Enhancing Software Developer Selection with Integrated F-AHP and F-TOPSIS Techniques

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Abstract: This study focuses on enhancing the selection process for software developers by integrating the Fuzzy Analytic Hierarchy Process (F-AHP) and the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (F-TOPSIS). The primary objective is to address the uncertainties and ambiguities in determining evaluation criteria and weights, thereby facilitating accurate decision-making when faced with multiple criteria and alternatives. Conducted within a software development company in Bandung, Indonesia, the study involved evaluating ten potential candidates for the software developer position. The methodology employed F-AHP to assess the importance of each criterion through pairwise comparisons, and F-TOPSIS to rank the candidates based on these criteria weights. The results revealed that Candidate CK-7 exhibited the highest closeness coefficient (CC_i), making them the top candidate, while CK-4 ranked the lowest. This integrated approach provided a systematic and transparent framework for decision-making, demonstrating its effectiveness in optimizing recruitment processes. The study contributes to the field by offering a robust decision-making tool that can be adapted to various industries, ensuring the selection of high-quality employees who meet necessary competencies, thereby improving overall productivity and performance.

Keywords: Employee Selection, F-AHP, F-TOPSIS, Multi-Criteria Decision Making (MCDM), Software Developer Recruitment.

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Introduction

In the rapidly evolving and competitive information technology (IT) industry, selecting the right employees is a crucial task for companies. High-quality employees who meet the necessary competencies significantly enhance productivity and performance, helping companies maintain a competitive edge. However, the process of employee selection is complex, involving various factors such as qualifications, experience, and interpersonal skills. One primary challenge is dealing with the uncertainty and ambiguity in determining the criteria and weights used to evaluate candidates. Additionally, decision-makers often face difficulties in making accurate decisions when confronted with multiple criteria and alternatives.

To address these challenges, this study proposes an integrated approach combining the Fuzzy Analytical Hierarchy Process (F-AHP) and the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (F-TOPSIS). The concept of fuzzy sets, introduced by Zadeh is applied in the context of Multi-Criteria Decision Making (MCDM) to tackle vagueness and uncertainty in human cognitive processes (Liu et al., 2020). F-AHP, using Chang's extent analysis approach, assesses the importance of each evaluation criterion (Irfan Ramadhan et al., 2020). Subsequently, F-TOPSIS ranks the alternatives for the software developer position based on the criteria weights determined through F-AHP (Okfalisa et al., 2020).

F-TOPSIS is recognized for its ease of implementation and stable results in decision-making processes (Sarucan et al., 2022). However, it lacks specific guidelines for assigning weights to each criterion (Çalik & Afşar, 2021). Therefore, a more systematic approach like F-AHP becomes essential for determining criteria weights with greater precision. F-AHP allows for consistent and reliable criteria weight determination, accommodating uncertainty and ambiguity through pairwise comparisons of evaluation criteria, whether quantitative or qualitative, using linguistic terms. Nevertheless, using F-AHP alone can be complex, especially when dealing with numerous alternatives or evaluation criteria due to the repetitive assessments and extensive pairwise comparisons involved. Hence, an integrated approach with F-TOPSIS is adopted following the F-AHP process to rank each (Aditya & Purwiantono, 2020).

The specific goal of this research is to integrate F-AHP and F-TOPSIS methods to optimize the selection process of software developer employees. This integration aims to enhance the effectiveness and efficiency of employee selection, ensuring that high-quality employees who meet the required competencies are obtained. This method addresses the issues of uncertainty and ambiguity in determining criteria and weights, as well as the difficulties in making accurate decisions when faced with multiple criteria and alternatives (Dhaher et al., 2023).

Despite advancements in using F-AHP and F-TOPSIS for decision-making, notable gaps remain in existing research. Most studies focus on individual applications of F-AHP or F-TOPSIS in various domains, but limited research exists on their combined application for employee selection in the IT industry. Additionally, while F-TOPSIS is praised for its implementation ease, its lack of guidelines for assigning criterion weights is a significant shortcoming that has not been fully addressed (Nenzhelele et al., 2023). Current literature also lacks comprehensive frameworks that integrate both methods to leverage their strengths and mitigate their individual weaknesses (Bektur, 2020). Furthermore, there is insufficient empirical evidence on the effectiveness of this integrated approach in real-world IT industry scenarios.

In the IT industry, characterized by rapid growth and intense competition, having a robust employee selection process is vital. Companies need to adapt to the dynamic nature of the industry by employing skilled individuals who can contribute to maintaining and advancing their competitive position. The integrated approach of F-AHP and F-TOPSIS offers a systematic and reliable solution to the complexities of employee selection, making it an urgent and necessary advancement. This method supports companies in selecting the most suitable employees efficiently and effectively, ultimately leading to positive impacts on productivity and performance in a competitive market environment (Okfalisa et al., 2020).

Through this integrated method, companies can overcome inherent challenges of employee selection, including precise determination of criteria weights and effective ranking of candidates. The use of fuzzy logic in both F-AHP and F-TOPSIS provides a comprehensive framework for dealing with uncertainties and ambiguities that typically characterize the selection process (Hu et al., 2020). By leveraging the strengths of both methods, this research contributes to developing more robust decision-making tools essential for the success of IT companies in today's fast-paced and competitive landscape (Zabihi et al., 2020).

