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MEREC-WISP(S) Integration Extended with Fermatean Fuzzy Set for Requirement Prioritization

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Abstract:

Software projects need efficient requirement prioritization. Time, budget, and quality often limit these projects. MCDM techniques help balance conflicting criteria. However, they struggle to rank options due to multiple parties. Current MCDM methods have drawbacks, like poor uncertainty management. This thesis presents a new technique, WISP-S, for requirement prioritization in software development. The dynamic WISP(S) approach and the MEREC method are merged. Fermatean fuzzy numbers manage qualitative data and uncertainty. This technique surpasses the restrictions of current MCDM methods. It offers an effective way to rank software requirements within limits. The research consists of two separate stages. The first phase introduces an enhanced MEREC technique. It's designed to compute the objective weights of each criteria within Fermatean Fuzzy Sets (FFS). By leveraging FFS features, this expansion improves the current MEREC technique. It allows a more thorough examination of criteria weights. The second phase integrates the WISP(S) method with the suggested generalized weighted Fermatean fuzzy aggregated operator and MEREC technology. This integration allows ranking and evaluating alternatives in a prioritization context. The study offers a robust strategy to prioritize alternatives. It considers both qualitative and uncertain data by integrating two novel methods. The approach's validity and robustness are confirmed through comparisons with existing models and sensitivity analysis. A real-world case study demonstrates the proposed approach. The WISP-S approach is a novel technique for integrated Fermatean fuzzy information-based decision-making. It can handle complex decision-making problems in software development. This approach could improve the success of software projects. It addresses the shortcomings of existing MCDM methods.

Keywords: MEREC; WISP(S); MCDM; Fuzzy Sets; Fermatean Fuzzy Sets; TOPSIS.

1. Introduction

A large portion of the software industry is actively engaged in innovative development as a result of the quickly rising usage of software applications. The lack of distinct goals or user requirements is one aspect of complexity. The system design is more profoundly impacted by the clearly defined objectives or requirements. If the objectives are not defined, it becomes difficult to design such systems or solutions. By carefully considering the needs of the user or stakeholder, such complexity can be reduced. With the use of a requirements prioritization approach, a collection of user needs is chosen based on the relevance of the requirements. To successfully create a high-quality software product, functional and non-functional requirements must be taken into equal consideration in earlier phases of the software development life cycle [1].

The requirements that describe how a system should function are known as the functional requirements. The non-functional requirements (NFRs), usually referred to as quality attributes, are used to rate the Functional requirement [2].

Requirements engineers' primary focus is on gathering and ranking only functional requirements (FRs). Therefore, it is essential to take both functional and non-functional requirements into account when setting priorities, and failing to do so could result in erroneous software project estimates that result in excessive maintenance costs.

Certain strategies have been developed specifically for MCDM prioritizing. Nevertheless, practically all of them come with some drawbacks. Scalability issues are the most prevalent. The inherent uncertainties play a significant role in the deliberate disregard of FRs along with NFRs. Accurate priority values are challenging to get due to the uncertainty in FRs and NFRs. The subjective and ambiguous characteristics of FRs and NFRs prevent them from being prioritized using traditional prioritizing methods. Additionally, the majority of the MCDM prioritization methods that are currently in use do not take non-binary assessment into account [3].

Because there are numerous stakeholders involved in requirement prioritizing and their differing viewpoints must be taken into consideration, it is an MCDM problem. Additionally, this results in uncertainty that conventional prioritization techniques typically cannot address. The decisions made by stakeholders on the order of needs are frequently incorrect. Inaccuracy, incompleteness, and ambiguity are other significant types of uncertainty discovered in FRs during their prioritization.

Nowadays, it is well acknowledged that requirements can differ in importance. In terms of requirements prioritization methodologies, there has still been no advancement, theoretically or practically [4]. Software engineering researchers provide examples of various criteria prioritization approaches. The type and goal of the project have a major impact on the priority method chosen. The needs prioritizing eliminates the complexity brought on by unclear requirements or objectives, which plays a crucial part in decision-making. The primary motive behind this research is the creation of a thorough, balanced, and multi-dimensional decision support model to assist with requirement prioritization. This technique must be able to consider a wide range of criteria and viewpoints. The secondary goal of the current research is to take into account the uncertainty and scalability involved at a variety of decision-making stages.

In this study, we provide a novel multi-criteria decision-making model for dealing with uncertainty in requirements prioritization. Our primary contribution consists in handling multiple aspects at once, such as scalability, uncertainty, and sensitivity analysis, which have been disregarded by previous prioritization techniques. These factors are taken into account by the suggested multi-criteria decision-making model, which also prioritizes FRs along with NFRs. In this thesis we are focusing on two main sorts of uncertainties: uncertainties resulting from inadequately defined requirements (linguistic uncertainties) and uncertainties resulting from a variety of viewpoints held by various stakeholders during the process of prioritizing requirements (inter-personal uncertainties). Multiple real-world case studies were used as the basis for an experiment to assess the suggested novel Multi-criteria decision-making model. Requirements were prioritized using a WISP-S approach provides a novel and effective technique for integrated Fermatean fuzzy information-based decision-making, which can handle complex decision-making problems in software development. The validity and robustness of the approach are confirmed through comparisons with existing models and sensitivity analysis.

This study is organized as follows: Section 2 presents a brief description of the related work on MCDM. Section 3 comprehensively elaborates on the research methodology including the definition of fundamental concepts, the overall workflow of MEREC-WISP, and detailed step-wise computational process of individual MCDM methods. Subsequently, a real-world case study and their evaluation using MEREC-WISP is presented in Section 4. This section provides detailed intermediate and final results of all the constituent phases of MEREC-WISP. The results of a sensitivity analysis and Comparative Analysis to demonstrate the robustness of the proposed model have also been presented in the last Section 5 followed by a conclusion in Section 6.

