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Evaluation and Selection of Non-Functional Requirement based on Integrated AHP, TOPSIS and Fuzzy TOPSIS

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Abstract- The process of evaluating and choosing non-functional requirements (NFRs) is difficult and demanding. Software malfunctions and up-marks can result from improper NFRs. Several evaluation factors must be taken into account in order to get good performance. It is necessary to ascertain how their methods change in accordance with the review and benchmarking process of NFRs in order to identify the limits of how the criteria are set. The evaluation and benchmarking of non-functional requirements using Multi Criteria Decision Making (MCDM) methods is the main topic of this paper. MCDM uses a variety of methods to identify the best option among several criteria and alternative situations. Weights are assigned to criterion using the Analytic Hierarchy Process (AHP), a multi-criteria decision making method. Distance metrics are used in the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to rank and choose various options. On the other hand, criterion weighting and alternative rating are done using FUZZY TOPSIS. NFRs are used for MCDM calculations, and all of these methods are attempted to be discussed. MCDM evaluates and chooses the best NFRs using performance, overhead, and configuration criteria, which helps in identifying solutions for future directions. The results indicate that, in comparison to other NFRs, functionality requirement received better ranking score records.

Keywords- Non-Functional Requirements; Multi Criteria Decision Making; NFRs evaluation and benchmarks

1. Introduction

Non-functional requirements (NFRs) describe quality attributes and constraints that influence whether a software system satisfies its expected quality goals [1]-[3]. Requirements prioritization and quality-requirements engineering have therefore received sustained attention in requirements engineering [4]-[6]. Inadequate treatment of quality requirements can create conflicts and management problems during software development [7]-[9]. NFRs are also commonly treated as quality-related properties that need to be identified, analyzed, and evaluated during requirements engineering [1]-[3], [5], [10]. This paper evaluates and ranks NFRs using Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Fuzzy TOPSIS. AHP is used to derive criteria weights, TOPSIS ranks alternatives according to their distance from ideal solutions, and Fuzzy TOPSIS extends this decision process to fuzzy values [11]-[15]. The evaluation uses Cost, Security, Conformance, Suitability, and Operability as performance criteria. Their relationship is summarized in Figure 1. The criteria are described as follows:

- **Cost:** Cost is the value of money that has been used up to produce deliver a service, and hence is not available for use any longer. In all software cost is money spend to avoid failure.
- **Security:** Security is the main issue, software should be safe and ensure the security. Functionality and usability are preferable in terms of Security.

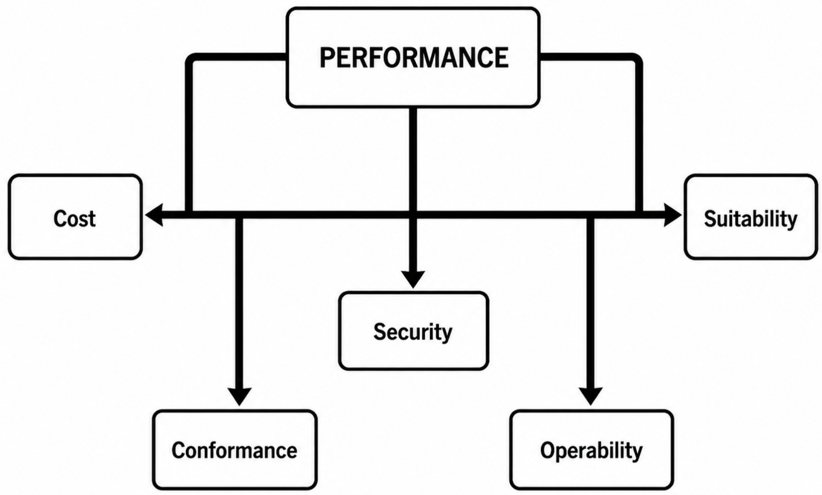

Figure 1: Criteria for performance.

- **Conformance:** Software must consist of Supplier should offer a product that can meet standards or grades Buyer provides sample, it should be easy and efficient. So, it is a preferable requirements as compared to other NFRs.
- **Suitability:** Suitability check the quality of the software is suitable or not. Functionality and Usability have minimum values. So, both of these are preferable NFRs in terms of suitability.
- **Operability:** The qualities of a system which work well over its lifetime, and software operability applies these core engineering principles to software systems. So, Functionality is preferable in terms of operability.

The remainder of this paper is organized as follows. Section 2 presents the methodology used for the evaluation and selection of NFRs. Section 3 describes the MCDM-based evaluation and ranking using AHP, TOPSIS, and Fuzzy TOPSIS. Section 4 reports and discusses the results, including the comparative analysis of the evaluated NFRs. Section 5 concludes the paper.