In system manufacturing, Sequeira et al. (2023) employed F-AHP and F-TOPSIS to evaluate the factors of affecting relocation decision. Similarly, the integrated methodology has been applied for third-party logistics selection (Hidayad & Utama, 2022), wind farm location selection (Abdullah et al., 2021), and evaluating agricultural production techniques (Rouyendegh & Savalan, 2022). In educational settings, (James et al., 2023) applied F-AHP and F-TOPSIS for student selection in higher education institutions, demonstrating the method's applicability in evaluating complex and subjective criteria in academic environments. Furthermore, F-AHP and F-TOPSIS have been used for evaluating green concept alternatives in product development, highlighting their utility in addressing environmental sustainability issues (Ayağ, 2021).

To further support the validity and applicability of this approach, recent studies have demonstrated its success in various domains such as ERP software package selection (Ayağ & Samanlioglu, 2021), facility layout design in railcar manufacturing (Nenzhelele et al., 2023), and sustainable supplier selection (Bektur, 2020). However, this research distinguishes itself from prior studies by addressing the integration of multi-criteria decision-making (MCDM) methods with artificial intelligence (AI) techniques to enhance decision-making accuracy and efficiency. Unlike previous research that focused on specific applications within isolated domains, this study provides a comprehensive framework that can be adapted across various industries, thus offering broader applicability. Furthermore, this research introduces an innovative hybrid model that combines the strengths of both qualitative and quantitative analysis, ensuring more robust and reliable decision outcomes. This advancement not only improves upon the methodologies used in earlier studies but also opens new avenues for future research in decision support systems.

The specific objectives of this study are to enhance the efficiency and effectiveness of the employee selection process for software developers by integrating F-AHP and F-TOPSIS. This integrated method ensures that companies can select high-quality employees who meet the necessary competencies, thereby improving overall productivity and performance. By addressing the challenges of uncertainty and ambiguity in criteria and weight determination, this research offers a significant contribution to the field of employee selection and decision-making in the competitive IT industry.

Research Method

This research employs the integration of the Fuzzy Analytic Hierarchy Process (F-AHP) using Chang's extent analysis method and the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (F-TOPSIS) to optimize the selection process of software developers. The F-AHP method, initially developed by Laarhoven and Pedrycz and later extended by Chang is used to assess the importance of each evaluation criterion. The study was conducted in a software development company based in Bandung, Indonesia, with a focus on evaluating and ranking ten potential candidates for the software developer position.

The integration of F-AHP and F-TOPSIS is implemented as follows: F-AHP, with Chang's extent analysis, is first utilized to determine the weights of the criteria. This involves conducting pairwise comparisons to evaluate the relative importance of each criterion. The extent analysis method converts these comparisons into numerical values, facilitating the calculation of criterion weights while accommodating the inherent uncertainty and ambiguity in human judgment.

Once the criteria weights are determined, F-TOPSIS is employed to rank the candidates. F-TOPSIS evaluates each candidate by comparing their performance against an ideal solution, considering both the positive and negative ideal solutions (Hwang & Yoon, 1981). This method provides a comprehensive ranking of the candidates based on their relative closeness to the ideal solution, ensuring a systematic and reliable decision-making process.

The application of this integrated approach aims to enhance the effectiveness and efficiency of the employee selection process. By addressing the challenges of uncertainty and ambiguity in criteria and weight determination, this research offers a significant contribution to the field of employee selection and decision-making in the competitive IT industry.

Materials and Equipment

To conduct this research, a combination of software tools, data collection instruments, and expert decision-makers were utilized to ensure comprehensive and accurate analysis.

Data Collection Instruments

To ensure a comprehensive and accurate evaluation of candidates, various data collection instruments were utilized. These instruments included policy documents, assessment forms, and candidate profiles, each playing a crucial role in the evaluation process.

1. Policy Documents
   The policy documents provided a structured framework and established the criteria for evaluating the candidates. These documents ensured that the entire evaluation process was in alignment with the company's established policies and standards. By adhering to these guidelines, the evaluation-maintained consistency and fairness, reflecting the company's commitment to its core values and expectations.

2. Assessment Forms
   Structured assessment forms were employed to gather both quantitative and qualitative data on each candidate. These forms were meticulously designed to capture critical information relevant to the evaluation criteria and sub-criteria. They included sections for rating general qualifications, technical skills, and soft skills, allowing decision-makers to systematically document their observations and judgments. The data collected through these forms provided a solid foundation for the subsequent analysis.

3. Candidate Profiles
   Detailed profiles of each candidate were compiled, encompassing their educational background, work experience, technical skills, and soft skills. These profiles served as the primary data source for the evaluation, offering a comprehensive overview of each candidate's capabilities and potential. By examining these profiles, decision-makers could

gain valuable insights into the candidates' qualifications and suitability for the software developer position.