2. Related Work

The use of multi-criteria decision-making (MCDM) processes has grown significantly as a reliable approach for evaluating diverse options based on many aspects. Numerous MCDM strategies have been created recently, either as a result of the addition of fresh methodologies or the modification of existing ones, creating new research areas [5]. These methods have been used to assess, examine, and rank options or strategic needs (SRs) in a variety of contexts. Supply Chain Management, Information Technology, Design Engineering, and Manufacturing Systems are a few examples of areas where MCDM concepts have been successfully applied [6].

Few methods for MCDM prioritization have been suggested in the RE literature. According to the key topics that we defined, the research that we found in the literature has been presented here.

The themes are listed below:

- Fuzzy Set Theory-based MCDM Prioritization Approaches
- Fuzzy Rough Set Theory-based MCDM Prioritization Approaches
- Artificial Intelligence-based MCDM Prioritization Approaches
- Other MCDM Prioritization Approaches

2.1. Fuzzy Set Theory-Based MCDM Prioritization Approaches

We found through the Literature review that Fuzzy set theory is very commonly used for MCDM-based requirement prioritization. To address the causes of uncertainty or imprecision, "Lotfi Aliasker Zadeh" invented fuzzy set theory (FST) in 1965. The two main mathematical techniques for simulating uncertainty in industrial applications are fuzzy sets and fuzzy logic. Common sense thinking is useful for facilitators when helping people make decisions. In the fields of science and engineering, fuzzy set theory has a variety of uses. The vagueness of human cognitive processes is intended to be modeled by the fuzzy set theory [7], which also offers a systematic mechanism for addressing the imprecision inherent in many issues. To prioritize and choose the alternatives or SRs, various MCDM procedures have been developed, including (a) "Analytic Hierarchy Process (AHP)", (b) "TOPSIS", (c) "PROMETHEE", (d) "Analytic Network Process" (ANP), (e) "VIKOR", etc.

The Analytical Hierarchies Process (AHP), developed by "Thomas Saaty," is one of the most well-known MCDM models that consider the relative relevance between pairs of evaluation criteria. To create the fuzzy AHP (FAHP), this fuzzy set theory was merged with the AHP. Numerous vast domains use fuzzy AHP. For instance, "Identity management product selection [8]" is based on the proposed customer needs and is used to evaluate and rank IDM goods. Authors used Fuzzy AHP to "prioritize the success factors of requirement change management" [9]. The TOPSIS algorithm (Technique for Order Preference by Similarity to Ideal Solution) is one of the most popular MCDM methods. Since the method's complexity and ease of implementation are mostly independent of the number of attributes, it is quite straightforward [10]. Fuzzy TOPSIS is also applied in enormous domains. Numerous research has been published in the literature that use TOPSIS to solve MCDM issues. [11] Presented TOPSIS to address the ambiguity in the responses and choose the best option from those offered. Research work [6] Focused on ranking the SRs by taking into account the various criteria as well as the ambiguity and incompleteness of the information. Gupta et al. proposed a modified fuzzy probabilistic TOPSIS method for the multi-criteria selection problem when the problem of uncertainty in the consideration of the alternatives in an MCDA problem [12].

Numerous research studies have combined the "Fuzzy AHP" and "Fuzzy TOPSIS" techniques to solve multi-criteria selection problems in a variety of domains. Solving the problem of selecting the appropriate Software requirements based on different criteria for the Institute Examination System is solved by a "hybrid Fuzzy AHP- TOPSIS approach" [1]. To overcome the problem of selecting a supplier of raw materials using both qualitative and quantitative criteria presented an "integrated Fuzzy AHP and Fuzzy TOPSIS Approach". The usage of Fuzzy AHP and Fuzzy TOPSIS [7] provides a methodology to assess the service quality of e-commerce websites used as a platform for consumers to buy things and merchants to sell their wares. [10] Also, give their contribution to the E-commerce sector using "Fuzzy AHP" and "Fuzzy TOPSIS" as well as used PROMETHEE II to select the top-rated online shopping platform. [13] Used hybrid Fuzzy AHP and Fuzzy TOPSIS methods for selecting the best ERP System which is based on various criteria.

2.2. Rough Set Theory-Based MCDM Prioritization Approaches

The ranking values of the SRs have been computed using a variety of fuzzy-based approaches. These techniques use various membership functions to model the linguistic variables. Because membership functions are chosen based on subjective judgment, it is challenging to determine the fuzzy set's boundary with accuracy [14]. Due to their emphasis on subjectivity and lack of objectivity, fuzzy-based approaches may have an impact on the SRs' ranking order. To overcome the limitations of the above fuzzy-based techniques "Zdzislaw Pawlak" proposed the Rough set theory to handle vagueness and uncertainty. Authors in research work [15] Has used rough set theory to prioritize the software requirements using the examination system of an educational institute case study.

2.3. Artificial Intelligence-Based MCDM Prioritization Approaches

According to a study of the literature, academics have focused on determining how artificial intelligence (AI) affects requirements prioritizing. The majority of this research uses artificial neural networks, logarithmic models, and fuzzy logic to prioritize requirements without regard to the type of requirements. However, we identified a few AI-based methods for ranking requirements in MCDM. These techniques include an artificial neural network model that employs ANN to give a specific normalized optimal priority weight vector and a positive degree of membership function in order to address the shortcomings of MCDM for requirement prioritization [16], [17]. To ensure excellent consistency in fuzzy decision-making, models based on logarithms offer a positive degree of membership function (between 0 and 1) [16].

2.4. Other MCDM Prioritization Approaches

A study was found that deals with Security requirements prioritization but is more focused on determining that only those security needs that are significant from a security standpoint can be elicited for identity, authentication, and authorization [18]. Another study [19] tries to determine the most suitable technique to represent a fresh way of representing linguistic data that is uncertain also modified a MULTIMOORA method is used to rank the different green suppliers.