2. Methodology

The methodology used for the evaluation and selection of Non-Functional Requirements (NFRs) is organized into three phases: preliminary study, research study design, and evaluation and selection. Figure 2 summarizes the complete process and shows how the initial identification of NFRs and research objectives leads to the application of Multi-Criteria Decision Making (MCDM) techniques and, ultimately, to the selection of the most suitable NFRs.

2.1. Preliminary Study

The preliminary study establishes the basis for the subsequent evaluation process. It begins with an investigation of existing NFRs, followed by identification of the problem to be addressed. Based on this initial analysis, the research questions and objectives are defined, and the evaluation and selection of NFRs are considered using the integrated AHP, TOPSIS, and Fuzzy TOPSIS approach. The preliminary study therefore consists of the following activities:

- Investigation of existing NFRs;
- Problem identification;
- Definition of research questions and objectives; and
- Evaluation and selection of NFRs.

2.2. Research Study Design

The second phase defines the research study design for selecting the NFRs. As illustrated in Figure 2, the selected requirements are evaluated through MCDM algorithms, including AHP, TOPSIS, and Fuzzy TOPSIS. These techniques provide the basis for the comparative evaluation performed in the next phase.

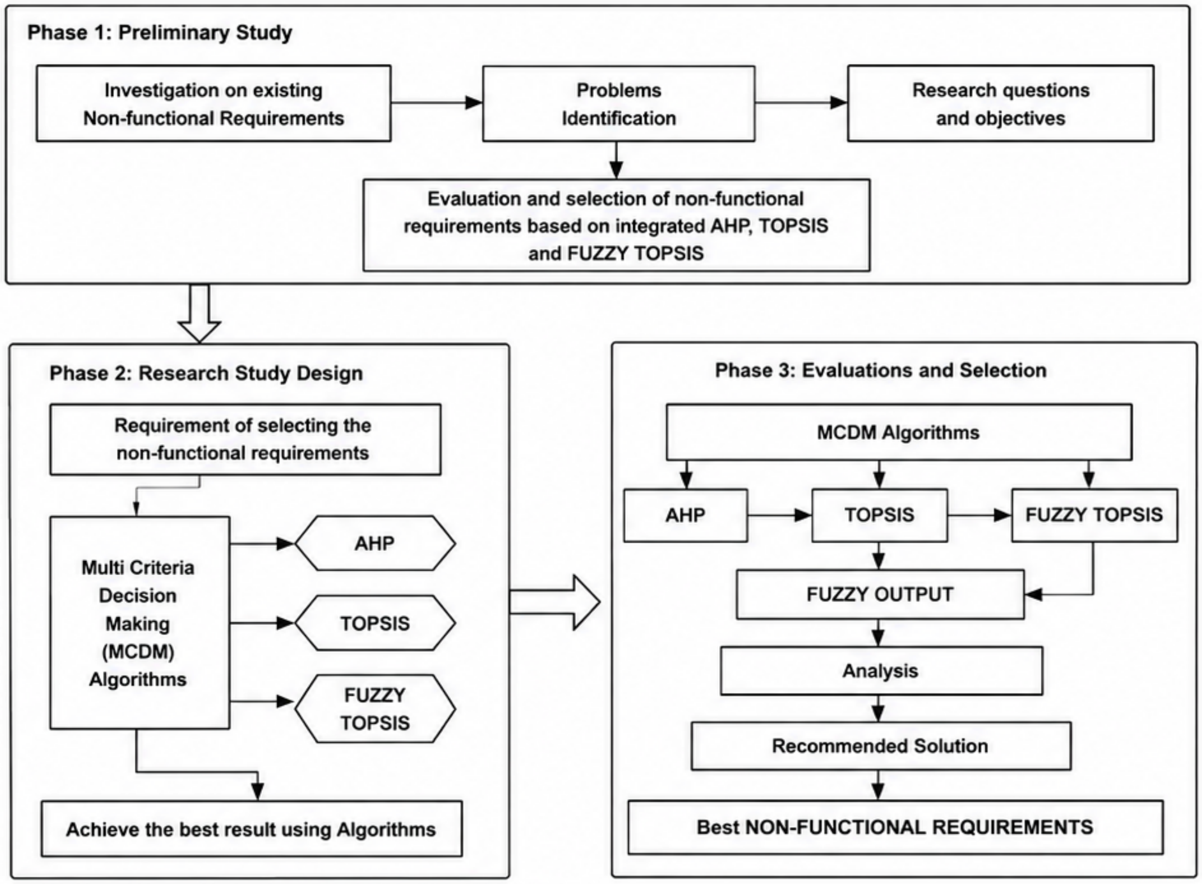

Figure 2: *Methodology for evaluation and selection of NFRs.*

2.3. Evaluation and Selection

The final phase applies the selected MCDM techniques to the NFR evaluation process. AHP, TOPSIS, and Fuzzy TOPSIS are used sequentially within the evaluation framework. The resulting outputs are analyzed to obtain a recommended solution and identify the best NFRs according to the considered criteria.