Decision Makers

The evaluation process involved the expertise of three key decision-makers, each contributing their unique perspective and knowledge to ensure a comprehensive assessment of the candidates. The Software Development Manager provided invaluable insights into the technical skills and practical experience required for the software developer position. With a deep understanding of the role's demands, the manager assessed candidates' proficiency in programming languages, software engineering principles, and relevant project experience, ensuring rigorous evaluation of their technical capabilities.

The Human Resources Development (HRD) Manager played a crucial role by contributing expertise on general qualifications and soft skills. This included assessing the candidates' educational background, certifications, and interpersonal skills. The HRD Manager ensured that the selected candidate not only met the technical requirements but also fit well within the company culture, demonstrating qualities such as teamwork, communication skills, and adaptability.

The Senior Software Engineer added a layer of technical scrutiny, focusing on the candidates' specific software development capabilities and problem-solving skills. This expert evaluated the practical application of technical knowledge, the ability to debug and troubleshoot software issues, and the overall approach to software design and implementation. By doing so, the Senior Software Engineer ensured that the candidates possessed the necessary technical acumen and problem-solving prowess critical for the position.

Methodology

The research methodology is comprised of several critical steps, each essential to ensuring an accurate and fair evaluation of the candidates. These steps are described in detail below.

Criteria and Sub-Criteria Determination

The first step involved identifying the criteria and sub-criteria for evaluating the candidates. This was done through a thorough review of policy documents and assessment forms. The main criteria included General Qualifications (KU), Technical Skills (KT), and Soft Skills (SK), each with their respective sub-criteria.

Fuzzy AHP Implementation Using Extent Analysis Chang

The Fuzzy Analytic Hierarchy Process (F-AHP) method is employed to determine the weights of the criteria and sub-criteria, addressing the uncertainties and ambiguities in decision-making. The Extent Analysis method by Chang is utilized in this process. Below are the detailed steps involved in the implementation.

1. Construct Pairwise Comparison Matrices

   Decision-makers perform pairwise comparisons for each criterion and sub-criterion using linguistic terms, which are then converted to Triangular Fuzzy Numbers (TFNs). Table 1 shows the linguistic terms and their corresponding TFNs.

Table 1 Triangular Fuzzy Numbers (TFNs)

Linguistic Term	TFN
Extremely Strong (SK)	(2, 5/2, 3)
Very Strong (KS)	(3/2, 2, 5/2)
Strong (CK)	(1, 3/2, 2)
Moderately Strong (AK)	(1, 1, 3/2)
Equal (S)	(1, 1, 1)
Moderately Weak (AL)	(2/3, 1, 1)
Weak (CL)	(1/2, 2/3, 1)
Very Weak (SL)	(2/5, 1/2, 2/3)
Extremely Weak (SLS)	(1/3, 2/5, 1/2)

The pairwise comparison matrix $A = [a_{ij}]$ is constructed for each set of criteria and sub-criteria. To aggregate the pairwise comparison matrices, geometric means are used with the following formula:

$$r_i = \left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}} \tag{1}$$

where a_{ij} are the values from the pairwise comparisons provided by the decision-makers, and n is the number of decision-makers.

2. Defuzzification of the Fuzzy Numbers

   One common defuzzification method is the centroid method, where the crisp value is calculated as:

$$C = \frac{l + m + u}{3} \tag{2}$$

3. Calculate the Fuzzy Synthetic Extent

   For each criterion, the fuzzy synthetic extent values are calculated as:

$$\boldsymbol{S_i} = \sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{j=1}^{n} \sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} \tag{3}$$

To obtain $\sum_{j=1}^{m} M_{gi}^{j}$, the fuzzy numbers are summed as follows:

$$\sum_{j=1}^{m} M_{gi}^{j} = \left[\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j\right] \tag{4}$$

To calculate the inverse of $\left[\sum_{j=1}^{n} \sum_{j=1}^{m} M_{gi}^{j}\right]^{-1}$, the following equation is used:

$$\left[\sum_{j=1}^{n} \sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} = \frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \tag{5}$$

4. Compute the Degree of Possibility

   The degree of possibility that one TFN $M_1 = (l_1, m_1, u_1)$ is greater than another TFN $M_2 = (l_2, m_2, u_2)$. is given by:

$$V(S_i \geq S_j) = \begin{cases} 1 & if\ m_i \geq m_j \\ 0 & if\ u_i \leq l_j \\ \dfrac{l_j - u_i}{(m_i - u_i) + (m_j - l_j)} & otherwise \end{cases} \tag{6}$$

5. Determine the Weight Vector (W')

   Calculate the degree of possibility for all pairs of criteria to form a weight vector W':

$$W' = \left(d'(A_1), d'(A_2), \dots, d'(A_n)\right)^T \tag{7}$$

   where $d'(A_i) = min\, V(S_i \geq S_k)$ for $k = 1, 2, \dots, n; k \neq i$.

6. Normalization of the Weight Vector

   Normalize the weight vector to obtain the normalized weights W.

$$W = (w_1, w_2, \dots, w_n)^T \tag{8}$$

where:

$$w_i = \frac{d'(A_i)}{\sum_{i=1}^{n} d'(A_i)} \tag{9}$$

Fuzzy TOPSIS Implementation

TOPSIS is a multi-criteria decision-making method that identifies solutions from a finite set of alternatives. The best alternative is the one that has the shortest distance from the positive ideal solution (PIS) and the farthest distance from the negative ideal solution (NIS). Fuzzy TOPSIS extends this method by incorporating fuzzy logic to handle uncertainties and ambiguities in the decision-making process.

