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An Improved Fuzzy AHP–TOPSIS Framework for Functional Requirements Selection and Rank-Reversal Mitigation

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ABSTRACT

Selecting appropriate functional requirements is a critical challenges in software requirements engineering. The difficulty arises from the need to reconcile conflicting stakeholder preferences, handle uncertainty inherent in linguistic assessments, and address the potential for rank reversal during the prioritization process. While existing fuzzy-based methods, especially those relying solely on Fuzzy TOPSIS, can handle vague judgments, they often lead to unstable rankings when new options are introduced or existing ones are removed. This study introduces a refined framework for selecting functional requirements that combines the Extent Fuzzy Analytic Hierarchy Process (FAHP) with the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Our framework uses Extent FAHP to determine the relative importance of non-functional requirements through pairwise comparisons in a fuzzy context, while Fuzzy TOPSIS is employed to rank functional requirements based on these calculated weights. We apply this framework to an Institute Examination System case study, evaluating fifteen functional requirements alongside five non-functional ones using triangular fuzzy numbers and linguistic variables. To ensure the framework's reliability, we validate it through three ranking scenarios: a baseline evaluation, the addition of a new functional requirement, and the removal of an existing one, all aimed at testing ranking stability. The experimental results show that our hybrid approach yields consistent and robust rankings, mitigating rank reversal and addressing uncertainties in stakeholder judgments. When compared to the traditional Fuzzy TOPSIS-based methods, our framework offers more dependable prioritization of requirements, and enhanced decision-making support for software engineers.

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INTRODUCTION

The eventual target of any software organization is to create systems that meet the stakeholder demands. Since there are usually more requirements than can be implemented, decision makers must face the challenges of selecting the right set of requirements. In order to select the correct set of requirements, the decision makers must understand the relative priorities of the requested requirements by selecting a subset of the requirements that are valuable for the end users, and can be implemented within budget. Making a decision involves weighing the pros and cons of two or more possibilities and then applying reasoning to select the best option.

During the decision-making process, decision makers may apply linguistic terms to specify their preferences instead of using numbers. For example, (a) the system should have more security, (b) the performance of the system should be very good. Here, 'more' and 'very good' are the linguistic variables. There are vagueness and imprecision in human judgment's; and it is difficult to represent it using exact numbers. In reality, the stakeholders may have thousands of requirements; and all the requirements of the stakeholders cannot be implemented due to the time and budget constraints and other limitations of the stakeholders.

Therefore, the importance of selected set of the software requirements (SRs) before the development phase of software, an effective method for the selection of SRs is highly needed.

And the vital aspect of these methods, is the one the handle rank reversal issue which occurs when the relative ranking of alternatives changes after adding or removing an alternative from the decision set. Hence, this study makes the following contributions: It develops an integrated Fuzzy AHP–TOPSIS framework for prioritizing functional requirements using non-functional requirements as evaluation criteria; It incorporates linguistic assessments through triangular fuzzy numbers to accommodate uncertainty and vagueness in stakeholder judgments; It evaluates ranking stability under alternative addition and removal scenarios using Spearman's rank correlation, Kendall's tau, and pairwise rank-reversal analysis, and finally, It compares the proposed framework with conventional Fuzzy TOPSIS to quantitatively assess its ability to mitigate rank reversal.

Related Work

Multicriteria decision-making (MCDM) techniques have been thoroughly explored and utilized in a variety of fields, especially focusing on fuzzy-based methods like fuzzy TOPSIS and fuzzy AHP. These approaches are well-regarded for their capability to manage uncertainty, accommodate linguistic preferences, and navigate complex decision-making scenarios.

In the field of software engineering, Mohd et al. (2022) used fuzzy TOPSIS to identify the best software requirements, tackling the challenge posed by the different linguistic terms that decision-makers often use. However, their research brought to light the problem of rank reversal, where the top choice can unexpectedly turn into the least favorable one under certain circumstances. In a comparative study, Mohd et al. (2022) further examined fuzzy AHP and fuzzy TOPSIS, noting the limited attention given to such comparisons in requirement selection contexts.

Extending this line of inquiry Veenu et al. (2023) introduced a hybrid fuzzy AHP–TOPSIS framework aimed at prioritizing parameters that influence testing, ensuring that software testing is both timely and effective. Similarly, Tarique et al. (2020) applied fuzzy TOPSIS in the context of healthcare software requirements engineering, stressing the need for systems that are both secure and reliable. Zaidan et al. (2020) expanded the use of MCDM by merging multilayer AHP with group TOPSIS to create a hiring framework for software programmers, showcasing its effectiveness in selecting candidates.

The applications of these techniques have also made waves in urban and environmental planning. Srdjevic et al. (2023) employed fuzzy AHP to rank urban parks in Novi Sad, Serbia, taking into account the impacts of climate change, resource limitations, and legislative challenges. Their results offered valuable insights for future city planning and the management of green spaces. Additionally, Tina et al. (2023) provided a thorough review of MCDM methods in wastewater treatment technologies, highlighting hybrid models like NSFDSS combined with artificial neural networks, alongside traditional methods such as AHP, TOPSIS, VIKOR, and ELECTRE.

In the fields of construction and engineering, Issa et al. (2022) came up with a hybrid AHP–fuzzy TOPSIS model aimed at selecting deep excavation support systems, showcasing its ability to effectively manage ambiguous and complex data. Siljung et al. (2023) took safety assessment methodologies for LPG-fueled marine engines a step further by blending fuzzy TOPSIS with failure mode and effect analysis (FMEA).

Meanwhile, Konstantinos et al. (2022) utilized fuzzy TOPSIS to tackle fuel price fluctuations in ship operations, concentrating on optimal bunkering contracts to help cut down operational costs. Shamsuzzoha et al. (2021) also turned to fuzzy TOPSIS for navigating complex project selection in engine manufacturing, while Ezhilarasan et al. (2020) fine-tuned fuzzy programming with TOPSIS to enhance product quality and lower costs.

Also, in the field of healthcare and pandemic response, there have been some groundbreaking applications, particularly with Fatih (2022), who rolled out intuitionistic fuzzy MAIRCA for assessing COVID-19 vaccines, offering a well-structured framework for group decision-making amid uncertainty.

When it comes to information security, Aliya et al. (2023) introduced aggregated metrics designed to boost monitoring and lessen resource demands, ultimately enhancing organizational resilience against cyber threats. The supplier selection process has also seen improvements through fuzzy methods, as Haddad et al. (2021) applied fuzzy TOPSIS in the oil and gas sector to evaluate contractors based on health, safety, and environmental criteria.

Lastly, Irina (2023) delved into methodological refinements, investigating the stability of various fuzzy AHP techniques, including arithmetic mean, geometric mean, extent analysis, and lambda max, to address concerns regarding accuracy and reliability.

These studies really highlight how adaptable MCDM techniques are, especially fuzzy TOPSIS and fuzzy AHP, when it comes to tackling decision-making hurdles in various fields like technology, the environment, healthcare, and organizations. The increasing trend towards hybrid approaches shows a desire to blend the best features of different methods, which ultimately boosts the strength and dependability of decisions in situations that are complex, uncertain, and filled with competing goals.

MATERIALS AND METHODS

Methodology

Proposed System

The aim of this section is to present a proposed method for the selection of the SRs using extent fuzzy AHP and fuzzy TOPSIS method under fuzzy environment where the vagueness and imprecision is handled with linguistic values parameterized by triangular fuzzy numbers. The following are the steps proposed to get the best among the elicited requirements.

i. Determination of non-functional requirements
ii. Construct Pair-wise comparison Matrix for non-functional requirements
iii. Apply extent fuzzy AHP
iv. Calculate weight of the non-functional requirements
v. Determination of functional requirement
vi. Assignment of rating to the FRs with respect to NFRs
vii. Compute aggregate fuzzy rating for the FRs
viii. Construct the fuzzy decision matrix for FRs
ix. Normalize the fuzzy decision matrix
x. Calculate the weighted normalized matrix
xi. Compute fuzzy positive and fuzzy negative ideal solutions
xii. Calculate the distance of each functional requirement from fuzzy PIS and fuzzy NIS
xiii. Calculate the closeness coefficients of each functional requirement
xiv. Select the functional requirements based on the ranking values of the closeness coefficients.