3. MCDM-Based Evaluation and Ranking

This section presents the application of AHP, TOPSIS, and Fuzzy TOPSIS for the evaluation and ranking of the selected NFRs. AHP determines the criteria weights, while TOPSIS and Fuzzy TOPSIS are used to rank the alternatives.

3.1. Analytic Hierarchy Process

AHP is a multi-criteria decision-making technique developed by Saaty [12]. It derives priorities from pairwise comparisons. The AHP workflow used in this study is summarized in Figure 3. The decision makers are represented by

$$DM = \{DM_1, DM_2, DM_3, DM_4, DM_5\}.$$

The aggregated pairwise judgments are presented in Table 1. The table contains the five evaluation criteria and the reciprocal comparisons used in the AHP calculation. The pairwise matrix is normalized column by column. Table 2 reports the normalized values used to derive the priority vector.

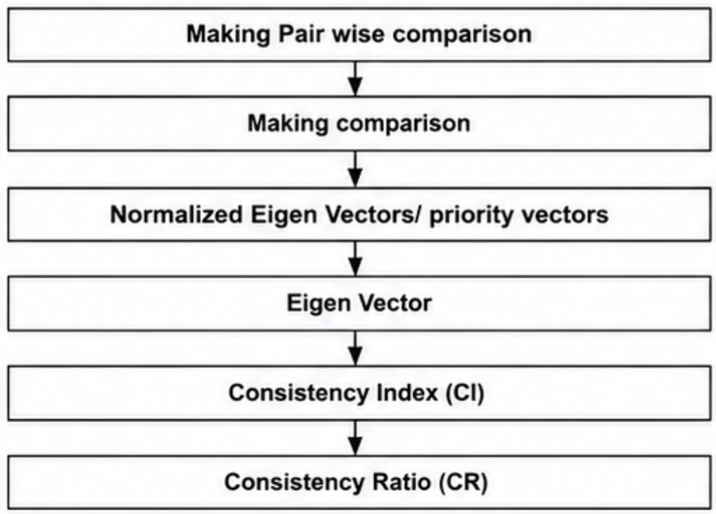

Figure 3: *AHP technique.*

Table 1: *Aggregated pairwise comparison matrix for the selected non-functional requirements.*

Criteria	Cost	Security	Conformance	Suitability	Operability
Cost	1	$\frac{1+\frac{1}{9}+\frac{1}{5}+\frac{1}{7}+\frac{1}{3}}{5} = 0.356$	$\frac{1+\frac{1}{7}+\frac{1}{5}+\frac{1}{3}+1}{5} = 0.534$	$\frac{\frac{1}{5}+\frac{1}{9}+\frac{1}{7}+\frac{1}{7}+\frac{1}{5}}{5} = 0.158$	$\frac{1+\frac{1}{7}+\frac{1}{9}+\frac{1}{9}+1}{5} = 0.472$
Security	2.808	1	$\frac{1+\frac{1}{7}+\frac{1}{7}+\frac{1}{9}+\frac{1}{3}}{5} = 0.344$	$\frac{\frac{1}{5}+\frac{1}{7}+\frac{1}{7}+\frac{1}{7}+\frac{1}{3}}{5} = 0.178$	$\frac{1+\frac{1}{7}+\frac{1}{7}+\frac{1}{9}+\frac{1}{3}}{5} = 0.344$
Conformance	1.872	2.906	1	$\frac{1+\frac{1}{7}+\frac{1}{7}+\frac{1}{5}+1}{5} = 0.496$	$\frac{\frac{1}{9}+\frac{1}{9}+\frac{1}{7}+\frac{1}{5}+\frac{1}{5}}{5} = 0.152$
Suitability	6.329	5.617	2.016	1	$\frac{1+\frac{1}{9}+\frac{1}{7}+\frac{1}{9}+\frac{1}{3}}{5} = 0.338$
Operability	2.118	2.906	6.578	2.958	1
Sum	**14.127**	**12.785**	**10.472**	**4.790**	**2.306**

Table 2: *Normalized eigenvector matrix.*

Criteria	Cost	Security	Conformance	Suitability	Operability
Cost	0.707	0.027	0.050	0.032	0.204
Security	0.198	0.078	0.032	0.037	0.149
Conformance	0.132	0.227	0.095	0.103	0.065
Suitability	0.448	0.439	0.192	0.208	0.146
Operability	0.149	0.227	0.628	0.617	0.433
Sum	**0.997**	**0.998**	**0.997**	**0.997**	**0.997**

The AHP calculation proceeds through the following steps:

