of this study align with those reported in recent hybrid MCDM literature. For example, Aggarwal et al. (2025) achieved strong method agreement in IT personnel selection using a fuzzy AHP–TOPSIS framework. Similarly, Nalbant (2025) demonstrated the effectiveness of Interval Type-2 Fuzzy TOPSIS in enhancing decision stability. Our FCRS-enhanced model showed high concordance between Fuzzy TOPSIS and Fuzzy VIKOR outputs, consistent with the convergence patterns reported in these studies. This reinforces the validity of hybrid integration in complex personnel evaluation scenarios.

Overall, this section demonstrates that the hybrid fuzzy MCDM technique not only produces theoretically valid and empirically consistent results, but also improves transparency, adaptability, and practical applicability in personnel selection scenarios.

6. Conclusion

This study developed and tested a robust hybrid decision-support framework for people selection that combines AHP, Fuzzy TOPSIS, and Fuzzy VIKOR. Designed primarily for medium-sized, service-oriented public institutions, the approach addresses complicated multi-criteria evaluation tasks under uncertainty by integrating expert-derived criteria weighting with fuzzy language assessments.

The empirical case study conducted at KSC demonstrated the framework's operational relevance and methodological consistency. Both full-time and part-time candidates were evaluated based on role-specific criteria, indicating high methodological congruence and validating the hybrid structure's reliability. The study made a novel theoretical addition by introducing the FCRS, which combines the outputs of Fuzzy TOPSIS and Fuzzy VIKOR into a single interpretable measure. This synthesis improved decision robustness, stability, and transparency, allowing decision-makers to address any ranking inconsistencies and ensure more equitable personnel selection outcomes.

This research highlights how combining geometric (TOPSIS) and compromise-based (VIKOR) reasoning improves the credibility and robustness of selection judgments. Role-based prioritizing (e.g., "Experience" for full-time, "Communication" for part-time) enhances contextual alignment and selection relevance. Fuzzy logic enhances the realism and interpretability of expert-based evaluations, in particular for confusing or partial data.

This approach adds to the MCDM literature by addressing a methodological gap in fuzzy-based decision-making for public enterprises with limited HR infrastructure. It provides a scalable, adaptive, and defensible solution to structured personnel evaluation.

Future study may investigate other fuzzy applications, such as interval type-2 fuzzy sets or hesitant fuzzy sets, to improve uncertainty modeling. The technique can also be used to group decision-making scenarios, combined with machine learning for predictive talent analytics, and tested in dynamic hiring situations. Furthermore, proving its scalability across diverse businesses, cross-cultural settings, or disciplines such as education, strategic sourcing, and project portfolio selection could provide useful insights into its generalizability and real-world application.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the research presented in this study.

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