Despite the existence of various MCDM methods for software requirements prioritization in software development, they struggle with defining the ranking order of options due to involvement from multiple parties and inappropriate management of uncertainties. Existing MCDM methods have several drawbacks, which hinder the success of software projects. The research gap in this field is the lack of a novel approach that can effectively prioritize software requirements while addressing the shortcomings of existing MCDM methods. Specifically, there is a need for a new method that can combine the Removal Effects of the Criteria (MEREC) method and the Simple Weighted Sum-Product (WISP) method while using Fermatean fuzzy numbers to handle qualitative data and uncertain information. Such an approach has the potential to provide a more efficient and effective way to prioritize software requirements within time, budget, and quality constraints. Therefore, the proposed WISP-S approach aims to fill this research gap and provide a novel and effective technique for integrated Fermatean fuzzy information-based decision-making that can handle complex decision-making problems in software development.

Each recommended approach has some form of restriction, as shown in the Comparative Analysis (CA) table i.e. Table 1. Scalability issues are the most prevalent. The majority of the MCDM prioritization techniques now in use have not been thoroughly tested against a large number of requirements. Uncertainty poses a big issue. Current MCDM techniques, as per the literature, fall short in handling uncertainties. Few studies tackle some aspects of uncertainty, but others remain unexplored. At present, minimal efforts have been made to address issues like improper scalability, uncertainty management, and neglect of robustness and stability validation in MCDM requirements prioritization. These gaps inspired our research.

3. Proposed Solution

The following section introduces the techniques used in this study. First up is a framework known as Fermatean Fuzzy Sets (FFS). It processes qualitative and uncertain information for requirement prioritization. FFS is an effective mathematical model. It considers the fuzziness and ambiguity in the prioritization process. The research also presents the WISP(S) and TOPSIS methodologies. They help rank and evaluate requirements. WISP(S) merges the MEREC method with the Simple Weighted Sum-Product (WISP) method to rank alternatives. On the other hand, the TOPSIS method ranks options based on their resemblance to the ideal answer and their distance from the unfavorable perfect solution. Figure 2 visually illustrates the general architecture of the FFS-MEREC-WISP model. It highlights the connections between the phases and the use of suitable MCDM techniques. This framework serves as a decision-making guide. It ensures a systematic and well-structured approach to decision-making in complex situations.

3.1. Fermatean Fuzzy Sets

Senapati and Yager [30] first proposed Fermatean fuzzy sets. They're a powerful tool for managing unclear information. Compared to traditional fuzzy sets, Fermatean fuzzy sets offer enhanced capabilities. They provide a fresh perspective on decision-making. Drawing from intuitionistic fuzzy sets and Pythagorean fuzzy sets, Fermatean fuzzy sets display more flexibility. They capture and present uncertain information effectively. They adapt to different uncertainty levels, allowing decision-makers to express and measure uncertainty in various elements. Fermatean fuzzy sets (FFSs) rely on three core elements. They are the degrees of membership (∞), non-membership (β), and indeterminacy (π). These elements are crucial for quantifying and presenting uncertainty in FFSs. This study uses various FFS operators and features to aid efficient decision-making.

Definition 01: Consider that μ is a universe of discourse. Then the following definition of the Fermatean fuzzy set F may be used:

$$\boldsymbol{F} = \{\langle \boldsymbol{\mu}, \boldsymbol{\alpha_R}(\boldsymbol{\mu}), \boldsymbol{\beta_R}(\boldsymbol{\mu})\rangle : \ \boldsymbol{\mu} \in \cup \} \tag{1}$$

Where αR(μ) : ∪ → [0.1] , βR(μ) : ∪ → [0.1] , and 0 ≤ (αR(μ))3 + (βR(μ))3 ≤ 1. In addition, the degree of indeterminacy is πR(μ) = $\sqrt[3]{1 - \left(\alpha\mathrm{R}(\mu)\right)^3 - (\beta\mathrm{R}(\mu))^3}$ For ease of application, we define F = (αR,βR) to denote. Within this FFS [30].

Figure 1 illustrates how the spaces for intuitionistic membership grades (IMGs), Pythagorean membership grades (PMGs), and Fermatean membership grades (FMGs) differ from one another.

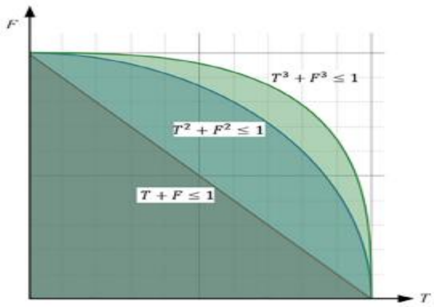

Figure 1: Data representation of IFS, PFS, and FFS [39]

Table 1: Comparative analysis with the existing MCDM requirement prioritization approach's