Functional Requirements of the Proposed System

i. The IES login module for several user categories, including teachers, administrators, and students
ii. To text or email students or parents to remind them to pay the exam fee before appearing in the examination.
iii. To show the students' result of various courses
iv. The system should determine the seating arrangements and deliver them to the students' email addresses and mobile devices.
v. To generate the date sheet of the theory and practical courses
vi. To create the qualified students' hall pass
vii. Filling of semester/annual examination form
viii. Approve examination form
ix. Exams for courses requiring numerous objective-based question papers are administered online.
x. To enter the results of the internal assessments and the theory and practical course marks at the end of the semester.
xi. Replacement access
xii. Library Access
xiii. To generate ID Card for those who submitted the examination fee
xiv. Ability to make correction
xv. Store initial data and the updated one

Non-Functional Requirements of the Proposed System

i. Security
ii. Performance
iii. Usability
iv. Flexibility
v. Availability

Working Principle of the Proposed System is Depicted in Figure 1

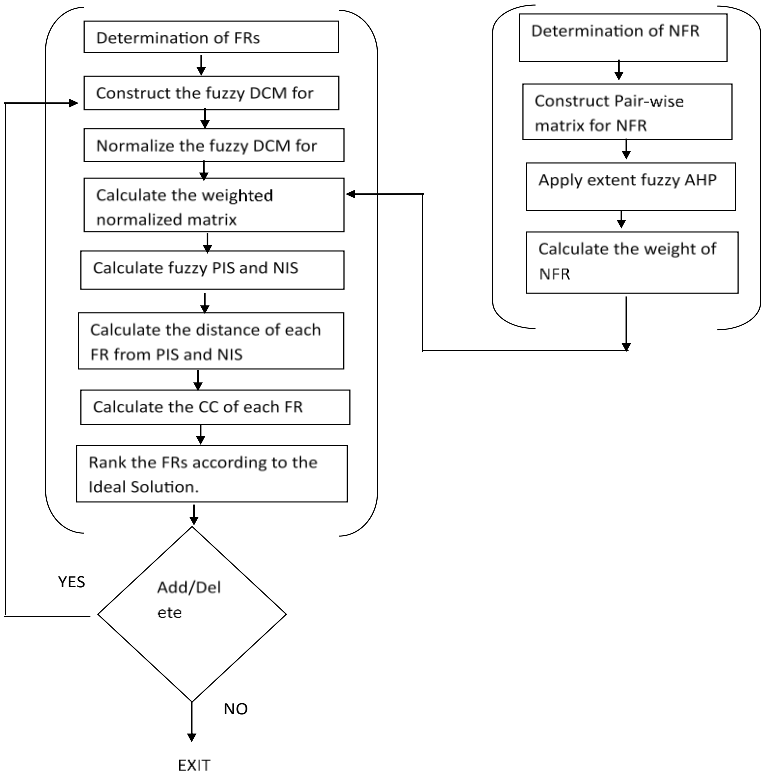

Figure 1: Flowchart of the Proposed System

Choice of Metrics

Table 1: The Linguistic Values for the Relationship Between FR and NFR Using Triangular Fuzzy Numbers in AHP Pair-Wise Matrices

S/NO	Linguistic values	Saaty's scale	TFN
1	Equal	1	(1,1,1)
3	Good (G)	5	(4,5,6)
4	Very Good (VG)	7	(6,7,8)

Source: Saaty, T., L. (2008) and Gumus (2009)

Table 2: Triangular Fuzzy Numbers (TFNs) of Linguistic Values for Each FRs, in TOPSIS Matrices

S/N	Linguistic Values	TFN
5	Medium (M)	(4, 6, 8)
6	Strong (S)	(6, 8, 10)
7	Very Strong (VS)	(8, 10, 10)

Source: Saaty, T., L. (2008) and Gumus (2009)

Triangular Fuzzy Numbers (TFN)

In this research, Triangular Fuzzy Numbers were used, due to their conceptual and computation simplicity in representing the decision makers linguistic information. So, TFN Ã is composed by the triplet (l, m, u) as it is showed in Figure 2 where (l, m, u) are real numbers and $(l < m < u)$. The value of x at m gives the maximal grade of $\mu_{\tilde{A}}(x) = 1$ which is the most probable value of the evaluation data. The values of x at l and m give the minimal grade of $\mu_{\tilde{A}}(x) = 0$ which is the least probable value of the evaluation data. Constants l and u are the lower and upper bounds of the available area for the data evaluation. In particular, (l, m, u) describe respectively the smallest, the most promising and the largest possible values related to a fuzzy event. Triangular fuzzy numbers are very commonly used in practical applications (Awasthi, 2010).

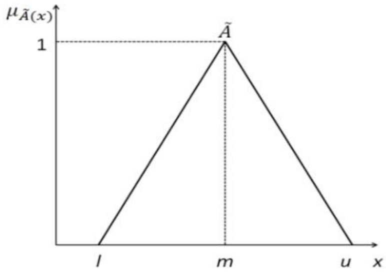

Figure 2: The Membership Function of a TFN Ã = (l, m, u)
Source: (Awasthi, 2010)

Consider $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_1, m_1, u_1)$.Then, the two TFN can be added together using the following formula:

$M_1 + M_2 = (l_1 + l_2,\ m_1 + m_2,\ u_1 u_2)\ eqn$ (1)

$M_1 \otimes M_2 = (l_1 l_2,\ m_1 m_2,\ u_1 u_2)\quad eqn$ (2)

$(l, m, u)^{-1} = \left(\frac{1}{u}, \frac{1}{m}, \frac{1}{l}\right)\quad eqn$ (3)

Fuzzy AHP Extent Analysis

The fuzzy AHP extent analysis method was developed by Da-Yong Chang (1996) to handle uncertainty, vagueness, and subjectivity in decision-making by extending the classical Analytic Hierarchy Process (AHP) with fuzzy logic. It allows decision-makers to express preferences more flexibly and derive robust priority weights even when judgments are imprecise. Provides a systematic way to compute fuzzy synthetic extent values from fuzzy pairwise comparison matrices and converts fuzzy judgments into crisp priority weights using defuzzification, making results interpretable and actionable

The fuzzy AHP extent analysis method was invented to bridge the gap between human linguistic judgment and mathematical decision models, making multi-criteria decision-making more realistic, flexible, and robust in uncertain environments.

Values of Extent Analysis of i-th Object for m Goals

Let $M_{gi}^1, M_{gi}^2, M_{gi}^3 \dots M_{gi}^m$ be values of extent analysis of i-th object for m goals. Then the value of fuzzy synthetic extent with respect to the i-th object is defined as

$Si = \sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} eqn$ (4)

The degree of possibility of $M_1 \geq M_2$

The degree of possibility of $M_1 \geq M_2$ is defined as:

$$V(M_1 \geq M_2) = sup\left[min\left(u_{M_1}(x), u_{M_1}(y)\right)\right] = hgt(M_1 \cap M_2) = u_{M_2}(d) \quad x \geq y$$

$$= \begin{cases} 1, if\ m_2 \geq m_1 \\ 0, l_1 \geq u_2 \\ \frac{(l_1 - u_2)}{(m_2 - u_2) - (m_1 - l_1)}, otherwise \quad eqn \end{cases} \quad (5)$$

The Degree of Possibility for a Convex Fuzzy Number to be Greater than k Convex

The degree of possibility for a convex fuzzy number to be greater than k convex fuzzy numbers can be defined by:

$V(S \geq S_1, S_2, \dots, S_K) = \min V(S \geq S_i)\,, i = 1,2, \dots k\ \ eqn$ (6)

Assume that $d'(A_i) = min\ V(S_i \geq S_k),\ \ i, k = 1,2, \dots, n; k \neq i$ eqn 5

Then the weight vector is given by $W' = \left(d'(A_1), d'(A_2), \dots, d'(A_k)\right)^T eqn$ (7)

Where $A_i (i = 1,2, \dots, n)$ are n elements.

Via normalization, we get the normalized weight vectors.

$W = (d(A_1), d(A_2), \dots, d(A_n),)^T\ eqn$ (8)

Where W is a non-fuzzy number.