The Fuzzy Technique for Order Preference by Similarity to Ideal Solution (F-TOPSIS) is utilized to rank the candidates based on the criteria weights obtained from F-AHP. The process involves the following detailed steps.

1. Construct the Fuzzy Decision Matrix.
   Candidates are evaluated against each sub-criteria using linguistic terms which are converted to Triangular Fuzzy Numbers (TFNs) as shown in Table 1.

2. Normalization of the Decision Matrix.
   Normalize the fuzzy decision matrix to ensure comparability among different criteria. The normalization is performed using the following formula:

$$v_{ij} = r_{ij} * w_j \tag{10}$$

   where l_j^*, m_j^*, u_j^* are the maximum values of the lower, middle, and upper bounds of all TFNs for each criterion j.

3. Calculate the Weighted Normalized Fuzzy Decision Matrix.
   Multiply the normalized decision matrix by the criteria weights obtained from F-AHP:

$$r_{ij} = \left(\frac{l_{ij}}{u_j^*}, \frac{m_{ij}}{m_j^*}, \frac{u_{ij}}{l_j^*}\right) \tag{11}$$

4. Determine the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS).
   FPIS (A^+) and FNIS (A^-) for each criterion are defined as follows:

$$\begin{aligned} A^+ &= \left(\tilde{v}_1^+, \tilde{v}_2^+, \cdots, \tilde{v}_n^+\right) \\ A^- &= \left(\tilde{v}_1^-, \tilde{v}_2^-, \cdots, \tilde{v}_n^-\right) \end{aligned} \tag{12}$$

5. Calculate the Distance of Each Alternative to FPIS and FNIS.
   The distance of each alternative i to FPIS (D_i^+) and FNIS (D_i^-) is calculated using the Euclidean distance formula:

$$\begin{aligned} D_i^+ &= \sqrt{\sum_{j=1}^{n} \left(\tilde{v}_j^+ - v_{ij}\right)^2} \\ D_i^- &= \sqrt{\sum_{j=1}^{n} \left(\tilde{v}_j^- - v_{ij}\right)^2} \end{aligned} \tag{13}$$

6. Compute the Closeness Coefficient (CC_i).
   The closeness coefficient (CC_i) for each alternative is calculated to determine the relative closeness to the FPIS:

$$CC_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{14}$$

7. Ranking of Candidates.
   Rank the candidates based on the Closeness Coefficient, where a higher value indicates a better candidate.

Result and Discussion

This research was conducted at a software development company located in Bandung, Indonesia, a growing company with more than 50 employees and over five years of operational experience. The study focuses on the recruitment process analysis within the company, specifically the selection of employees for the software developer position. Three experts were involved in this process: the Software Development Manager, the HRD Manager, and a Senior Software Engineer, referred to as decision-makers (DM-1, DM-2, and DM-3).

There were ten potential candidates ($m = 10$) for the software developer role. The role involves designing, developing, testing, and maintaining software to meet company or client needs. These developers aim to create efficient, reliable, and innovative software solutions, engage in problem-solving and product improvement, collaborate with cross-disciplinary teams, ensure software security and quality standards, and stay updated with the latest technological advancements.

Criteria and Sub-Criteria

The relevant criteria and sub-criteria were determined through policy documents and designed assessment forms. The main criteria included General Qualifications (KU), Technical Skills (KT), and Soft Skills (SK). Each criterion was further divided into specific sub-criteria as shown in Table 2.

Table 2 Criteria and Sub-Criteria for Software Developer Evaluation

Criteria	Code	Sub-Criteria	Code
General Qualifications	KU	Last Education	KU-1
		Relevant Certifications	KU-2
		Project Portfolio	KU-3
		Work Experience	KU-4
Technical Skills	KT	Software Engineering Principles	KT-1
		Programming Languages	KT-2
		Libraries and Frameworks	KT-3
		Testing and debugging	KT-4
		System Analysis and Design	KT-5
		Application System Security	KT-6
Soft Skills	SK	Foreign Languages	SK-1

		Verbal and Written Communication	SK-2
		Teamwork	SK-3
		Problem Solving	SK-4
		Independent Working	SK-5
		Working Under Pressure	SK-6
		Working with Various Technologies	SK-7
		Adapting to Changes	SK-8

Pairwise Comparison and TFN Conversion

Within the F-AHP framework, decision-makers performed pairwise comparisons for all criteria and sub-criteria. These assessments used linguistic terms and corresponding membership functions represented by triangular fuzzy numbers (TFN), as detailed in Table 3.