Ref	Solution Type		MCDM Approach		Uncertainty Handled	No. of Criteria's	Dataset / Case study	Validation	Robustness & Stability Validation
	Single	Hybrid	Weight Assessment	Evaluation					
[1]	-	✓	Fuzzy AHP	Fuzzy TOPSIS	None	03 Criteria's	FR – 16 & NFR – 03	None	None
[5]	✓	-	Fuzzy AHP	Fuzzy AHP	None	09 Criteria's	FR - 21	None	None
[6]	✓	-	Fuzzy Linguistic 2-Tuples	Fuzzy Linguistic 2-Tuples	None	04 Criteria's	FR - 04	None	None
[7]	-	✓	Fuzzy AHP	Fuzzy TOPSIS	Yes	04 Criteria's	Case Study (05 Suppliers)	Tested with existing cases	None
[4]	✓	-	Adaptive Fuzzy Hierarchical Cumulative Voting (AFHCV)	(AFHCV)	Yes	Not mentioned	HLR – 08 & LLR - 11	Compared with existing techniques	None
[8]	✓	-	Fuzzy Probabilistic TOPSIS	TOPSIS	Yes	04 Criteria's	Real-life Multi-criteria Case Study	None	None
[9]	-	✓	LFTA	ANN	None	04 criteria's	Case Study (FR – 04)	None	None
[10]	-	✓	Linear Programmin g	MULTIMOO RA	Yes	02 Criteria's	Case Study (04 Suppliers)	Compares with existing techniques	None
[11]	-	✓	Information Entropy Method (IEM)	TOPSIS	None	05 Criteria's	Case Study	None	Sensitivit y Analysis
[12]	✓	-	Entropy Distance-Based Approach	Entropy Distance-Based Approach	None	07 Criteria's	Data Set (Requireme nts - 16)	None	None
[9]	✓	-	Logarithmic Fuzzy Trapezoidal AHP	AHP	None	03 Criteria's	Case Study	None	None
[13]	-	✓	Fuzzy AHP	TOPSIS	None	07 Criteria's	Case Study (02 Websites)	None	None
[14]	✓	-	Intuitionistic Fuzzy Sets	Intuitionistic Fuzzy Set	None	02 Criteria's	Case Study (Requireme nts - 27)	None	None
[15]	✓	-	StakeQP	TOPSIS	None	02 criteria	Dataset of the RALIC industrial project	Compare with existing techniques	None
[16]	-	✓	LFPP	ANN	None	07 criteria	Case study adopted from Ozcan et al	The test was conducted on MATLAB software	None
[17]	-	✓	HFL – AHP	HFL - VIKOR	Yes	04 Criteria's	04 Alternatives	None	None
[18]	-	✓	HFL – AHP	HFL - COPRAS	Yes	06 Criteria's	04 Alternatives	None	None
[19]	✓	-	Fuzzy COPRAS	Fuzzy COPRAS	None	10 Criteria's	E-Learning Websites - 08	Validate with TOPSIS	None

[20]	-	✓	Fuzzy AHP,	TOPSIS, and PROMTHE E	None	10 Criteria's	Alternatives - 08	None	None
[21]	✓	-	Fuzzy TOPSIS	Fuzzy TOPSIS	None	02 criteria	(Case Study) FR – 40	None	None
[22]	✓	-	Fuzzy AHP	Fuzzy AHP	Yes	04 criteria	23 Success Factors	None	None
[23]	✓	-	Rough Set Theory	Rough Set Theory	None	03 Criteria	FR – 10 & NFR – 03	Compare with existing techniques	None
[24]	-	✓	AHP	TOPSIS	None	06 Criteria's	Alternatives – 04	None	None
[25]	✓	-	Fuzzy Set theory	Fuzzy Set theory	None	03 Criteria	FR – 10 & NFR – 03	None	None
[26]	✓	-	Fuzzy Soft set theory	Fuzzy Soft set theory	None	03 Criteria	FR – 10 & NFR – 03	Compare with the existing technique	None
[27]	✓	-	Intuitionistic Fuzzy Sets	Intuitionistic Fuzzy Sets	Yes	02 Criteria's	Data Set (Requireme nts - 12)	Validation with a dataset of a real software developme nt project	None
[28]	✓	-	Fuzzy TOPSIS	Fuzzy TOPSIS	None	03 Criteria's	FR – 10 & NFR – 03	Compare with the existing technique	None
[29]	✓	-	Moscow	Moscow	None	03 Criteria	FR – 10 & NFR – 03	None	None
[32]	✓	-	MEREC	-	Yes	07 Criteria	Alternatives – 10	Compare with CRITIC, Entropy and Standard Deviation	Statistics Analysis
[33]	✓	-	WISP	WISP	Yes	06 Criteria	Alternatives – 04	Compare with the existing technique	None
[34]	-	✓	MEREC	WISP	Yes	07 Criteria	Alternatives – 06	Compare with the existing technique	None

Definition 02: Assume that F and S are two Fermatean fuzzy sets and that ($\lambda > 0$) is a positive real number. then FFS can be defined for the following operators [30].

$$F \oplus S = \left(\sqrt[3]{{\propto_R}^3 + {\propto_S}^3 - {\propto_R}^3 {\propto_S}^3}\ , \beta_R \beta_S\right) \quad (1)$$

$$F \otimes S = \left(\beta_R \beta_S\, , \sqrt[3]{{\beta_R}^3 + {\beta_S}^3 - {\beta_R}^3 {\beta_S}^3}\right) \quad (2)$$

$$\lambda.\mathrm{F} = \left\{\sqrt[3]{1 - (1 - {\propto_R}^3)^{\lambda}}\ , {\beta_R}^{\lambda}\right\} \quad (3)$$