TOPSIS Methodology

Hwang and Yoon (1981) established the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) which has now become one of the widely used multicriteria decision making techniques (MCDM). The concept of fuzzy TOPSIS, is to define the positive ideal solution and negative ideal solution.The alternative which possesses the shortest distance from the positive ideal solution (PIS) and also possesses the farthest distance from the negative ideal solution (NIS), is considered to be superlative alternative (Amiri-arif, 2012). However, it is sometimes challenging for a decision maker to give an option an exact performance grade for the features being taken into account. The benefit of employing a fuzzy TOPSIS technique is that fuzzy numbers can be used to assign various metric values. Let, Ñ = (l_1, m_1, u_1) and Ù = (l_2, m_2, u_2) be two triangular fuzzy numbers, then the distance between two triangular fuzzy numbers can be calculated as:

dv(Ñ,Ù) = $\sqrt{\frac{1}{3}[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2]}\ \ eqn$ (9)

The MCDM is a practical tool for selecting and ranking a number of alternatives and it has several applications. The most frequently used MCDM techniques are Simple Additive Weighting (SAW), Analytical Hierarchy Process (AHP), Elimination and Choice Expressing Reality (ELECTRE), Preference Ranking Organization Method for enrichment evaluations (PROMETHEE), PROSPECT theory and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).

Constructing the Fuzzy Decision Matrix for Software Requirements

Fuzzy decision matrix (FDM) is to be constructed after evaluating the Functional Requirements (FRs) as Alternative and Non-functional requirements (NFRs) as Criteria by a team of Decision Makers (DM). The fuzzy ratings of all the DMs are described as TFNs $\tilde{A}_k = (l_k, m_k, u_k)\ where\ k = 1, 2, 3, \dots k$. The aggregated fuzzy rating can be determined as Ã = (l, m, u) k = 1, 2, . . . , K.

Here,

$i = \min\{g_k\}$,h = $\frac{1}{k}\sum_{k=1}^{k} h_k\ u = \max(u_k)\ eqn$ (10)

If the fuzzy rating of the team of the DM is $\tilde{A}_{ijk} = \left(l_{ijk}, m_{ijk}, u_{ijk}\right)\ where\ i = 1, 2, 3, \dots m\ and\ j = 1, 2, 3 \dots n$. Here, m and n are the number of FRs and NFRs, respectively. The aggregated fuzzy rating (x_{ij}) of FRs with respect to NFRs can be calculated as $x_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right)$.

Here,

$l_{ij=\min\{l_{ijk}\}} m = \frac{1}{k}\sum_{k=1}^{k} h_{ijk}\ u = \max\{u_{ijk}\}\ eqn$ (11)

If the importance weight of the team of DM is $w_{ijk} = w_{jk1}, w_{jk2}, w_{jk3}$, then the aggregated fuzzy weights (w_{ij}) of each NFR is computed as:

$$w_j = w_{j1}, w_{j2}, w_{j3}$$

Here,

$w_{j1} = \min\{l_{ij1}\}$ $w_{j2} = \frac{1}{k}\sum_{k=1}^{k} h_{ij2}$ $w_{j3} = \max\{u_{ij3}\}$ eqn (12)

After that, the fuzzy decision matrix (FDM) is constructed as:

$$F = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2n} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3n} \\ . & . & . & . & . \\ x_{m1} & x_{m2} & x_{m3} & \cdots & x_{mn} \end{bmatrix}$$

$$w = [w_1, w_2, w_3, \dots, w_n]$$

Here, $x_{ij} = (l_{ij}, m_{ij}, u_{ij})$ and $w_j = (w_{j1}, w_{j2}, w_{j3})$; i = 1, 2, . . . , m, j = 1, 2, . . . , n can be approximated by positive TFNs.

Construct Normalized and Weighted Normalized Decision Matrix

$Z = [z_{ij}]mxn$ $i = 1,2,3,\dots m$ $j = 1,2,3,\dots n$ eqn (13)

Where $z_{ij} = \left\{\frac{l_{ij}}{u_j^*}, \frac{m_{ij}}{u_j^*}, \frac{u_{ij}}{u_j^*}\right\} u_j^* = max(u_{ij})$

The weighted normalized fuzzy decision matrix (WNFDM) is computed by multiplying each row of the normalized decision matrix by its associated weight. The element $w_{ij}^{\sim}$ of this new matrix is:

$w^{\sim} = [w_{ij}^{\sim}]mxn$ $i = 1,2,3,\dots.m$ $j = 1,2,3,\dots n$ eqn (14)

$$w_{ij}^{\sim} = z_{ij}\,(.)wj$$

Here, $\boldsymbol{wj}$ represents the importance weight of each NFR.

Determining the Fuzzy Positive Ideal V^+ and fuzzy Negative Ideal V^- Solutions

$V^+ = V_1^+, V_2^+, v_3^+ \dots V_n^+$ eqn (15)

$V^- = V_1^-, V_2^-, v_3^- \dots V_n^-$ eqn (16)

Where,

$V_j^+ = \max(V_{ij3})$ and $V_j^- = \min(V_{ij1})$ where $\boldsymbol{i} = 1,2,3,.m$ $j = 1,2,3,\dots n$

Find Distance of Each Alternative from V^+ and V^-

The distance of each FR from $\boldsymbol{V^+}$ and $\boldsymbol{V^-}$ are calculated as:

$$S_i^+ = \sqrt{\sum_{j=1}^{n}\left(w_{ij}^{\sim} - V_j^+\right)^2}\ \boldsymbol{i} = 1,2,3,\dots.m \quad j = 1,2,3,\dots n \quad eqn\ (17)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}\left(w_{ij}^{\sim} - V_j^-\right)^2}\ i = 1,2,3,\dots.m \quad j = 1,2,3,\dots n\ eqn \quad (18)$$

Where S_i^+ is the distance of i^{th} alternative of Positive Ideal Solution (PIS) and S_i^- is the distance of i^{th} of Negative Ideal Solution (NIS).

Find Closeness Coefficient (CC_i) of Each Functional Requirement

The closeness coefficients (CC_i) represent the distances to V^+ and V^-. The closeness coefficient of each FR is calculated as:

$$CC_i = \frac{S_i^-}{(S_i^+) + S_i^-} i = 1,2,3,\dots.m$$

Where $CC_i \in \{0,1\}$. Finally, rank the alternatives according to the relative closeness.

Quantitative Measure Rank Stability

i. ***Spearman's Rank Correlation:*** Measures how well two sets of rankings agree in terms of overall order

$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$ eqn (19)

$$where: d_i = difference\ between\ the\ ranks\ of\ FR_i\ in\ two\ scenarios$$
$$n = number\ of\ common\ FRs.$$

A value close to $\rho = 1$ means very strong ranking

ii. ***Kendall's Tau:*** Measure agreement between two rankings by looking at pairs of items.

$\tau = \frac{C-D}{\frac{n(n-1)}{2}}$ eqn (20)

$$where\ C = concordant\ pairs$$
$$D = discordant\ pairs\ and$$
$$C + D = \frac{n(n-1)}{2}$$

iii. ***Proportion of Pairwise Reversals:*** This is simply the fraction of discordant pairs out of all possible pairs. It is a direct measure of instability which shows that how often the relative order flips between two rankings.