- **Step 1: Pairwise comparison.** Pairwise comparison is defined in terms of which item is preferred over another and the strength of that preference. The scale uses the values $\{1, 3, 5, 7, 9\}$.
- **Step 2: Reciprocal matrix.** The lower triangle is formed by taking the inverse of the corresponding upper-triangular values in the comparison matrix shown in Table 1.
- **Step 3: Normalization and priority vector.** The matrix is normalized by column and the priority vector is obtained by averaging across each row of the normalized matrix in Table 2. The reported priority vector is

$$\mathbf{w} = \{0.0766,\ 0.0988,\ 0.124,\ 0.286,\ 0.410\}. \tag{1}$$

- **Step 4: Maximum eigenvalue.** The reported maximum eigenvalue is calculated as

$$\begin{aligned} \lambda_{\max} &= (0.0766)(14.127) + (0.0988)(12.785) + (0.124)(10.472) \\ &\quad + (0.286)(4.79) + (0.410)(2.306) \\ &= 1.082 + 1.263 + 1.298 + 1.369 + 0.945 = 5.957. \end{aligned} \tag{2}$$

- **Step 5: Consistency index.** The Consistency Index (CI) is calculated as

$$CI = \frac{\lambda_{\max} - n}{n - 1} = \frac{5.957 - 5}{5 - 1} = 0.239. \tag{3}$$

- **Step 6: Consistency ratio.** Using the Random Index (RI), the Consistency Ratio (CR) is

$$CR = \frac{CI}{RI} = \frac{0.239}{1.12} = 0.213. \tag{4}$$

3.2. TOPSIS

TOPSIS was introduced by Hwang and Yoon [13]. The method ranks an alternative by considering its distance from the positive ideal solution (PIS) and the negative ideal solution (NIS). In this study, Conformance, Suitability, and Operability are treated as cost criteria. The sequence of TOPSIS calculations is shown in Figure 4. The decision matrix used for TOPSIS is given in Table 3. The normalization denominators are obtained from the squared column values shown in Table 4. Using these denominators, the normalized decision matrix is obtained as reported in Table 5.

Table 3: *Decision matrix for the selected non-functional requirements.*

NFRs	Cost	Security	Conformance	Suitability	Operability
Functionality	3	9	7	1	1
Usability	3	7	3	2	2
Efficiency	3	6	7	3	2
Portability	5	5	4	5	3

Table 4: *Normalization calculations for the decision matrix.*

Calculating x_{ij}^2 for each column					
NFRs	**Cost**	**Security**	**Conformance**	**Suitability**	**Operability**
Functionality	9	81	49	1	1
Usability	9	49	9	4	4
Efficiency	9	36	49	9	4
Portability	25	25	16	25	9
$\sum x_{ij}^2$	52	191	123	39	18
$\sqrt{\sum x_{ij}^2}$	7.211	13.820	11.091	6.245	4.243