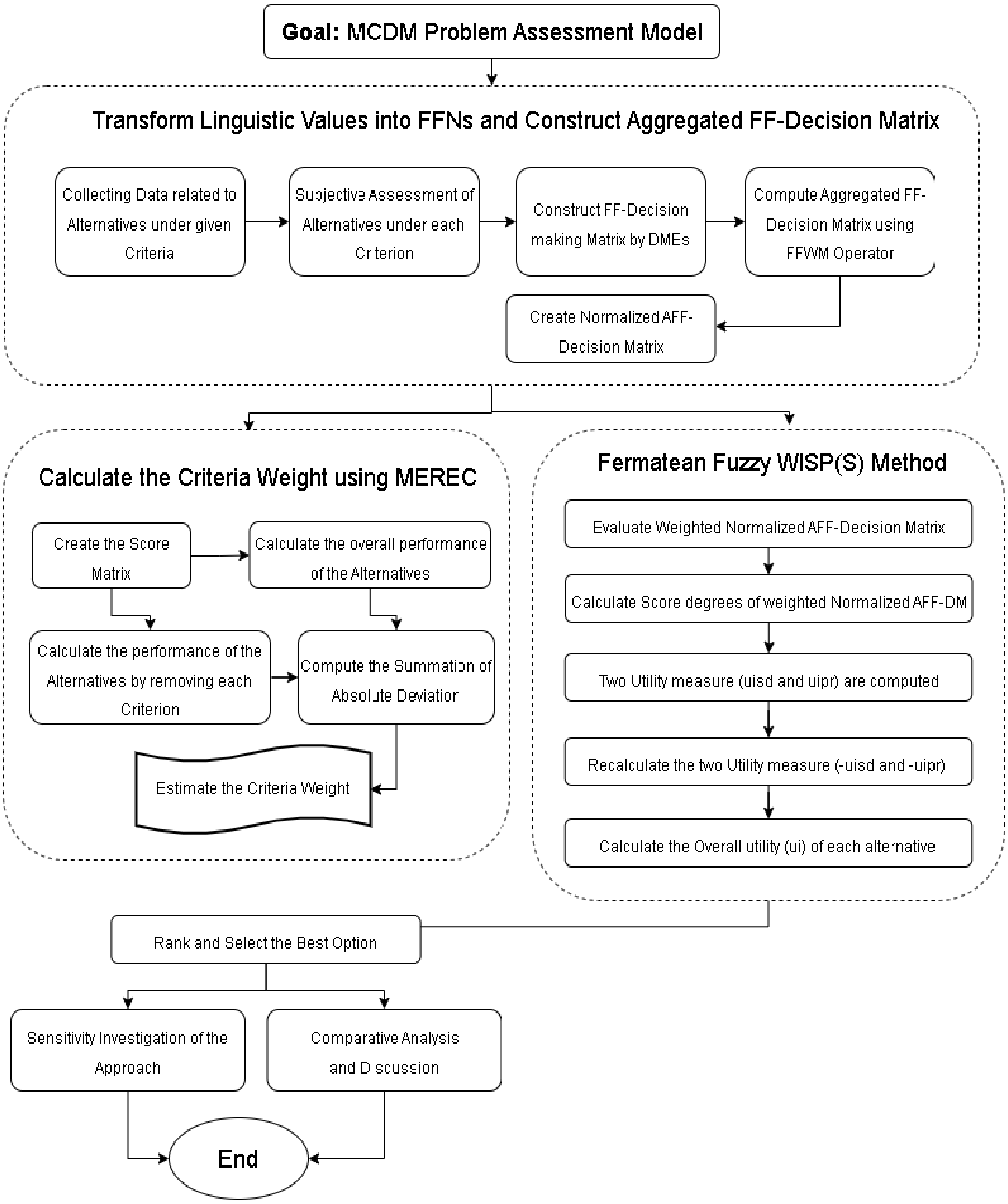

Figure 2: Conceptual framework and overview of the FFS-MEREC-WISP

$$F^{\lambda} = \left\{ \propto_R{}^{\lambda}, \sqrt[3]{1-\left(1-\beta_R{}^3\right)^{\lambda}} \right\} \tag{4}$$

Definition 3: Let's suppose FFS is F = (αR, βR). The following definitions apply to the score function (T) and accuracy function (A) for this FFS [30].

$$T(F) = \propto_R{}^3 - \beta_R{}^3 \tag{5}$$

$$A(F) = \propto_R{}^3 + \beta_R{}^3 \tag{6}$$

These two functions, F = (αR, βR) and S = (αS, βS), can be used to compare two FFSs. When we compare them, there are several criteria [30].

1. If T(F) < T(S), then F < S;

2. If T(F) > T(S), then F > S;

3. If T(F) = T(S), then

a. If A(F) < A(S), then F < S;

b. If A(F) > A(S), then F > S;

c. If A(F) = A(S), then F = S;

Definition 4: According to [30], the complement of an FFS F = (αR, βR) is as follows:

$$Com(F) = (\beta\mathrm{R}, \alpha\mathrm{R}) \tag{7}$$

Definition 5. Compute AFF-DM using FF-aggregation Operator

$$Vij = (\mu ij, vij) = FFGWM = \left(\frac{1}{d}\sum\nolimits_{K=1}^{d} \alpha Eijk \ , \qquad \frac{1}{d}\sum\nolimits_{K=1}^{d} \beta Eijk\right) \tag{8}$$

The FFWGM operator is used to aggregate the preferences of the DMEs and generate the aggregated Fuzzy Fermatean Decision Matrix (AFF-DM) ZA = [vij] mxn, where vij represents the aggregated preference value of alternative Ai over criterion Cj and d is the number of decision-makers. This AFF-DM captures the collective preferences of the DMEs and provides a more comprehensive and reliable basis for the subsequent steps of the decision-making process. By using Equation 9 the FFWGM operator, the proposed methodology can integrate the individual preferences of the DMEs and account for the inherent uncertainty and imprecision in their evaluations, leading to more accurate and robust decision-making results.

3.2. Weight Assessment by FFS-MEREC Approach

The MEREC model calculates objective weights effectively, assessing each criterion's impact on alternative effectiveness. Adapted to work with FFSs in our proposed method, FFSs offer a more precise and flexible depiction of decision-making uncertainty. The expanded MEREC model estimates criteria weights, utilizing collective evaluations of DMEs and FFSs for this estimation, leading to a more reliable and comprehensive foundation for decision-making steps. Weighting criteria is necessary for many decision-making problems as not all criteria hold the same importance. Let's denote the criterion set weight as w = (w1, w2… wn), where the weights must satisfy the condition $\sum_{j=1}^{n} wj = 1$ and wj ∊ [0, 1]. The classical MEREC model is extended to estimate these weights under the Fuzzy Fermatean Set (FFS) environment.