$proportion = \frac{D}{\frac{1}{2}n(n-1)}$ eqn (21)

$$where\ N = \frac{1}{2}n(n-1)$$

RESULTS AND DISCUSSION

Fuzzy AHP NFR Weights for Extent Analysis Method

Step 1: PCM is constructed by four DM for the five NFR. This PCM are given below

Table 2: PCM by DM1

NFR	Security (S)	Performance (P)	Usability (U)	Flexibility (F)	Availability (A)
Security (S)	1,1,1	6,7,8	4,5,6	1,1,1	1,1,1
Performance (P)	$\frac{1}{8},\frac{1}{7},\frac{1}{6}$	1,1,1	4,5,6	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$	$\frac{1}{8},\frac{1}{7},\frac{1}{6}$
Usability (U)	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$	$\frac{1}{6},\frac{1}{5},\frac{1}{4},$	1,1,1	6,7,8	6,7,8
Flexibility (F)	1,1,1	4,5,6	$\frac{1}{8},\frac{1}{7},\frac{1}{6}$	1,1,1	4,5,6
Availability (A)	1,1,1	6,7,8	$\frac{1}{8},\frac{1}{7},\frac{1}{6}$	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$	1,1,1

Table 3: PCM by DM2

NFR	Security (S)	Performance (P)	Usability (U)	Flexibility (F)	Availability (A)
Security (S)	1,1,1	4,5,6	4,5,6	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$
Performance (P)	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$	1,1,1	6,7,8	$\frac{1}{8},\frac{1}{7},\frac{1}{6},$	$\frac{1}{8},\frac{1}{7},\frac{1}{6},$
Usability (U)	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$	$\frac{1}{8},\frac{1}{7},\frac{1}{6},$	1,1,1	4,5,6	6,7,8
Flexibility (F)	4,5,6	6,7,8	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$	1,1,1	$\frac{1}{8},\frac{1}{7},\frac{1}{6},$
Availability (A)	4,5,6	6,7,8	$\frac{1}{8},\frac{1}{7},\frac{1}{6},$	6,7,8	1,1,1

Table 4: PCM by DM3

NFR	Security (S)	Performance (P)	Usability (U)	Flexibility (F)	Availability (A)
Security (S)	1,1,1	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$	6,7,8	1/5	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$
Performance (P)	4,5,6	1,1,1	4,5,6	$\frac{1}{8},\frac{1}{7},\frac{1}{6},$	$\frac{1}{8},\frac{1}{7},\frac{1}{6},$
Usability (U)	$\frac{1}{8},\frac{1}{7},\frac{1}{6},$	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$	1,1,1	6,7,8	4,5,6
Flexibility (F)	4,5,6	6,7,8	$\frac{1}{8},\frac{1}{7},\frac{1}{6},$	1,1,1	1,1,1
Availability (A)	4,5,6	6,7,8	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$	1,1,1	1,1,1

Table 5: PCM by DM4

NFR	Security (S)	Performance (P)	Usability (U)	Flexibility (F)	Availability (A)
Security (S)	1,1,1	1,1,1	4,5,6	4,5,6	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$
Performance (P)	1,1,1	1,1,1	1,1,1	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$
Usability (U)	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$	1,1,1	1,1,1	$\frac{1}{8},\frac{1}{7},\frac{1}{6},$	$\frac{1}{8},\frac{1}{7},\frac{1}{6},$
Flexibility (F)	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$	4,5,6	6,7,8	1,1,1	$\frac{1}{6},\frac{1}{5},\frac{1}{4}$
Availability (A)	4,5,6	4,5,6	6,7,8	4,5,6	1,1,1

Step 2: By using equation (3) and taking the average value, we obtain the aggregate PCM table for the five DM's as shown in Table 6.

Table 6: Aggregate Table for Five DM's

NFRs	Security	Performance	Usability	Flexibility	Availability
Security (S)	(1,1,1)	(2.79,3.3,3.8)	(4.5,5.5,6.5)	(2.29,2.8,3.3)	(0.375,0.4,0.44)
Performance (P)	(1.3,1.59,1.85)	(1,1,1)	(3.75,4.5,5.25)	(0.15,0.17,0.21)	(0.125,0.14,0.17)
Usability (U)	(0.16,0.19,0.23)	(0.36,0.39,0.42)	(1,1,1)	(4,4.8,5.5)	(4,4.8,5.5)
Flexibility (F)	(2.29,2.8,3.3)	(5,6,7)	(1.6,1.9,2.15)	(1,1,1)	(1.3.1.6,1.85)
Availability (A)	(3.25,4,4.75)	(5.5,6.5,7.5)	(1.6,1.9,2.15)	(2.6,3.1,3.63)	(1,1,1)

Step 3: By using equation (eqn 4) against Table 6, we have

$S_{1 = 10.955,13,15.04 \otimes \left(\frac{1}{70.5},\frac{1}{61.4},\frac{1}{51.94}\right)} = 0.155, 0.212, 0.29$

$S_{2 = 6.325,7.4,8.48 \otimes \left(\frac{1}{70.5},\frac{1}{61.4},\frac{1}{51.94}\right)} = 0.09, 0.121, 0.163$

$S_{3 = 9.52,11.2,12.65 \otimes \left(\frac{1}{70.5},\frac{1}{61.4},\frac{1}{51.94}\right)} = 0.135,0.182,0.244$

$S_{4 = 11.19,13.3,15.3 \otimes \left(\frac{1}{70.5},\frac{1}{61.4},\frac{1}{51.94}\right)} = 0.159,0.217,0.295$

$S_{5 = 13.95,16.5,19.03 \otimes \left(\frac{1}{70.5},\frac{1}{61.4},\frac{1}{51.94}\right)} = 0.198,0.269,0.366$

Using eqn (5), we have:

$V(S_1 \geq S_2) = 1$, $V(S_1 \geq S_3) = 1$

$$V(S_1 \geq S_4) = \frac{0.159 - 0.29}{(0.212 - 0.29) - (0.217 - 0.159)} = 0.96$$

$$V(S_1 \geq S_5) = \frac{0.198 - 0.29}{(0.212 - 0.29) - (0.269 - 0.198)} = 0.62$$

$V(S_2 \geq S_5) = 0$

$$V(S_3 \geq S_1) = \frac{0.155 - 0.244}{(0.182 - 0.244) - (0.212 - 0.155)} = 0.75$$

$V(S_3 \geq S_2) = 1$

$$V(S_3 \geq S_4) = \frac{0.159 - 0.244}{(0.182 - 0.244) - (0.217 - 0.159)} = 0.71$$

$$V(S_3 \geq S_5) = \frac{0.198 - 0.244}{(0.182 - 0.244) - (0.269 - 0.198)} = 0.35$$

$V(S_4 \geq S_1) = 1; V(S_4 \geq S_2) = 1; V(S_4 \geq S_3) = 1$

$$V(S_4 \geq S_5) = \frac{0.198 - 0.244}{(0.217 - 0.295) - (0.269 - 0.198)} = 0.65$$

$V(S_5 \geq S_1) = 1$; $V(S_5 \geq S_2) = 1$; $V(S_5 \geq S_3) = 1$; $V(S_5 \geq S_4) = 1$

Finally by using eqn (6) we obtain:

$$d'(C_1) = V(S_1 \geq S_2 \geq S_3 \geq S_4 \geq S_5) = min(1, 1, 0.96, 0.62)$$

$$d'(C_2) = V(S_2 \geq S_1 \geq S_3 \geq S_4 \geq S_5) = min(0)$$

$d'(C_3) = V(S_3 \geq S_1 \geq S_2 \geq S_4 \geq S_5)$
$= min(0.75, 1, 0.71, 0.35)$
$d'(C_4) = V(S_4 \geq S_1 \geq S_2 \geq S_3 \geq S_5) = min(1, 1, 1, 0.65)$
$d'(C_5) = V(S_5 \geq S_1 \geq S_2 \geq S_3 \geq S_4) = min(1, 1, 1, 1)$
Therefore, $W' = (0.62, 0, 0.35, 0.65, 1)^{\intercal}$.
Via normalization, we have obtained the weight vectors with respect to the decision criteria $C_1, C_2, C_3, C_4, C_{5.}$ $W = (0.24, 0, 0.13, 0.25, 0.38)$
The results show that Availability emerged as the most critical non-functional requirement for the IES, contributing to over 38% of the overall importance. This finding reflects the paramount need to ensure availability of the system, followed by Flexibility for improving system longevity, reducing cost and time when system upgrade is needed, as well as to ensures that the system can adapt, grow, and remain efficient in changing environment. Security followed to ensure security of the system, secure authentication, secure data transmission, and secure access management in examination systems. Usability followed, emphasizing the demand for fast, responsive, and user-friendly interfaces, then finally Performance followed which is completely dominated by other criteria across all pairwise comparisons.

Fuzzy TOPSIS Method for Ranking Alternatives
Base Line FR Ranking
Step 4: In this step, we first define the Triangular Fuzzy Numbers for the different linguistic variables used in our study, as shown in Table 2.