Table 3 Triangular Fuzzy Numbers (TFN) Evaluation Values

Linguistic Term	Membership Function
Extremely Strong (SK)	(2, 5/2, 3)
Very Strong (KS)	(3/2, 2, 5/2)
Strong (CK)	(1, 3/2, 2)
Moderately Strong (AK)	(1, 1, 3/2)
Equal (S)	(1, 1, 1)
Moderately Weak (AL)	(2/3, 1, 1)
Weak (CL)	(1/2, 2/3, 1)
Very Weak (SL)	(2/5, 1/2, 2/3)
Extremely Weak (SLS)	(1/3, 2/5, 1/2)

After determining the criteria and sub-criteria, the next step involved constructing the pairwise comparison matrix to assess the importance or relationships between elements within the hierarchy. Experts provided relative values for each pair of elements. The pairwise comparisons for the main criteria by the three decision-makers are shown in Table 4.

Table 4 Pairwise Comparison for Main Criteria

	KU	KT	SK
KU	(S, S, S)	(LS, AL, LS)	(CL, AL, CL)
KT	(KS, AK, KS)	(S, S, S)	(S, S, AK)
SK	(CK, AK, CK)	(S, S, AL)	(S, S, S)

Similarly, pairwise comparisons for sub-criteria under General Qualifications (KU) are presented in Table 5.

Table 5 Pairwise Comparison of General Qualification Sub-Criteria (KU)

	KU-1	KU-2	KU-3	KU-4
KU-1	(S, S, S)	(AL, AK, CL)	(AL, AL, LS)	(CL, CL, LS)
KU-2	(AK, AL, CK)	(S, S, S)	(AL, AK, CL)	(CL, AL, LS)
KU-3	(AK, AK, KS)	(AK, AL, CK)	(S, S, S)	(S, S, AK)

	KU-1	KU-2	KU-3	KU-4
KU-4	(CK, CK, KS)	(CK, AK, KS)	(S, S, AL)	(S, S, S)

All pairwise comparison results were converted based on TFN values as in Table 3. The conversion results for the main criteria are shown in Table 6. Similar methods were applied to convert the sub-criteria. Conversion to TFN aims to integrate uncertainty into decision analysis, allowing decision-makers to address ambiguities in the data or information used.

Table 6 TFN Conversion Matrix for Main Criteria

	KU	KT	SK
DM-1	(1, 1, 1)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)
DM-2	(1, 1, 1)	(2/3, 1, 1)	(2/3, 1, 1)
DM-3	(1, 1, 1)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)

The next step involved calculating the average values of elements in the pairwise comparison matrices for each criterion using Equation (1). The results for the main criteria are presented in Table 7. The calculation for sub-criteria under General Qualifications (KU) is shown in Table 8. Similar methods were applied to other sub-criteria.

Table 7 Average Pairwise Comparison Matrix for Main Criteria

	KU			KT			KS		
	L	*m*	*u*	*l*	*M*	*u*	*l*	*m*	*u*
KU	1,000	1,000	1,000	0,489	0,667	0,778	0,556	0,778	1,000
KT	1,333	1,667	2,167	1,000	1,000	1,000	1,000	1,000	1,167
KS	1,000	1,333	1,833	0,889	1,000	1,000	1,000	1,000	1,000

Table 8 Average Pairwise Comparison Matrix for General Qualification Sub-Criteria

	KU-1			KU-2			KU-3			KU-4		
	l	*M*	*u*	*l*	*m*	*U*	*l*	*m*	*u*	*l*	*m*	*u*
KU-1	1,000	1,000	1,000	0,722	0,722	0,722	0,578	0,578	0,578	0,467	0,467	0,467
KU-2	0,889	0,889	0,889	1,000	1,000	1,000	0,722	0,722	0,722	0,522	0,522	0,522
KU-3	1,167	1,167	1,167	0,889	0,889	0,889	1,000	1,000	1,000	1,000	1,000	1,000
KU-4	1,167	1,167	1,167	1,167	1,167	1,167	0,889	0,889	0,889	1,000	1,000	1,000

After obtaining the average pairwise comparison values, the next step involved defuzzification as per Equation (2). The results were then normalized by dividing each element of the defuzzified matrix by the sum of its column. Table 9 shows the defuzzified results for the main criteria, while Table 10 presents the normalized results. Sub-criteria were processed similarly to the main criteria.

Table 9 Defuzzification of Results for Main Criteria

	KU	KT	KS
KU	1,000	0,656	0,778
KT	1,694	1,000	1,028
KS	1,361	0,981	1,000
Sum	4,056	2,637	2,806

Using the pairwise comparison matrices, the synthetic fuzzy values (S_i), weights from extent analysis (W_i'), and normalized weights (W_i) were calculated. Table 11 presents the calculations for the main criteria. Similar methods were applied to sub-criteria to ensure consistency in evaluation.

Table 10 Normalized Results for Main Criteria

	KU	KT	KS
KU	0,247	0,249	0,277
KT	0,418	0,379	0,366
KS	0,336	0,372	0,356

Table 11 Synthetic Fuzzy Values (S_i), Weights (W_i'), and Normalized Weights (W_i) for Main Criteria

	S_i			W_i'	W_i
	l	m	U		
KU	0,187	0,259	0,336	0,196	0,097
KT	0,305	0,388	0,524	1,000	0,497
KS	0,264	0,353	0,464	0,818	0,406

The final weights for all sub-criteria were obtained by multiplying the main criteria weights by the sub-criteria weights in each main criteria group. This process illustrates the relative contribution of each sub-criteria to its main criteria group. The results are shown in Table 12 and used in the F-TOPSIS calculation.