Step 01: **Create Normalized AFF-DM**

The MEREC model calculates objective weights effectively. The AFF-DM ZA = [vij] mxn is generated, followed by the application of a simple linear normalization technique, which scales the AFF-DM elements to produce the normalized AFF-DM ℕ = (sij)mxn. Normalization is a crucial step in decision-making, ensuring equal treatment of criteria and accurately estimating their weights. The following equation is used for normalization to distinguish between the benefit-type criterion set (tb) and the non-beneficial-type criteria set (tn) [34]:

$$Sij = (uij \ , vij) = \begin{Bmatrix} vij = (uij, vij), j \in tb \\ (uij)^c = (vij, uij), j \in tn \end{Bmatrix} \tag{9}$$

Step 02: **Compute the Score Matrix**

To calculate the score matrix $\Omega = (\eta ij)_{mxn}$ of each Fuzzy Fermatean Number (FFN) Sij, the proposed methodology utilizes the following formula [31].

$$nij = \frac{1}{2}((uij)^3 - (vij)^3 + 1) \tag{10}$$

Step 03: **Compute the Overall Performance of the Alternatives**

The MEREC model calculates objective weights effectively. Following this, the score matrix Ω = (ηij)mxn is calculated for each FFN Sij. Subsequently, the next stage assesses the overall performances of the alternatives, utilizing a logarithmic scale for this assessment, where the criteria are given equal weights on this scale. Smaller values of ij equate to higher performances because normalized values from the previous phase are used to ensure this. For this calculation, the following equation is used specifically [34]:

$$Si = ln\left\{1 + \left(\frac{1}{n}\sum_{j}|\ln(nij)|\right)\right\} \tag{11}$$

Step 04: **Compute the Performance of the Alternative by Removing Each Criterion**

Similar to the previous stage, the logarithmic measure is once more applied in this step. However, in this instance, each criterion is eliminated separately to determine how well the options perform. As a result, we get n sets of performances connected to n criteria, each set representing how well an option performs overall when a particular criterion is disregarded. Let S′i represent how well the ith alternative performed overall in terms of eliminating the jth criterion. This equation is used to determine these performances [34]:

$$Sij = ln\left\{1 + \left(\frac{1}{n}\sum_{k,k\neq j}|\ln(nij)|\right)\right\} \tag{12}$$

Step 05: **Compute the Summation of Absolute Deviation**

Using the data from Steps 3 and 4, this step's goal is to determine the elimination effect of the jth criterion. The values of Vj, which represent the result of eliminating the jth criterion, are calculated for this purpose using the method given below [34]:

$$Vj = \sum_{i}(|s'ij - si|) \tag{13}$$

Step 06: **Estimate the Criteria Weight**

On the basis of the removal effects discovered in phase 5, the objective weights of each criterion are established in this phase. Let wj stand for the jth criterion's weight. The final weights for the criteria are obtained using Equation (7) [34].

$$Wj = \frac{Vj}{\sum_{j=1}^{n} Vj} \tag{14}$$

The MEREC model is highly effective in calculating objective weights and efficiently reduces the number of comparisons in MCDM problems, rendering it a practical tool for decision-making. In our study, we expanded the MEREC approach under the FFS environment, employing it to determine criteria weight, thereby enabling more accurate decision-making, especially in contexts with uncertainty.

3.3. Extended WISP(S) Method within FFS Approach

This research proposes a new decision-making method, the extended WISP(S) approach. It addresses multi-criteria decision-making problems under uncertainty. The method integrates WISM and MEREC. It estimates criteria weights and ranks alternatives. The WISP(S) approach uses Fermatean Fuzzy Sets (FFS). It considers the uncertainty and vagueness of decision-makers' preferences. This makes it more accurate and reasonable for decision-making in uncertain situations.

Step 01: **Create Weighted Normalized AFF-DM**

The Aggregated Fuzzy Fermatean Decision Matrix (AFF-DM) ZA = [vij] mxn is generated first. Then, a simple linear normalization technique is applied in step 01. It uses the MEREC approach to scale the AFF-DM elements. This produces the normalized AFF-DM ℕ = (sij)mxn. Normalization is crucial. It ensures equal treatment of criteria in decision-making and accurate weight estimation. The weights of the criteria are calculated using the MEREC approach. These weights are then multiplied by the normalized decision matrix. An equation is used for normalization to distinguish between the benefit-type criteria set (tb) and the non-beneficial-type criteria set (tn).

$$Sij = (uij\,, vij) = \begin{Bmatrix} vij = (uij, vij), j \in tb \\ (uij)^c = (vij, uij), j \in tn \end{Bmatrix} * W \tag{15}$$

Step 02: **Compute the Score Matrix**

To calculate the score matrix Ω = (ηij)mxn of each Fuzzy Fermatean Number (FFN) Sij, the proposed methodology utilizes the following formula [31].

$$nij = \frac{1}{2}((uij)^3 - (vij)^3 + 1) \tag{16}$$

Step 03: **Compute the Two Utility Measures (Ui ^{sd} and Ui ^{pr})**

In decision-making, two utility measures (Uisd and Uipr) help compare alternatives. They reflect a decision maker's preference for one alternative over another, based on two criteria. These two attributes are typically non-commensurable, meaning they lack a common scale for comparison. The suggested methodology employs a specific formula. [32].

$$Ui^{sd} = \sum_{j \in \pi max} rijWj - \sum_{j \in \pi min} rijWj \tag{17}$$

$$Ui^{pr} = \frac{\prod_{j \in \pi max} rijWj}{\prod_{j \in \pi min} rijWj} \tag{18}$$

Step 04: **Compute the Recalculated Two Utility Measures (Ui $^{-sd,}$ and Ui $^{-pr}$)**

Two utility measures (Ui-sd and Ui-pr) are recalculated. This involves updating utility values based on changes in decision-makers' preferences or criteria values. The same process used to calculate the initial two utilities measure is followed for this. [32].

$$Ui^{-sd} = \frac{1 + Ui^{sd}}{1 + \max i\, Ui^{sd}} \tag{19}$$

$$Ui^{-pr} = \frac{1 + Ui^{pr}}{1 + \max i\, Ui^{pr}} \tag{20}$$

Step 05: **Compute the Overall Utility Ui of Each Alternative**

In the WISP method, the total utility of each alternative is determined. It's done by merging the expected utilities for each scenario with their respective probabilities. Mathematically, this can be represented as follows: [32]:

$$Ui = \frac{1}{2}(Ui^{-sd} + Ui^{-pr}) \tag{21}$$

Step 06: **Compute the Final Ranking**

After calculating the overall utility of each alternative in the WISP method, they are then ranked in descending order based on their utility scores. The MEREC model calculates objective weights effectively. In this model, the most suitable alternative is identified by having the highest utility score (Ui), while the least suitable one has the lowest score. This ranking system offers clarity and conciseness, aiding decision-makers in comparing and evaluating alternatives. They find it particularly useful in selecting the best option among the available choices.