Table 7: Evaluation of the FR on the Basis of NFRs by 4 Decision Maker's (DM)

FRs	DMs	NFRs				
		NFR1	NFR2	NFR3	NFR4	NFR5
FR1	DM1	M	S	VS	M	VS
	DM2	S	V	S	M	S
	DM3	M	S	M	S	VS
	DM4	S	S	VS	VS	M
FR2	DM1	M	M	S	S	M
	DM2	S	S	M	S	VS
	DM3	S	VS	VS	S	VS
	DM4	VS	M	VS	S	M
FR3	DM1	S	S	S	VS	S
	DM2	S	S	S	VS	S
	DM3	S	M	VS	S	M
	DM4	VS	M	VS	S	M
FR4	DM1	S	VS	M	VS	S
	DM2	M	VS	S	VS	S
	DM3	S	S	S	S	VS
	DM4	VS	S	M	S	VS
FR5	DM1	M	VS	VS	M	S
	DM2	M	M	VS	M	VS
	DM3	S	M	S	M	VS
	DM4	VS	S	S	S	VS
FR6	DM1	M	S	VS	S	M
	DM2	S	S	M	VS	M
	DM3	S	S	M	VS	M
	DM4	S	S	M	VS	M
FR7	DM1	VS	S	M	S	VS
	DM2	VS	M	M	S	VS
	DM3	VS	S	VS	S	M
	DM4	S	VS	VS	S	S
FR8	DM1	S	S	S	S	S
	DM2	S	S	S	S	S
	DM3	S	S	S	S	S
	DM4	S	S	S	S	S
FR9	DM1	S	S	S	VS	VS
	DM2	VS	M	S	VS	VS
	DM3	S	M	M	S	VS
	DM4	M	M	VS	S	VS
FR10	DM1	M	M	S	VS	VS
	DM2	M	M	S	VS	S
	DM3	S	S	VS	M	M
	DM4	S	S	S	M	M
FR11	DM1	VS	S	M	M	VS
	DM2	VS	VS	S	S	VS
	DM3	S	M	S	S	S

FRs	DMs	NFRs				
		NFR1	**NFR2**	**NFR3**	**NFR4**	**NFR5**
	DM4	S	M	S	S	M
FR12	DM1	VS	S	M	S	S
	DM2	S	S	M	M	M
	DM3	M	M	M	S	S
	DM4	VS	S	M	S	S
FR13	DM1	S	VS	S	VS	M
	DM2	S	M	S	S	M
	DM3	M	S	M	S	S
	DM4	M	M	VS	S	S
FR14	DM1	VS	S	VS	M	S
	DM2	VS	S	VS	S	S
	DM3	VS	M	S	S	S
	DM4	VS	M	VS	M	S
FR15	DM1	S	M	VS	M	VS
	DM2	S	M	S	S	M
	DM3	S	M	VS	S	M
	DM4	S	M	VS	M	M

Step 5: After computing the aggregate fuzzy rating of the FR on the basis of the results of Table 7, we replaced the linguistic variable with their fuzzy corresponding scale, as shown in Table 8 while the result of aggregation of table 8 are shown in table 9. After that, now we normalize the Table 9, and after normalization the results are shown in Table 10. The weighted normalized matrix is given in Table 11.

Table 8: TFN Correspondence Evaluation of the FR on the Basis of NFRs by 4 (DM's)

FRs	DMs	NFRs				
		NFR1	**NFR2**	**NFR3**	**NFR4**	**NFR5**
FR1	DM1	(4,6,8)	(6,8,10)	(8,10,10)	(4,6,8)	(8,10,10)
	DM2	(6,8,10)	(8,10,10)	(6,8,10)	(4,6,8)	(6,8,10)
	DM3	(4,6,8)	(6,8.10)	(4,6,8)	(6,8,10)	(8.10,10)
	DM4	(6,8,10)	(6,8,10)	(8,10,10)	(8,10,10)	(4,6,8)
FR2	DM1	(4,6,8)	(4,6,8)	(6,8,10)	(6,8,10)	(4,6,8)
	DM2	(6,8,10)	(6,8,10)	(4,6,8)	(6,8,10)	(8,10,10)
	DM3	(4,6,8)	(8,10,10)	(8,10,10)	(6,8,10)	(8,10,10)
	DM4	(8,10,10)	(4,6,8)	(8,10,10)	(6,8,10)	(4,6,8)
FR3	DM1	(6,8,10)	(6,8,10)	(6,8,10)	(8,10,10)	(6,8,10)
	DM2	(6,8,10)	(6,8,10)	(6,8,10)	(8,10,10)	(6,8,10)
	DM3	(6,8,10)	(4,6,8)	(8,10,10)	(6,8,10)	(4,6,8)
	DM4	(8,10,10)	(4,6,8)	(8,10,10)	(6,8,10)	(4,6,8)
FR4	DM1	(6,8,10)	(8,10,10)	(4,6,8)	(8,10,10)	(6,8,10)
	DM2	(4,6,8)	(8,10,10)	(6,8,10)	(8,10,10)	(6,8,10)
	DM3	(6,8,10)	(6,8,10)	(6,8,10)	(6,8,10)	(8,10,10)
	DM4	(8,10,10)	(6,8,10)	(4,6,8)	(6,8,10)	(8,10,10)
FR5	DM1	(4,6,8)	(8,10,10)	(8,10,10)	(4,6,8)	(6,8,10)
	DM2	(4,6,8)	(4,6,8)	(8,10,10)	(4,6,8)	(8,10,10)
	DM3	(6,8,10)	(4,6,8)	(6,8,10)	(4,6,8)	(8,10,10)
	DM4	(8,10,10)	(6,8,10)	(6,8,10)	(6,8,10)	(8,10,10)
FR6	DM1	(4,6,8)	(6,8,10)	(8,10,10)	(6,8,10)	(4,6,8)
	DM2	(6,8,10)	(6,8,10)	(4,6,8)	(8,10,10)	(4,6,8)
	DM3	(6,8,10)	(6,8,10)	(4,6,8)	(8,10,10)	(4,6,8)
	DM4	(6,8,10)	(6,8,10)	(6,8,10)	(8,10,10)	(4,6,8)
FR7	DM1	(8,10,10)	(6,8,10)	(6,8,10)	(6,8,10)	(8,10,10)
	DM2	(8,10,10)	(6,8,10)	(4,6,8)	(6,8,10)	(8,10,10)
	DM3	(8,10,10)	(4,6,8)	(4,6,8)	(6,8,10)	(4,6,8)
	DM4	(6,8,10)	(6,8,10)	(8,10,10)	(6,8,10)	(6,8,10)
FR9	DM1	(6,8,10)	(6,8,10)	(6,8,10)	(8,10,10)	(8,10,10)
	DM2	(8,10,10)	(4,6,8)	(6,8,10)	(8,10,10)	(8,10,10)
	DM3	(6,8,10)	(4,6,8)	(4,6,8)	(6,8,10)	(8,10,10)
	DM4	(4,6,8)	(4,6,8)	(8,10,10)	(6,8,10)	(8,10,10)
FR10	DM1	(4,6,8)	(4,6,8)	(6,8,10)	(8,10,10)	(8,10,10)