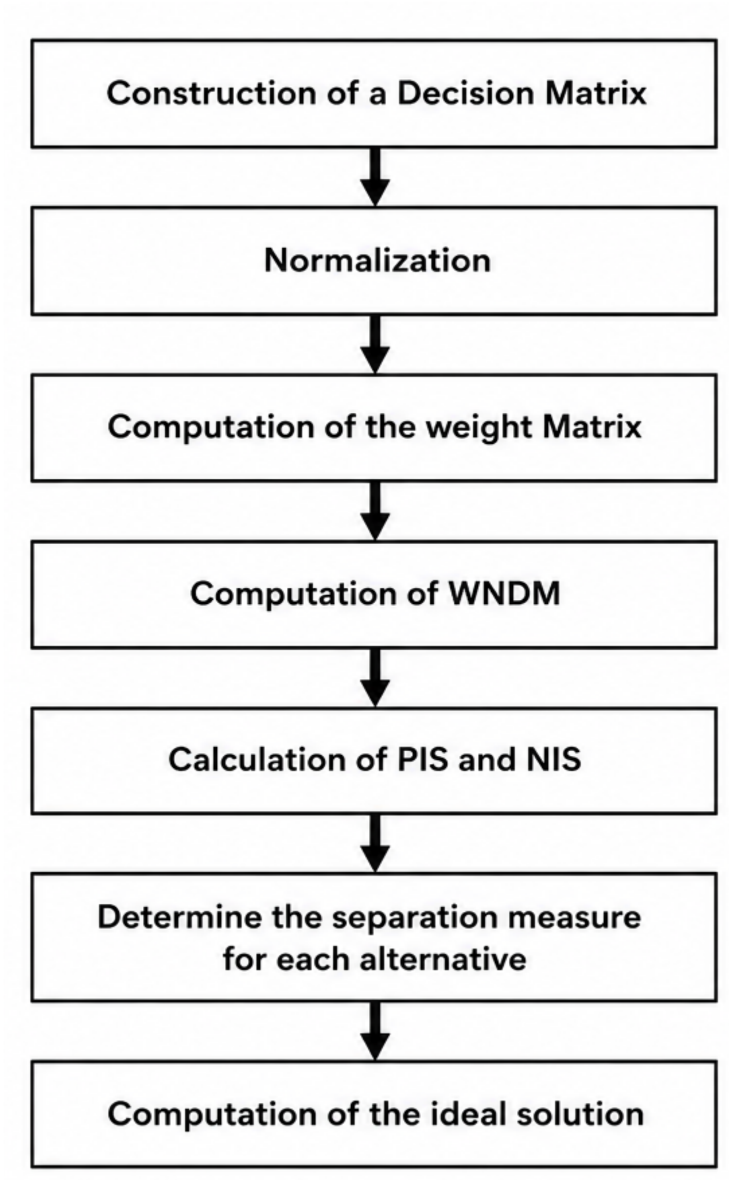

Figure 4: *TOPSIS technique.*

Table 5: *Normalized decision matrix.*

NFRs	Cost	Security	Conformance	Suitability	Operability
Functionality	0.42	0.65	0.63	0.16	0.24
Usability	0.42	0.51	0.27	0.32	0.47
Efficiency	0.42	0.43	0.63	0.48	0.47
Portability	0.69	0.36	0.36	0.80	0.71

The AHP weight vector is then applied to the normalized decision matrix. Table 6 shows the element-wise products used in this step. The PIS and NIS are selected from the weighted normalized values. Table 7 reports the positive ideal solution, while Table 8 reports the negative ideal solution. The separation of each alternative from the positive and negative ideal solutions is then calculated. These values are reported in Tables 9 and 10, respectively.

Table 6: *Weighted normalized decision matrix.*

NFRs	Cost	Security	Conformance	Suitability	Operability
Weights	**0.0766**	**0.0988**	**0.124**	**0.286**	**0.410**
Functionality	0.0766×0.416	0.0988×0.651	0.124×0.631	0.286×0.160	0.410×0.236
Usability	0.0766×0.416	0.0988×0.507	0.124×0.271	0.286×0.320	0.410×0.471
Efficiency	0.0766×0.416	0.0988×0.434	0.124×0.631	0.286×0.480	0.410×0.471
Portability	0.0766×0.693	0.0988×0.362	0.124×0.361	0.286×0.801	0.410×0.707

Table 7: *Positive ideal solution (PIS).*

	Benefit Criteria (J)		Cost Criteria (J')		
Functions	**Cost**	**Security**	**Conformance**	**Suitability**	**Operability**
Functionality	**0.046**	**0.056**	**0.039**	**0.097**	**0.094**
Usability	0.041	**0.056**	0.059	**0.097**	0.192
Efficiency	0.030	0.048	0.059	0.148	0.192
Portability	0.030	0.031	0.079	0.197	0.295
A^+	**0.046**	**0.056**	**0.039**	**0.097**	**0.094**

Table 8: *Negative ideal solution (NIS).*

	Benefit Criteria (J)		Cost Criteria (J')		
Functions	**Cost**	**Security**	**Conformance**	**Suitability**	**Operability**
Functionality	0.046	0.056	0.078	0.097	0.094
Usability	0.041	0.056	0.059	0.097	0.192
Efficiency	0.030	0.048	0.059	0.148	0.192
Portability	0.030	0.031	0.079	0.197	0.295
A^-	**0.030**	**0.031**	**0.079**	**0.197**	**0.295**

Table 9: *Separation measures from the positive ideal solution (PIS).*

NFRs	Cost	Security	Conformance	Suitability	Operability	$\sum(v_{ij} - v_j^+)^2$	S_i^+
Functionality	$(0.046 - 0.046)^2$	$(0.056 - 0.056)^2$	$(0.078 - 0.078)^2$	$(0.097 - 0.097)^2$	$(0.094 - 0.094)^2$	0	0
Usability	$(0.041 - 0.046)^2$	$(0.056 - 0.056)^2$	$(0.059 - 0.078)^2$	$(0.097 - 0.097)^2$	$(0.192 - 0.094)^2$	0.009990	0.099
Efficiency	$(0.030 - 0.046)^2$	$(0.048 - 0.056)^2$	$(0.059 - 0.078)^2$	$(0.148 - 0.097)^2$	$(0.192 - 0.094)^2$	0.012886	0.113
Portability	$(0.030 - 0.046)^2$	$(0.031 - 0.056)^2$	$(0.079 - 0.078)^2$	$(0.197 - 0.097)^2$	$(0.295 - 0.094)^2$	0.051283	0.226