4. Application to E-Learning Portal UpFlex Evaluation

In this section, we address a requirement prioritization problem using the proposed Fermatean fuzzy MEREC-WISP method. UpFlex is made to make submissions, registration, communication, and making of panels easier for the Master's Students and teachers. The goal is to minimize the communication gap between students and their supervisors and also to minimize the workload of the teachers when it comes to the marking of these submissions and meetings. This case study contains 28 requirements including both functional and non-functional requirements. We are going to perform a real-world case study on which currently BS-CS students are working on their final year project (FYP) at NUCES FAST ISB. We conducted multiple meetings with these students and collected the requirements shown in Table 2.

Step 01: This case study contains 2 members and these three members worked as multiple decision-makers in an evaluation process. These Decision makers give their individual opinion of requirements against certain criteria.

Step 02: We identify the criteria for the requirement prioritization process. Two types of criteria are beneficial criteria and non-beneficial criteria. Beneficial criteria for requirement prioritization are those that the stakeholders find beneficial. These requirements indicate qualities or features that the product's stakeholders like to have, and their inclusion increases the product's value. In Every case study we considered the Risk and Value beneficial criteria because if it is more than anticipated, it will have a beneficial impact on the project. Criteria that don't directly add to the value or acceptability of the software product are considered non-beneficial. These requirements must typically be met as restrictions or limitations, although their absence has no detrimental effects on the worth of the product.

Table 2: Requirements of case study UpFlex

REQ_ID	REQUIREMENTS
FR01	The students will be able to register in UpFlex.
FR02	The students will be able to register for Thesis-I and then Thesis-II
FR03	The students will be able to register their topics and change them
FR04	The students will be able to request for a supervisor and even request to change them
FR05	The students will be able to view their grades
FR06	The students will be able to see their submissions record

FR07	The students will be able to contact their supervisors
FR08	The students will be able to request for grade change
FR09	The supervisors will be able to contact students being supervised by them
FR010	The supervisors will be able to request the change of an examiner
FR011	The supervisors will be able to view the academic calendar
FR012	The supervisors will be able to manage their dashboard
FR013	The supervisors will be able to approve topic change of the students supervised by them
FR014	The supervisors will be able to view the submissions record
FR015	The examiners will be able to manage their dashboard
FR016	The examiners will be able to view academic calendar
FR017	The examiners will be able to change the grades on request by the students
FR018	The examiners will be able to give marks
FR019	The examiners will be able to manage load
FR020	The MSRC can generate panels
NFR01	The educational portal shall have a user-friendly interface for easy navigation.
NFR02	The educational portal shall be accessible from any device with an internet connection.
NFR03	The educational portal shall have a responsive design to support use on different screen sizes and devices.
NFR04	System will permit easy reversal of actions
NFR05	System will be available 24/7 as reliable cloud servers will be used
NFR06	System application will be compatible with all browsers
NFR07	System will respond to the user requests in a quick manner
NFR08	System's user interface will be easy to use and learn

In every case study we considered the Cost and Detriment non-beneficial criteria because if it is higher than anticipated, it will have a negative influence on the project.

Step 03: The decision-makers were entrusted with establishing linguistic phrases to capture the various levels of a specific attribute during this step. A nine-level scale from "very very low" to "very very high" was adopted to aid with this procedure. According to Boran et al.'s [] proposal, intuitionistic fuzzy sets provided a structured and all-inclusive framework for representing and analyzing uncertain information. These sets were used to derive the meanings of the linguistic concepts. Table 3 shows the nine linguistic word levels and the corresponding FFSs.

Step 04: The decision-makers used the linguistic terms created in Step 3 to independently evaluate each alternative using each criterion. The subjective assessments made by each decision-maker were recorded and tallied for additional examination. Table 4 shows the allocated linguistic terms attributed to each decision-maker's assessments of the alternatives in relation to their perceived weights for each criterion.

Table 3: Linguistic terms and FFS

Linguistic Terms	Values
Very Very Low (VVL)	(0.1,0.9)
Very Low (VL)	(0.1,0.75)
Low (L)	(0.25,0.6)
Medium Low (ML)	(0.4,0.5)
Medium (M)	(0.5,0.4)
Medium High (MH)	(0.6,0.3)
High (H)	(0.7,0.2)
Very High (VH)	(0.8,0.1)
Very Very High (VVH)	(0.9,0.1)

Step 05: The individual evaluations from each decision-maker are merged to create a thorough assessment of the alternatives by using the defined aggregation procedure. The given linguistic terms and their related weights, as shown in Table 3, are taken into account during the aggregation procedure. Equation (09), when used, produces FFSs that reflect the consensus and overall perception established by taking into account the assessments of all decision-makers.

Step 06: The decision matrix is changed to a normalized form using Equation (10) and the normalization procedure shown in Table 5, which enables meaningful comparisons and analysis. The normalization makes sure that the matrix's values are scaled appropriately, taking into account the original data's range and magnitude.

Step 07: Using the MEREC approach, determine the criteria weights, Using Equation (12), we determine the overall performances of the different values. Using Equation (13), we eliminate each criterion to arrive at the alternatives' overall performances (S'ij). We then use the deviation-based formula in Equation (14) to calculate the removal effect of each criterion on the overall effectiveness of the alternatives. Based on how the removal of each criterion affects the performance Vj of the alternatives, the weights of each criterion are calculated. The criteria weights are determined using Equation (15) shown in Table 6.

Step 08: Before applying the WISP method we calculated the criteria weight using the MEREC Approach to use these Weights to compute the two utility measures that are Utility Sum (Usd) using Equation (18) and Utility Product (Upr) using Equation (19) as a result shown in Table 7.

Step 09: Using the result of these two utility measures again to compute the recalculated two utility measures that is Utility Sum (U-sd) using Equation (20) and Utility Product (U-pr) using Equation (21) as a result shown in Table 7.