In the F-TOPSIS stage, decision-makers evaluated each candidate (software developer candidates CK-1 to CK-10) based on individual sub-criteria using linguistic terms described in Table 13.

Evaluations for the ten alternatives considering 18 sub-criteria by three decision-makers (DM-1, DM-2, and DM-3) used the linguistic terms in Table 13. The evaluation results for general qualifications are shown in Table 14. Similar methods were applied to evaluate other qualifications.

Table 13 Final Weights from F-AHP

Criteria Code	W_i	Sub Criteria Code	W_{ij}	Final Weight
KU	0,097	**KU-1**	0,139	0,014
		KU-2	0,207	0,020
		KU-3	0,294	0,029
		KU-4	0,360	0,035
KT	0,497	**KT-1**	0,143	0,071
		KT-2	0,184	0,092
		KT-3	0,204	0,101
		KT-4	0,161	0,080
		KT-5	0,195	0,097
		KT-6	0,112	0,056
KS	0,406	**KS-1**	0,085	0,034
		KS-2	0,102	0,041
		KS-3	0,139	0,056

		KS-4	0,175	0,071
		KS-5	0,137	0,056
		KS-6	0,082	0,033
		KS-7	0,133	0,054
		KS-8	0,147	0,060

Table 13 Fuzzy Evaluation Values for Each Alternative in F-TOPSIS

Linguistic	Code	Membership
Very Poor	SK	(0, 0, 1)
Poor	K	(0, 1, 3)
Fair	CK	(1, 3, 5)
Average	S	(3, 5, 7)
Good	CB	(5, 7, 9)
Very Good	B	(7, 9, 10)
Excellent	SB	(9, 10, 10)

Table 14 Alternative Evaluations for General Qualifications by Three Decision-Makers

	KU-1			KU-2			KU-3			KU-4		
	DM-1	DM-2	DM-3	DM-1	DM-2	DM-3	DM-1	DM-2	DM-3	DM-1	DM-2	DM-3
CK-1	S	SB	B	S	CK	B	S	SB	SB	CB	SB	B
CK-2	S	CB	B	CK	SB	B	CK	CK	S	CB	CB	CK
CK-3	CK	S	SB	CB	B	CB	SB	CK	S	CK	CB	S
CK-4	CK	S	SB	CB	SB	CK	SB	CK	SB	SB	B	S
CK-5	B	S	CK	CB	B	CB	B	CK	SB	B	CK	B
CK-6	CB	CB	CK	B	CB	B	B	SB	SB	S	SB	CK
CK-7	B	SB	S	S	CB	S	S	B	SB	B	S	B
CK-8	B	B	CB	CK	CB	SB	SB	S	B	CB	S	CB
CK-9	CB	SB	CB	S	S	SB	S	B	B	B	SB	B
CK-10	CB	S	CK	B	B	CB	CK	B	CB	B	S	B

These linguistic terms were then converted to corresponding TFNs as shown in Table 13. The fuzzy decision matrix for the main criteria is presented in Table 15.

Table 15 Fuzzy Decision Matrix for Main Criteria

	KU-1									KU-2									KU-3									KU-4								
	DM-1			DM-2			DM-3			DM-1			DM-2			DM-3			DM-1			DM-2			DM-3			DM-1			DM-2			DM-3		
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
CK-1	3	5	7	9	10	10	7	9	10	3	5	7	1	3	5	7	9	10	3	5	7	9	10	10	9	10	10	5	7	9	9	10	10	7	9	10
CK-2	3	5	7	5	7	9	7	9	10	1	3	5	9	10	10	7	9	10	1	3	5	1	3	5	3	5	7	5	7	9	5	7	9	1	3	5
CK-3	1	3	5	3	5	7	9	10	10	5	7	9	7	9	10	5	7	9	9	10	10	1	3	5	3	5	7	1	3	5	5	7	9	3	5	7
CK-4	1	3	5	3	5	7	9	10	10	5	7	9	9	10	10	1	3	5	9	10	10	1	3	5	9	10	10	9	10	10	7	9	10	3	5	7
CK-5	7	9	10	3	5	7	1	3	5	5	7	9	7	9	10	5	7	9	7	9	10	1	3	5	9	10	10	7	9	10	1	3	5	7	9	10
CK-6	5	7	9	5	7	9	1	3	5	7	9	10	5	7	9	7	9	10	7	9	10	9	10	10	9	10	10	3	5	7	9	10	10	1	3	5
CK-7	7	9	10	9	10	10	3	5	7	3	5	7	5	7	9	3	5	7	3	5	7	7	9	10	9	10	10	7	9	10	3	5	7	7	9	10
CK-8	7	9	10	7	9	10	5	7	9	1	3	5	5	7	9	9	10	10	9	10	10	3	5	7	7	9	10	5	7	9	3	5	7	5	7	9
CK-9	5	7	9	9	10	10	5	7	9	3	5	7	3	5	7	9	10	10	3	5	7	7	9	10	7	9	10	7	9	10	9	10	10	7	9	10
CK-10	5	7	9	3	5	7	1	3	5	7	9	10	7	9	10	5	7	9	1	3	5	7	9	10	5	7	9	7	9	10	3	5	7	7	9	10

All sub-criteria were assumed to be benefit criteria (B). Using Equation (10) and Equation (11), the normalized fuzzy decision matrix was formed, as shown in Table 16.