FRs	DMs	NFRs				
		NFR1	**NFR2**	**NFR3**	**NFR4**	**NFR5**
	DM2	(4,6,8)	(4,6,8)	(6,8,10)	(8,10,10)	(6,8,10)
	DM3	(6,8,10)	(6,8,10)	(8,10,10)	(4,6,8)	(4,6,8)
	DM4	(6,8,10)	(6,8,10)	(6,8,10)	(4,6,8)	(4,6,8)
FR11	DM1	(8,10,10)	(6,8,10)	(4,6,8)	(4,6,8)	(8,10,10)
	DM2	(8,10,10)	(8,10,10)	(6,8,10)	(6,8,10)	(8,10,10)
	DM3	(6,8,10)	(4,6,8)	(6,8,10)	(6,8,10)	(6,8,10)
	DM4	(6,8,10)	(6,8,10)	(6,8,10)	(6,8,10)	(4,6,8)
FR12	DM1	(8,10,10)	(6,8,10)	(6,8,10)	(6,8,10)	(6,8,10)
	DM2	(6,8,10)	(6,8,10)	(4,6,8)	(4,6,8)	(4,6,8)
	DM3	(4,6,8)	(4,6,8)	(4,6,8)	(6,8,10)	(6,8,10)
	DM4	(8,10,10)	(6,8,10)	(4,6,8)	(6,8,10)	(6,8,10)
FR13	DM1	(6,8,10)	(8,10,10)	(6,8,10)	(8,10,10)	(4,6,8)
	DM2	(6,8,10)	(4,6,8)	(6,8,10)	(6,8,10)	(4,6,8)
	DM3	(4,6,8)	(6,8,10)	(4,6,8)	(6,8,10)	(6,8,10)
	DM4	(4,6,8)	(4,6,8)	(8,10,10)	(6,8,10)	(6,8,10)
FR14	DM1	(8,10,10)	(6,8,10)	(8,10,10)	(4,6,8)	(6,8,10)
	DM2	(8,10,10)	(6,8,10)	(8,10,10)	(6,8,10)	(6,8,10)
	DM3	(8,10,10)	(4,6,8)	(6,8,10)	(6,8,10)	(6,8,10)
	DM4	(8,10,10)	(4,6,8)	(8,10,10)	(4,6,8)	(6,8,10)
FR15	DM1	(6,8,10)	(4,6,8)	(6,8,10)	(6,8,10)	(8,10,10)
	DM2	(6,8,10)	(4,6,8)	(8,10,10)	(6,8,10)	(4,6,8)
	DM3	(6,8,10)	(4,6,8)	(8,10,10)	(4,6,8)	(4,6,8)
	DM4	(6,8,10)	(4,6,8)	(4,6,8)	(4,6,8)	(4,6,8)

Table 9: Aggregated Fuzzy Decision Matrix Table

FRs	NFR1	NFR2	NFR3	NFR4	NFR5
FR1	(4,7,10)	(6,8.5,10)	(4,8.5,10)	(4,7.5,10)	(4,8.5,10)
FR2	(4,7.5,10)	(4,7.5,10)	(4,8.5,10)	(6,8,10)	(4,8,10)
FR3	(6,8.5,10)	(4,7,10)	(6,9,10)	(6,9,10)	(4,7,10)
FR4	(4,8,10)	(6,9,10)	(4,7,10)	(6,9,10)	(6,9,10)
FR5	(4,7.5,10)	(4,7.5,10)	(6,9,10)	(4,6.5,10)	(6,9.5,10)
FR6	(4,7.5,10)	(6,8,10)	(4,7.5,10)	(6,9.5,10)	(4,6,8)
FR7	(6,9.5,10)	(4,7.5,10)	(4,7.5,10)	(6,8,10)	(4,8.5,10)
FR8	(6,8,10)	(6,8,10)	(6,8,10)	(6,8,10)	(6,8,10)
FR9	(4,8,10)	(4,6.5,8)	(4,8,10)	(6,9,10)	(8,10,10)
FR10	(4,7,10)	(4,7,10)	(6,8.5,10)	(4,8,10)	(4,7.5,10)
FR11	(6,9,10)	(4,7.5,10)	(4,7.5,10)	(4,7.5,10)	(4,8.5,10)
FR12	(4,8.5,10)	(4,7.5,10)	(4,6.5,10)	(4,7.5,10)	(4,7.5,10)
FR13	(4,7,10)	(4,7.5,10)	(4,8,10)	(6,8.5,10)	(4,7,10)
FR14	(8,10,10)	(4,7,10)	(6,9.5,10)	(4,7,10)	(6,8,10)
FR15	(6,8,10)	(4,6,8)	(4,8.5,10)	(4,7,10)	(4,7,10)

Table 10: Normalized Fuzzy Decision Matrix with Criteria

FRs	NFR1	NFR2	NFR3	NFR4	NFR5
FR1	(0.4,0.7,1)	(0.6,0.85,1)	(0.4,0.85,1)	(0.4,0.75,1)	(0.4,0.85,1)
FR2	(0.4,0.75,1)	(0.4,0.75,1)	(0.4,0.85,1)	(0.6,0.8,1)	(0.4,0.8,1)
FR3	(0.6,0.85,1)	(0.4,0.7,1)	(0.6,0.9,1)	(0.6,0.9,1)	(0.4,0.7,1)
FR4	(0.4,0.8,1)	(0.6,0.9,1)	(0.4,0.7,1)	(0.6,0.9,1)	(0.6,0.9,1)
FR5	(0.4,0.75,1)	(0.4,0.75,1)	(0.6,0.9,1)	(0.4,0.65,1)	(0.6,0.95,1)
FR6	(0.4,0.75,1)	(0.6,0.8,1)	(0.4,0.75,1)	(0.6,0.95,1)	(0.4,0.6,0.8)
FR7	(0.6,0.95,1)	(0.4,0.75,1)	(0.4,0.75,1)	(0.6,0.8,1)	(0.4,0.85,1)
FR8	(0.6,0.8,1)	(0.6,0.8,1)	(0.6,0.8,1)	(0.6,0.8,1)	(0.6,0.8,1)
FR9	(0.4,0.8,1)	(0.4,0.65,1)	(0.4,0.8,1)	(0.6,0.9,1)	(0.8,1,1)
FR10	(0.4,0.7,1)	(0.4,0.7,1)	(0.6,0.85,1)	(0.4,0.8,1)	(0.4,0.75,1)
FR11	(0.6,0.9,1)	(0.4,0.75,1)	(0.4,0.75,1)	(0.4,0.75,1)	(0.4,0.85,1)
FR12	(0.4,0.85,1)	(0.4,0.75,1)	(0.4,0.65,1)	(0.4,0.75,1)	(0.4,0.75,1)
FR13	(0.4,0.7,1)	(0.4,0.75,1)	(0.4,0.8,1)	(0.6,0.85,1)	(0.4,0.7,1)
FR14	(0.8,1,1)	(0.4,0.7,1)	(0.6,0.95,1)	(0.4,0.7,1)	(0.6,0.8,1)

FR15	(0.6,0.8,1) 0.24	(0.4,0.6,0.8) 0	(0.4,0.85,1) 0.13	(0.4,0.7,1) 0.25	(0.4,0.7,1) 0.32

Table 11: Weighted Normalized Fuzzy Decision Matrix

FRs	NFR1	NFR2	NFR3	NFR4	NFR5
FR1	(0.096,0.168,0.24)	0	(0.052,0.1105,0.13)	(0.1,0.1875,0.25)	(0.152,0.323,0.38
FR2	(0.096,0.18,0.24)	0	(0.052,0.1105,0.13)	(0.15,0.2,0.25)	(0.152,0.304,0.38)
FR3	(0.144,0.204,0.24)	0	(0.078,0.117,0.13)	(0.15,0.225,0.25)	(0.152,0.266,0.38)
FR4	(0.096,0.192,0.24)	0	(0.052,0.091,0.13)	(0.15,0.225,0.25)	(0.228,0.342,0.38)
FR5	(0.096,0.18,0.24)	0	(0.078,0.117,0.13)	(0.1,0.1625,0.25)	(0.228,0.361,0.38)
FR6	(0.096,0.18,0.24)	0	(0.052,0.0975,0.13)	(0.15,0.2375,0.25)	(0.152,0.228,0.304)
FR7	(0.144,0.228,0.24)	0	(0.052,0.0975,0.13)	(0.15,0.2,0.25)	(0.152,0.323,0.38)
FR8	(0.144,0.192,0.24)	0	(0.078,0.104,0.13)	(0.15,0.2,0.25)	(0.228,0.304,0.38)
FR9	(0.096,0.192,0.24)	0	(0.052,0.104,0.13)	(0.15,0.225,0.25)	(0.304,0.38,0.38)
FR10	(0.096,0.168,0.24)	0	(0.078,0.1105,0.13)	(0.1,0.2,0.25)	(0.152,0.285,0.38)
FR11	(0.144,0.216,0.24)	0	(0.052,0.0975,0.13)	(0.1,0.1875,0.25)	(0.152,0.323,0.38)
FR12	(0.096,0.204,0.24)	0	(0.052,0.0845,0.13)	(0.1,0.1875,0.25)	(0.152,0.285,0.38)
FR13	(0.096,0.168,0.24)	0	(0.052,0.104,0.13)	(0.15,0.2125,0.25)	(0.152,0.266,0.38)
FR14	(0.192,0.24,0.24)	0	(0.078,0.1235,0.13)	(0.1,0.175,0.25)	(0.228,0.304,0.38)
FR15	(0.144,0.192,0.24)	0	(0.052,0.1105,0.13)	(0.1,0.175,0.25)	(0.152,0.266,0.38)