Table 10: *Separation measures from the negative ideal solution (NIS).*

NFRs	Cost	Security	Conformance	Suitability	Operability	$\sum(v_{ij} - v_j^-)^2$	S_i^-
Functionality	$(0.046 - 0.030)^2$	$(0.056 - 0.031)^2$	$(0.078 - 0.079)^2$	$(0.097 - 0.197)^2$	$(0.094 - 0.295)^2$	0.051283	0.226
Usability	$(0.041 - 0.030)^2$	$(0.056 - 0.031)^2$	$(0.059 - 0.079)^2$	$(0.097 - 0.197)^2$	$(0.192 - 0.295)^2$	0.021755	0.147
Efficiency	$(0.030 - 0.030)^2$	$(0.048 - 0.031)^2$	$(0.059 - 0.079)^2$	$(0.148 - 0.197)^2$	$(0.192 - 0.295)^2$	0.013699	0.117
Portability	$(0.030 - 0.030)^2$	$(0.031 - 0.031)^2$	$(0.079 - 0.079)^2$	$(0.197 - 0.197)^2$	$(0.295 - 0.295)^2$	0	0

The Relative Closeness Coefficient is calculated as

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-}. \tag{5}$$

Table 11 summarizes the reported closeness coefficients and the resulting TOPSIS ranking.

Table 11: *Closeness coefficients of the evaluated functions.*

Functions	Closeness Coefficient Calculation	C_i	Conclusion
Functionality	$C_i = \frac{S_i^-}{S_i^+ + S_i^-} = 1.000$	**1.000**	**Best**
Usability	$C_i = \frac{S_i^-}{S_i^+ + S_i^-} = 0.597$	0.597	-
Efficiency	$C_i = \frac{S_i^-}{S_i^+ + S_i^-} = 0.506$	0.506	-
Portability	$C_i = \frac{S_i^-}{S_i^+ + S_i^-} = 0.469$	0.469	-

Based on the reported coefficients, the ranking is

$$\text{Functionality} > \text{Usability} > \text{Efficiency} > \text{Portability}. \tag{6}$$

Table 12: *Fuzzy rating scale for alternatives and criteria weights.*

Alternatives	Criteria Weights	Triangular Fuzzy Numbers
Very Poor (VP)	Very Low (VL)	$(1, 1, 3)$
Poor (P)	Low (L)	$(1, 3, 5)$
Fair (F)	Medium (M)	$(3, 5, 7)$
Good (G)	High (H)	$(5, 7, 9)$
Very Good (VG)	Very High (VH)	$(7, 9, 9)$

Table 13: *Aggregated fuzzy decision matrix.*

NFRs	Cost	Security	Conformance	Suitability	Operability
Functionality	(3.000, 5.000, 7.000)	(7.000, 9.000, 9.000)	(1.000, 3.667, 7.000)	(1.000, 4.333, 7.000)	(1.000, 3.667, 7.000)
Usability	(3.000, 6.333, 9.000)	(3.000, 6.333, 9.000)	(1.000, 3.000, 5.000)	(1.000, 3.667, 7.000)	(1.000, 3.667, 7.000)

Table 14: *Weighted normalized fuzzy decision matrix.*

NFRs	Cost	Security	Conformance	Suitability	Operability
Functionality	(1.287, 4.046, 9.000)	(3.890, 7.667, 9.000)	(0.142, 0.997, 7.000)	(0.426, 1.150, 7.000)	(0.142, 0.997, 0.994)
Usability	(1.000, 3.983, 9.000)	(2.780, 6.532, 9.000)	(0.200, 1.221, 7.000)	(0.426, 1.360, 7.000)	(0.142, 0.997, 7.000)

Table 15: *Calculated values of the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS).*

Ideal Solution	Cost	Security	Conformance	Suitability	Operability
FPIS $\tilde{A}^+$	(9.000, 9.000, 9.000)	(9.000, 9.000, 9.000)	(7.000, 7.000, 7.000)	(7.000, 7.000, 7.000)	(0.994, 0.994, 0.994)
FNIS $\tilde{A}^-$	(1.000, 1.000, 1.000)	(2.780, 2.780, 2.780)	(0.200, 0.200, 0.200)	(0.426, 0.426, 0.426)	(0.142, 0.142, 0.142)

3.3. Fuzzy TOPSIS

Fuzzy set theory was introduced by Zadeh [14], and Fuzzy TOPSIS extends TOPSIS to decision settings in which ratings and criteria weights are represented by fuzzy values [15]. The Fuzzy TOPSIS workflow used in this study is shown in Figure 5.