Table 16 Normalized Fuzzy Decision Matrix with Weights

	KU-1			KU-2			KU-3			KU-4		
	l	*m*	*u*	*l*	*m*	*U*	*l*	*m*	*u*	*l*	*m*	*u*
CK-1	0,300	0,800	1,000	0,100	0,567	1,000	0,300	0,833	1,000	0,500	0,867	1,000
CK-2	0,300	0,700	1,000	0,100	0,733	1,000	0,100	0,367	0,700	0,100	0,567	0,900
CK-3	0,100	0,600	1,000	0,500	0,767	1,000	0,100	0,600	1,000	0,100	0,500	0,900
CK-4	0,100	0,600	1,000	0,100	0,667	1,000	0,100	0,767	1,000	0,300	0,800	1,000
CK-5	0,100	0,567	1,000	0,500	0,767	1,000	0,100	0,733	1,000	0,100	0,700	1,000
CK-6	0,100	0,567	0,900	0,500	0,833	1,000	0,700	0,967	1,000	0,100	0,600	1,000
CK-7	0,300	0,800	1,000	0,300	0,567	0,900	0,300	0,800	1,000	0,300	0,767	1,000
CK-8	0,500	0,833	1,000	0,100	0,667	1,000	0,300	0,800	1,000	0,300	0,633	0,900
CK-9	0,500	0,800	1,000	0,300	0,667	1,000	0,300	0,767	1,000	0,700	0,933	1,000
CK-10	0,100	0,500	0,900	0,500	0,833	1,000	0,100	0,633	1,000	0,300	0,767	1,000

The next step involved calculating the positive ideal solution (PIS) and negative ideal solution (NIS) using Equation (12). Then, the distance of each alternative to the PIS and NIS was calculated using Equation (13). Considering the distance from the fuzzy positive ideal solution (D_i^+) and the distance from the fuzzy negative ideal solution (D_i^-), the closeness coefficient (CC_i) was calculated using Equation (14). The calculation results are shown in Table 17.

Table 17 F-AHP and F-TOPSIS Results

	D_i^+	D_i^-	CC_i	Rank
CK-1	0,301	0,172	0,364	9
CK-2	0,278	0,180	0,393	7
CK-3	0,305	0,200	0,396	6
CK-4	0,305	0,173	0,362	10
CK-5	0,296	0,198	0,401	5
CK-6	0,288	0,207	0,418	4
CK-7	0,206	0,257	0,555	1
CK-8	0,296	0,182	0,381	8
CK-9	0,235	0,261	0,526	2
CK-10	0,259	0,229	0,469	3

From Table 17, CK-7 has the highest closeness coefficient (CC_i), thus receiving the highest rank, whereas CK-4 has the lowest CC_i and is ranked last. These rankings can be used as the basis for decision-making or selecting the best alternative.

The primary findings from this study reveal that Candidate CK-7 exhibited the highest closeness coefficient (CC_i), positioning them as the top candidate for the software developer role. Conversely, Candidate CK-4 had the lowest CC_i, ranking last among the evaluated candidates. The application of the Fuzzy Analytic Hierarchy Process (F-AHP) and Fuzzy Technique for Order Preference by Similarity to Ideal Solution (F-TOPSIS) methodologies provided a comprehensive and structured evaluation framework. This framework successfully integrated qualitative and quantitative aspects, ensuring a thorough assessment of each candidate's suitability based on multiple criteria and sub-criteria. These findings underscore the efficacy of using advanced fuzzy multi-criteria decision-making methods in optimizing the recruitment process.

The results obtained in this study directly address the formulated problem of enhancing the recruitment process for software developers by providing a systematic and transparent evaluation mechanism. The utilization of F-AHP allowed for the precise determination of the weights of various criteria and sub-criteria, addressing uncertainties and ambiguities in decision-making. This structured approach facilitated a detailed comparison among the candidates.

The F-TOPSIS method further extended this analysis by ranking the candidates based on their relative closeness to an ideal solution. This ranking process considered both the positive and negative ideal solutions, ensuring that the best candidate was selected based on their overall performance across all criteria.

Previous studies have shown that multi-criteria decision-making (MCDM) methods are effective in dealing with complex decision-making scenarios. For instance, traditional methods like the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) have been widely used in various domains, including supplier selection, project management, and performance evaluation. However, these conventional approaches often struggle with handling uncertainties and the inherent vagueness in human judgments. For example, research by Wang and Elhag (2006) highlighted the limitations of AHP in dealing with linguistic terms and qualitative data, which are often imprecise and subjective. Similarly, Chen and Hwang (1992) pointed out that traditional TOPSIS lacks the flexibility to adequately address ambiguity in decision-making scenarios.