Step 6: In Tables 12 and 13, we compute the distance of each FR from Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS), respectively, using eqn (9)

D1+ =

d(FR1, FR*) $\sqrt{\frac{1}{3}[0.24-0.096)^2+(0.24-0.168)^2+(0.24-0.24)^2]}$

$= 0.093$

D1¯=

d(FR1,

FR*) $\sqrt{\frac{1}{3}[0.096-0.096)^2+(0.096-0.168)^2+(0.096-0.24)^2]}$

$= 0.09295$

The results of the remaining steps are summarized in Tables 12 and 13

Table 12: Distance Between FRi (i= 1,2,…,15) and FR+ with Respect to NFRs FPIS; Maximum Values Across all FRs for Each NFR

Distance	NFR1	NFR2	NFR3	NFR4	NFR5	SUM
D1+ = d(FR1, FR*)	0.093	0	0.04641928	0.093819	0.135687	0.368877
D2+ = d(FR1, FR*)	0.0901	0	0.04641928	0.06455	0.138756	0.339792
D3+ = d(FR1, FR*)	0.0592	0	0.03094619	0.059512	0.147173	0.296826
D4+ = d(FR1, FR*)	0.0876	0	0.05034878	0.059512	0.090458	0.287954
D5+ = d(FR1, FR*)	0.0901	0	0.03094619	0.10026	0.08844	0.309713
D6+ = d(FR1, FR*)	0.0901	0	0.0487861	0.058184	0.164179	0.361216
D7+ = d(FR1, FR*)	0.0559	0	0.0487861	0.06455	0.135687	0.30488
D8+ = d(FR1, FR*)	0.062	0	0.03356586	0.06455	0.098116	0.258199
D9+ = d(FR1, FR*)	0.0876	0	0.04746929	0.059512	0.043879	0.238495
D10+ = d(FR1, FR*)	0.093	0	0.03206374	0.091287	0.142606	0.358908
D11+ = d(FR1, FR*)	0.0571	0	0.0487861	0.093819	0.135687	0.335424
D12+ = d(FR1, FR*)	0.0857	0	0.05213524	0.093819	0.142606	0.374257
D13+ = d(FR1, FR*)	0.093	0	0.04746929	0.061661	0.147173	0.349255
D14+ = d(FR1, FR*)	0.0277	0	0.03025585	0.096825	0.098116	0.252909
D15+ = d(FR1, FR*)	0.062	0	0.04641928	0.173805	0.147173	0.429366

Table 13: Distance Between FRi (i= 1,2,…,15) and FR- with Respect to NFRs FNIS; Minimum Values Across all FRs for Each NFR

DISTANCE	NFR1	NFR2	NFR3	NFR4	NFR5	SUM
D1¯=d(FR1, FR*)	0.092952	0	0.056292	0.10026	0.164545	0.414048
D2¯=d(FR1, FR*)	0.092952	0	0.056292	0.06455	0.158207	0.372
D3¯=d(FR1, FR*)	0.065361	0	0.037528	0.072169	0.147173	0.32223
D4¯=d(FR1, FR*)	0.09992	0	0.050349	0.072169	0.109697	0.332134
D5¯=d(FR1, FR*)	0.09625	0	0.037528	0.093819	0.116609	0.344206
D6¯=d(FR1, FR*)	0.09625	0	0.052135	0.076716	0.098116	0.323217
D7¯=d(FR1, FR*)	0.073648	0	0.052135	0.06455	0.164545	0.354878
D8¯=d(FR1, FR*)	0.061968	0	0.033566	0.06455	0.098116	0.258199
D9¯=d(FR1, FR*)	0.09992	0	0.054123	0.072169	0.062054	0.288266
D10¯=d(FR1, FR*)	0.092952	0	0.035404	0.104083	0.152395	0.384834
D11¯=d(FR1, FR*)	0.069282	0	0.052135	0.10026	0.164545	0.386222

D12¯=d(FR1, FR*)	0.103923	0	0.048786	0.10026	0.152395	0.405365
D13¯=d(FR1, FR*)	0.092952	0	0.054123	0.068084	0.147173	0.362332
D14¯=d(FR1, FR*)	0.039192	0	0.039893	0.096825	0.098116	0.274025
D15¯=d(FR1, FR*)	0.061968	0	0.056292	0.096825	0.147173	0.362257

Step 7: Finally, by finding their values of closeness coefficients as follows, we rank the FRs

$CC_1 = \frac{0.414048}{0.368877+0.414048} = 0.528847$

CC_1= 0.528847, CC_2= 0.524826, CC_3= 0.520519, CC_4= 0.535624, CC_5= 0.526374, CC_6= 0.472241, CC_7= 0.537891, CC_8= 0.5, CC_9= 0.547242, CC_{10}= 0.51743, CC_{11}= 0.5352, CC_{12}= 0.51995, CC_{13}= 0.50919, CC_14= 0.52004, CC_{15}= 0.45761

The CC values are used to find out the ranking values of the FRs. Based on the CC values, the ranking values of the FRs are given below:

FR1 = 5, FR2 = 7, FR3 = 8, FR4 = 3, FR5 = 6, FR6 = 14, FR7 = 2, FR8 = 13, FR9 = 1, FR10 = 11, FR11 = 4, FR12 = 10, FR13 = 12, FR14 = 9, FR15 = 15.

Addition of FR

Step 8: In this step, we introduced another functional requirement as attached in Table 7 (linguistic values) to the initial 15 to test rank reversal possible occurrence, the result is given below.

FR1 = 7, FR2 = 6, FR3 = 12, FR4 = 2, FR5 = 5, FR6 = 15, FR7 = 3, FR8 = 14, FR9 = 1, FR10 = 11, FR11 = 4, FR12 = 9, FR13 = 10, FR14 = 13, FR15 = 8, FR16 = 16.

Removal of FR

Step 9: In this step, we remove functional requirement as attached in table 7 (linguistic values) to the initial 15 to test rank reversal possible occurrence, the result is shown below.

FR1 = 5, FR2 = 7, FR3 = 8, FR4 = 3, FR5 = 6, FR6 = 13, FR7 = 2, FR8 = 3, FR9 = 11, FR10 = 4, FR11 = 10, FR12 = 12, FR13 = 9, FR14 = 14.

For Conventional Method

Base Line FR Ranking

Step 10: After following the series of steps from 4 to 7, we obtained the result of TOPSIS ranking as shown below for the conventional method, which we used in our study to compare the proposed method.

FR1 = 8, FR2 = 9, FR3 = 7, FR4 = 6, FR5 = 1, FR6 = 14, FR7 = 3, FR8 = 12, FR9 = 4, FR10 = 11, FR11 = 5, FR12 = 10, FR13 = 13, FR14 = 2, FR15 = 15.

Addition of FR

Step 11: In this step, we introduced another functional requirement as attached in table 7 (linguistic values) to the initial 15 to test rank reversal possible occurrence, the result is given below.

FR1 = 11, FR2 = 7, FR3 = 13, FR4 = 2, FR5 = 9, FR6 = 12, FR7 = 1, FR8 = 14, FR9 = 3, FR10 = 15, FR11 = 5, FR12 = 10, FR13 = 8, FR14 = 4, FR15 = 6, FR16 = 16.

Removal of FR

Step 12: In this step, we remove functional requirement as attached in table 7 (linguistic values) to the initial 15 to test rank reversal possible occurrence, the result is shown below.

FR1 = 8, FR2 = 9, FR3 = 7, FR4 = 6, FR5 = 1, FR6 = 13, FR7 = 3, FR8 = 4, FR9 = 11, FR10 = 5, FR11 = 10, FR12 = 12, FR13 = 2, FR14 = 14.