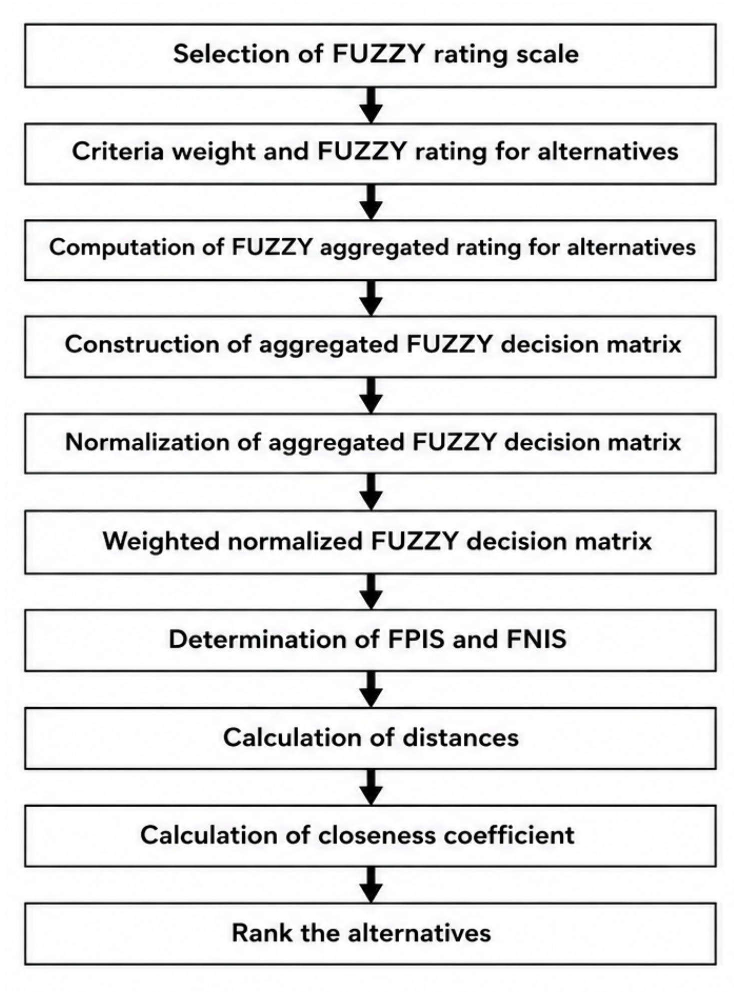

Figure 5: *Fuzzy TOPSIS technique.*

The linguistic terms and triangular fuzzy numbers used for the evaluation are listed in Table 12. The aggregated fuzzy ratings for Functionality and Usability are reported in Table 13. After normalization, the AHP criteria weights are applied to obtain the weighted normalized fuzzy decision matrix shown in Table 14. The fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) are summarized in Table 15. For two triangular fuzzy numbers $\widetilde{A} = (a_1, a_2, a_3)$ and $\widetilde{B} = (b_1, b_2, b_3)$, the vertex distance is calculated as

$$d(\widetilde{A}, \widetilde{B}) = \sqrt{\frac{1}{3}\left[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2\right]}. \tag{7}$$

The criterion-level distances from FPIS and FNIS are reported in Table 16.

Table 16: *Distances from the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS).*

Distance Measure	**Cost**	**Security**	**Conformance**	**Suitability**	**Operability**
FPIS Functionality	$d(\tilde{v}_{11}, \tilde{v}_1^+) = 5.292$	$d(\tilde{v}_{12}, \tilde{v}_2^+) = 3.049$	$d(\tilde{v}_{13}, \tilde{v}_3^+) = 5.262$	$d(\tilde{v}_{14}, \tilde{v}_4^+) = 5.080$	$d(\tilde{v}_{15}, \tilde{v}_5^+) = 0.491$
FPIS Usability	$d(\tilde{v}_{21}, \tilde{v}_1^+) = 5.451$	$d(\tilde{v}_{22}, \tilde{v}_2^+) = 3.863$	$d(\tilde{v}_{23}, \tilde{v}_3^+) = 5.152$	$d(\tilde{v}_{24}, \tilde{v}_4^+) = 5.000$	$d(\tilde{v}_{25}, \tilde{v}_5^+) = 3.502$
FNIS Functionality	$d(\tilde{v}_{11}, \tilde{v}_1^-) = 4.945$	$d(\tilde{v}_{12}, \tilde{v}_2^-) = 4.611$	$d(\tilde{v}_{13}, \tilde{v}_3^-) = 3.952$	$d(\tilde{v}_{14}, \tilde{v}_4^-) = 3.818$	$d(\tilde{v}_{15}, \tilde{v}_5^-) = 0.696$
FNIS Usability	$d(\tilde{v}_{21}, \tilde{v}_1^-) = 4.929$	$d(\tilde{v}_{22}, \tilde{v}_2^-) = 4.193$	$d(\tilde{v}_{23}, \tilde{v}_3^-) = 3.969$	$d(\tilde{v}_{24}, \tilde{v}_4^-) = 3.833$	$d(\tilde{v}_{25}, \tilde{v}_5^-) = 3.990$

The aggregated distances of the weighted alternatives are then summarized in Table 17.

Table 17: *Distances of each weighted alternative from FPIS and FNIS.*

Distance Measure	Functionality	Usability
Distance from FPIS (D_i^+)	19.174	22.968
Distance from FNIS (D_i^-)	18.022	20.914

The closeness coefficient is computed as

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}. \tag{8}$$

Using the reported distances in Table 17, the source values are

$$CC_{\text{Functionality}} = 0.4845, \qquad CC_{\text{Usability}} = 0.4765.$$

Thus, Functionality has the larger reported Fuzzy TOPSIS closeness coefficient.