The integration of fuzzy logic into these methods, as demonstrated in our study, significantly enhances their robustness and flexibility, making them more suitable for real-world applications where uncertainty is a critical factor. Unlike the traditional AHP and TOPSIS methods, the F-AHP and F-TOPSIS methodologies utilized in this study effectively handle the imprecision associated with human judgments by incorporating triangular fuzzy numbers (TFNs) and fuzzy set theory. This integration provides a more realistic and practical approach to decision-making, which has been less emphasized in previous research.

The robustness and flexibility of the applied methodologies highlight their potential applicability in other recruitment scenarios and industries. The approach demonstrated in this study ensures a comprehensive assessment of candidates, considering a wide range of qualifications and skills, thereby improving the decision-making process in recruitment.

Compared to previous research, which often relied on more rigid and less adaptive decision-making frameworks, our study showcases the superior adaptability of fuzzy MCDM methods in addressing the nuanced and multifaceted nature of recruitment.

The integration of F-AHP and F-TOPSIS methodologies was crucial in dealing with the complexities and uncertainties inherent in the recruitment process. The F-AHP method enabled a detailed and structured approach to determining the importance of each criterion and sub-criteria by converting qualitative assessments into quantitative weights. This conversion was achieved through pairwise comparisons and the use of TFNs, which effectively captured the linguistic terms used by decision-makers. This is a significant advancement over traditional AHP, which often fails to capture the ambiguity of qualitative judgments accurately.

The F-TOPSIS method then utilized these weights to rank the candidates based on their performance across all criteria. By calculating the distance of each candidate to the positive ideal solution (PIS) and the negative ideal solution (NIS), the F-TOPSIS method provided a clear and objective ranking. The closeness coefficient (CC_i) calculated for each candidate indicated their relative suitability for the role, with higher CC_i values representing better performance. This methodological advancement ensures a more nuanced and precise ranking compared to previous TOPSIS applications, which did not incorporate fuzzy logic to the same extent.

This combined approach ensured that the recruitment process was not only systematic and transparent but also capable of handling the inherent ambiguities in candidate evaluation. The methodologies used in this study can be applied to other relevant problems, such as project management, supplier selection, and other decision-making scenarios where multiple criteria need to be considered. Prior research often highlighted the limitations of traditional MCDM methods in these areas, suggesting a need for more adaptive and comprehensive approaches like those presented in our study.

The findings from this study demonstrate the effectiveness of using fuzzy multi-criteria decision-making methods in improving recruitment processes. By providing a comprehensive and detailed evaluation framework, these methods enhance the ability of decision-makers to select the best candidates, ensuring that the recruitment process is fair, transparent, and based on a thorough assessment of all relevant qualifications and skills. Compared to previous methodologies, our approach offers significant improvements in handling uncertainty and providing a more accurate and reliable assessment framework.

These principal findings and the discussion provide valuable insights into the application of advanced decision-making methodologies in recruitment. The systematic approach used in this study can be generalized to other fields, demonstrating its versatility and potential for improving decision-making processes across various domains. The enhanced adaptability and robustness of fuzzy MCDM methods underscore their superiority over traditional techniques, marking a significant advancement in the field of decision support systems.

Conclusions

Based on the findings of this study, it is concluded that the integration of Fuzzy Analytic Hierarchy Process (F-AHP) and Fuzzy Technique for Order Preference by Similarity to Ideal Solution (F-TOPSIS) methodologies provides an effective and comprehensive framework for optimizing the recruitment process for software developers. The study demonstrated that these advanced fuzzy multi-criteria decision-making methods could handle the complexities and uncertainties inherent in candidate evaluations, resulting in a systematic and transparent selection process. The evaluation highlighted Candidate CK-7 as the most suitable for the software developer role, illustrating the robustness of the applied methodologies. This approach not only addresses the formulated concerns and research purposes by ensuring a thorough assessment based on multiple criteria but also contributes to the field of recruitment by providing a scalable and adaptable evaluation model.

This research contributes to the scientific community by demonstrating the applicability and effectiveness of fuzzy multi-criteria decision-making (MCDM) methods in practical, real-world scenarios. By integrating Fuzzy Analytic Hierarchy Process (F-AHP) and Fuzzy Technique for Order Preference by Similarity to Ideal Solution (F-TOPSIS), the study provides a comprehensive framework for assessing candidates' qualifications and skills in recruitment processes. This advancement highlights the potential of fuzzy MCDM methods to handle the complexities and uncertainties inherent in decision-making, thus enhancing informed and fair selections across various industries.

However, the study has several limitations. Firstly, the methodology relies heavily on expert judgments for determining criteria weights, which can introduce subjective bias. Secondly, the study's focus on a specific recruitment scenario may limit the generalizability of the findings to other contexts or industries. Lastly, the computational complexity of the fuzzy MCDM methods may pose practical challenges for organizations with limited resources or expertise in these techniques.

To address these limitations, future research should explore the following areas: developing standardized criteria and weight determination methods to reduce subjective bias, applying the fuzzy MCDM framework to a broader range of decision-making scenarios to test its generalizability, and simplifying the computational processes to make these advanced techniques more accessible to organizations. By addressing these areas, future studies can further enhance the robustness and applicability of fuzzy MCDM methods in diverse decision-making contexts.

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