Quantitative Rank-Stability Analysis

Comparative Results

The proposed Improved Fuzzy AHP-TOPSIS framework was compared with conventional TOPSIS using Spearman's rank correlation coefficient (ρ), Kendall's tau (τ), and the proportion of pairwise reversals (PPR). The objective is to determine whether the proposed framework provides greater ranking stability and mitigates rank reversal when alternatives are added or removed.

iv. Spearman’s Rank Correlation for the proposed method

Table 14: Spearman’s Rank Correlation

Alternative	**BASE (R1)**	**ADDITIVE (R2)**	**d = R1-R2**	**d2**
FR9	1	1	0	0
FR7	2	3	-1	1
FR4	3	2	1	1
FR11	4	4	0	0
FR1	5	7	-2	4
FR5	6	5	1	1
FR2	7	6	1	1
FR3	8	12	-4	16
FR14	9	13	-4	16
FR12	10	9	1	1
FR10	11	11	0	0
FR13	12	10	2	4
FR8	13	14	-1	1
FR6	14	15	-1	1
FR15	15	8	7	49
n = 15				$\sum d^2 = 96$

By employing eqn (19) and substituting the values, we have:

$\rho = 1 - \frac{6(96)}{15(15^2-1)}$

$\rho = 0.8286$

v. Kendall’s Tau

Step 13: For every pair of FRs, we compare their ordering in BASE with their ordering in ADDITIVE as shown in Table 14.

For illustration, the comparison between Pair FR9 vs. FR7 and Pair FR1 vs. FR2 is presented in Table 15. As indicated, similar pairwise evaluations were conducted across both the proposed and conventional methods to derive the values of Concordant (C) and Discordant (D).

Table 14 illustrates the Spearman's rank correlation calculation for the Base → Additive scenario. The same procedure was applied across all scenarios—Base → Additive, Base → Removal, and Additive → Removal—under both the proposed and conventional methods.

Table 15: Comparative Result for Obtaining Value of C and D

Method	Pair	Result
BASE	FR9(1) < FR7(2)	Their relationship ordering is maintained. Therefore Concordant (C)
ADDITIVE	FR9(1) < FR7(3)	
BASE	FR1(5) < FR2(7)	Their relationship ordering is changed. Therefore discordant (D)
ADDITIVE	FR1(7) > FR2(6)	

By examining every pair of alternatives we obtain:
$C = 88\ concordant\ pairs;\ D = 17\ discordant\ pairs$
Using eqn (20) and substituting the values, we have:

$$\tau = \frac{88 - 17}{88 + 17}$$

$$\tau = 0.6762$$

vi. Pairwise reversal rate

Also, using eqn (21):

$$PRR = \frac{17}{105} \times 100$$

$$PRR = 16.2\%$$

Summary of Comparative Results

The results compare the proposed method with conventional TOPSIS under three experimental comparisons: Base → Additive, Base → Removal, and Additive → Removal. The comparison uses Spearman's rank correlation (ρ), Kendall's tau (τ), and the pairwise rank-reversal proportion (PRR). The values below are taken directly from the supplied results document.

Table 16: Summary of Comparative Results

Comparison	Method	Spearman ρ	Kendall τ	PRR
Base → Additive	Proposed	0.8286	0.6762	16.19%
Base → Additive	Conventional	0.4857	0.3143	34.2857%
Base → Removal	Proposed	0.1912	0.1868	39.56%
Base → Removal	Conventional	0.3100	-0.0110	50.55%
Additive → Removal	Proposed	0.1452	0.2088	39.56%
Additive → Removal	Conventional	-0.2180	-0.0990	54.95%

The summary table reports the three scenario comparisons and their corresponding rank-agreement and pairwise-reversal measures.

Table 17: Quantitative Improvement of the Proposed Method

Comparison	Spearman Improvement	Kendall Improvement	Reduction in PPR
Base → Additive	+0.3429	+0.3619	18.1 percentage points
Base → Removal	-0.1188	+0.1978	10.99 percentage points
Additive → Removal	+0.3632	+0.3077	15.39 Percentage points

vii. Base-to-Additive Comparison

The Base-to-Additive experiment shows the clearest advantage of the proposed framework. The proposed method records a Spearman's rho of 0.8286 and Kendall's tau of 0.6762, compared with 0.4857 and 0.3143, respectively, for conventional TOPSIS. It also produces a lower pairwise rank-reversal proportion of 16.19%, compared with 34.2857% for conventional TOPSIS. Thus, when an alternative is added, the proposed framework preserves the relative ordering of the functional requirements substantially better.

The reported improvements are +0.3429 in Spearman's rho and +0.3619 in Kendall's tau, together with an 18.1-percentage-point reduction in PRR. This is the strongest evidence in the reported experiments for improved ranking stability under an additive change.

viii. Base-to-Removal Comparison

The Base-to-Removal experiment presents a mixed result. The proposed method has a higher Kendall's tau (0.1868) than conventional TOPSIS (-0.0110), and it reduces PRR from 50.55% to 39.56%. These findings indicate improved pairwise stability under the reported removal experiment. However, the proposed method has a lower Spearman's rho (0.1912) than conventional TOPSIS (0.3100). Therefore, the proposed method should not be described as outperforming conventional TOPSIS on every rank-agreement measure in this scenario.

The reported changes are -0.1188 in Spearman's rho, +0.1978 in Kendall's tau, and a 10.99-percentage-point reduction in PRR. The appropriate interpretation is therefore that the proposed framework improves some dimensions of ranking stability during removal, particularly Kendall-based agreement and pairwise reversal rate, while Spearman agreement is lower than that of conventional TOPSIS.

ix. Additive-to-Removal Comparison

In the Additive-to-Removal comparison, the proposed method again shows stronger Kendall agreement and a lower pairwise reversal proportion than conventional TOPSIS. Kendall's tau increases from -0.0990 for conventional TOPSIS to 0.2088 for the proposed method, while PRR decreases from 54.95% to 39.56%. Spearman's rho changes from -0.2180 under conventional TOPSIS to 0.1452 under the proposed method.

The reported improvements are +0.3632 for Spearman's rho and +0.3077 for Kendall's tau, with a 15.39-percentage-point reduction in PRR. These results provide evidence that the proposed framework offers greater stability than conventional TOPSIS for this comparison.

x. Overall Interpretation

The comparative results indicate that the proposed Improved Fuzzy AHP–TOPSIS framework generally provides greater ranking stability than conventional TOPSIS. In the Base-to-Additive scenario, the proposed method achieves substantially higher Spearman and Kendall rank correlations and reduces the pairwise rank-reversal proportion from 34.29% to 16.19%. In the Base-to-Removal scenario, the proposed method improves Kendall's tau and reduces pairwise reversals, although its Spearman correlation is lower than that of conventional TOPSIS. In the Additive-to-Removal comparison, the proposed framework improves both rank correlation measures and reduces pairwise reversals. Overall, the findings suggest that the proposed framework mitigates, rather than completely eliminates, rank reversal and provides improved ranking stability under the tested decision-set modifications.

CONCLUSION

This research addresses the challenges of functional requirement selection in software development projects by introducing an innovative fuzzy-based decision support framework. The study employs Fuzzy AHP extent analysis to manage imprecision in evaluating non-functional requirements, allowing decision makers to express preferences more flexibly than with traditional crisp AHP. The fuzzy-derived weights are then integrated into Fuzzy TOPSIS, which ranks functional requirements by measuring proximity to the positive ideal and distance from the negative ideal, thereby capturing both strengths and weaknesses of alternatives.

The resulting rankings provide clear, data-driven prioritization of requirements, validated through a case study. While the framework demonstrates strong applicability to requirement prioritization problems, further empirical testing is needed to confirm its scalability across larger datasets and diverse domains. Importantly, the methodology mitigates the rank reversal issue common in decision-making approaches by embracing uncertainty. The findings affirm that combining Fuzzy AHP extent analysis with Fuzzy TOPSIS yields superior, explainable, and justifiable prioritizations, ultimately supporting more successful software project outcomes.

Limitation and Future Work

This study was evaluated using a single case study involving an Institute Examination System. Although the case study provides an empirical basis for assessing the proposed Fuzzy AHP extent analysis-TOPSIS framework and its ranking stability, the findings should not be interpreted as evidence of universal generalizability. Future studies should evaluate the framework using multiple software projects, different stakeholder groups and application domains to further assess its scalability, robustness and generalizability.

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