4. Results and Discussion

The results obtained from AHP, TOPSIS, and Fuzzy TOPSIS are summarized in this section. The detailed calculations are reported in Section 3, while this section focuses on the resulting weights, rankings, and comparative criterion values.

4.1. AHP Results

The AHP analysis produces the reported priority vector

$$\mathbf{w} = \{0.0766,\ 0.0988,\ 0.124,\ 0.286,\ 0.410\}. \tag{9}$$

The normalized matrix from which these criteria weights are derived is reported in Table 2. The weights are subsequently used in the TOPSIS and Fuzzy TOPSIS calculations.

4.2. TOPSIS Results

The TOPSIS closeness coefficients are summarized in Table 11. Functionality has the highest reported coefficient, followed by Usability, Efficiency, and Portability. The resulting order is

$$\text{Functionality} > \text{Usability} > \text{Efficiency} > \text{Portability}. \tag{10}$$

4.3. Fuzzy TOPSIS Results

The Fuzzy TOPSIS distances used to calculate the closeness coefficients are reported in Table 17. The reported coefficients are

$$CC_{\text{Functionality}} = 0.4845, \qquad CC_{\text{Usability}} = 0.4765. \tag{11}$$

Functionality therefore has the higher reported closeness coefficient among the alternatives evaluated using Fuzzy TOPSIS.

4.4. Comparative Analysis of NFRs

The criterion values used to compare the ranked NFRs are summarized in Table 18. It shows that Functionality has the highest Cost value and shares the highest Security value with Usability. It also has the lowest reported Conformance and Operability values, while Functionality and Usability have the same reported Suitability value. The same criterion values are visualized in Figure 6. Overall, the reported TOPSIS and Fuzzy TOPSIS results identify Functionality as the highest-ranked NFR among the evaluated alternatives.

5. Conclusion

This paper evaluated and ranked Non-Functional Requirements (NFRs) using three Multi-Criteria Decision Making (MCDM) techniques: AHP, TOPSIS, and Fuzzy TOPSIS. AHP was used to determine the weights of the evaluation criteria, while TOPSIS and Fuzzy TOPSIS were applied to rank the considered NFR alternatives. The analysis considered

Table 18: *Comparison of NFRs across the evaluation criteria.*

NFR	Cost	Security	Conformance	Suitability	Operability
Functionality	9	7	2	2	1
Usability	8	7	3	2	2
Efficiency	6	6	3	3	2
Portability	6	4	4	4	3

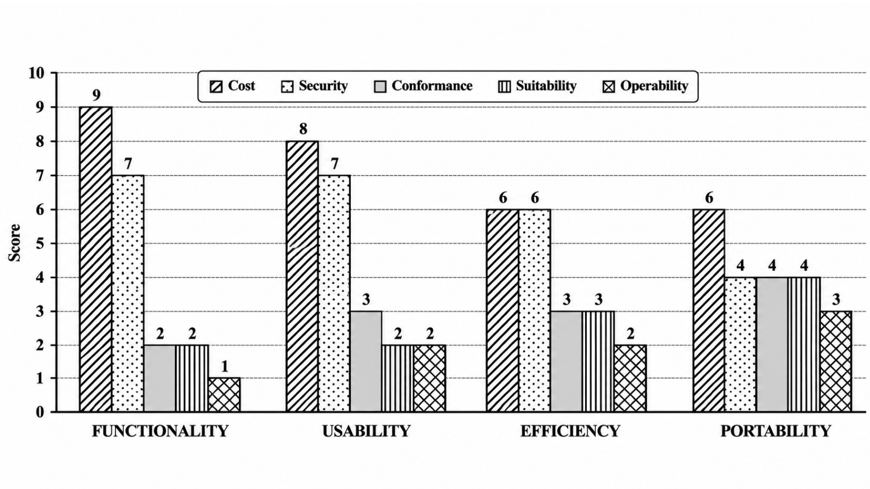

Figure 6: *Comparison of NFRs across the evaluation criteria.*

Functionality, Usability, Efficiency, and Portability using Cost, Security, Conformance, Suitability, and Operability as evaluation criteria. The TOPSIS results ranked Functionality first, followed by Usability, Efficiency, and Portability. The Fuzzy TOPSIS results also gave Functionality a higher reported closeness coefficient than Usability. Therefore, within the criteria and alternatives considered in this study, Functionality emerged as the highest-ranked NFR. The results show how AHP, TOPSIS, and Fuzzy TOPSIS can be integrated to support the evaluation and selection of NFRs. AHP provides criteria weightage, whereas TOPSIS and Fuzzy TOPSIS use relative closeness measures to support the ranking process. The use of fuzzy values further provides a mechanism for representing uncertainty during the evaluation process.

Author Declarations

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