Step 10: The overall Utility measures (Ui) of alternatives are computed using Equation (22) as a result shown in Table 7.

In the end, finally, calculate the Final Ranking Each alternative is first given an overall utility score using the WISP approach, and then they are sorted in descending order using those utility ratings. The option with the highest utility score (Ui) is thought to be the best choice, and the one with the lowest score is thought to be the worst. The Final Ranking using the MEREC-WISP integration extended with Fermatean Fuzzy sets is shown in Table 7.

5. Results and Discussion

A quantitative study was part of our experiment's fourth stage. The MEREC-WISP method's prioritization outcomes were examined. Comparative and sensitivity analyses were the approaches used. The aim was to assess the effectiveness of the two prioritization methods. We wanted to verify the robustness of prioritization outcomes in various contexts. The comparative analysis compared prioritization outcomes from MEREC and WISP. We looked for result inconsistencies or contradictions. Both methods' final priority was compared. We examined the handling of interpersonal uncertainties by the two techniques. These uncertainties stemmed from stakeholders' differing and conflicting viewpoints. The goal of the sensitivity analysis was to see the effect of changes in prioritization criteria weights on final priorities. We observed the outcomes' sensitivity to changes in the relative importance of both positive and negative criteria. Our understanding of the prioritization results' robustness was enhanced by this research. It aided us in identifying the criteria that had a significant impact on the final priorities. We gained insights into the effectiveness of the MEREC-WISP method for requirements prioritization. Comparative and sensitivity analyses provided these insights. These findings can enhance the efficiency of software engineering prioritization strategies. They can also guide future research in requirements prioritization.

5.1. Comparative Analysis

We compared the results of FF-MEREC-WISP with several earlier techniques. These included Fermatean Fuzzy CRITIC, ENTROPY, and TOPSIS. This was done to confirm the effectiveness of the proposed method.

Table 4: Preference values assigned by 02 decision makers

REQ_ID	COST(C1)	RISK(C2)	VALUE(C3)	DETRIMENT(C4)
Decision Maker 01				
FR01	L	VL	VVH	VVL
FR02	M	L	VVH	VVL
FR03	M H	M	H	VL
FR04	M	M	H	H
FR05	L	H	VVH	H
FR06	L	L	M	VL
FR07	M	VL	VL	VL
FR08	M	H	VVH	VVH
FR09	M	VL	VL	VL
FR010	H	M H	VH	H
FR11	VVL	VL	M L	VVL
FR12	H	M H	L	M
FR13	H	VH	VVH	H
FR14	M	M	VH	VVH
FR15	H	M H	L	M
FR16	VVL	VL	M L	VVL
FR17	VH	H	VVH	VH
FR18	M	VVH	VVH	VH
FR19	L	L	M L	L
FR20	VH	M H	H	M H
NFR01	VH	H	VVH	H
NFR02	M	VVL	VVH	VH
NFR03	VVH	H	VVH	VH
NFR04	VVH	VH	M	H
NFR05	VH	H	VVH	VH
NFR06	VL	L	L	L

NFR7	VH	H	VH	M L
NFR08	VH	M L	VH	L
Decision Maker 02				
FR01	H	VVH	VVH	VVH
FR02	M	H	H	M
FR03	M	L	H	M
FR04	M	L	H	M
FR05	VL	L	M	L
FR06	VL	L	M	L
FR07	L	M	M	M
FR08	VL	L	M	L
FR09	L	L	H	H
FR010	VL	L	H	M
FR11	VVL	VVL	VVL	VVL
FR12	M	M	H	VH
FR13	M	M	H	H
FR14	L	VL	M	M
FR15	M	M	H	VH
FR16	VL	VL	L	L
FR17	M	M	VH	VH
FR18	M	M	VH	VH
FR19	H	H	VVH	VVH
FR20	VH	VH	VVH	VVH
NFR01	M	M	VVH	VH
NFR02	M	L	H	H
NFR03	M	M	VH	VH
NFR04	M	M	M	M
NFR05	VVH	VVH	VVH	VH
NFR06	H	M	H	H
NFR7	VVH	H	VVH	VH
NFR08	M	M	VVH	VVH

Table 5: Normalized decision matrix

REQ_ID	COST(C1)	RISK(C2)	VALUE(C3)	DETRIMENT(C4)
Decision Matrix				
R01	0.478414	0.475883	0.864	0.5
FR02	0.4695	0.478414	0.754313	0.623813
FR03	0.43825	0.536133	0.6675	0.581555
FR04	0.4695	0.536133	0.6675	0.4055
FR05	0.651094	0.478414	0.663688	0.478414
FR06	0.651094	0.600188	0.5305	0.651094
FR07	0.536133	0.581555	0.418445	0.581555
FR08	0.581555	0.478414	0.663688	0.426383
FR09	0.536133	0.651094	0.478414	0.521586
FR010	0.521586	0.50718	0.70925	0.4055
FR11	0.864	0.780258	0.336313	0.864
FR12	0.4055	0.43825	0.521586	0.3705
FR13	0.4055	0.3705	0.754313	0.3325
FR14	0.536133	0.581555	0.6295	0.336313
FR15	0.4055	0.43825	0.521586	0.3705
FR16	0.780258	0.710438	0.433977	0.708258
FR17	0.3705	0.4055	0.806563	0.2445

FR18	0.4695	0.336313	0.806563	0.2445
FR19	0.478414	0.478414	0.623813	0.426383
FR20	0.2445	0.3325	0.754313	0.293063
NFR01	0.3705	0.4055	0.864	0.3325
NFR02	0.4695	0.708258	0.754313	0.3325
NFR03	0.336313	0.4055	0.806563	0.2445
NFR04	0.336313	0.3705	0.5305	0.3705
NFR05	0.193438	0.245688	0.864	0.29075
NFR06	0.521586	0.536133	0.521586	0.29075
NFR7	0.193438	0.3325	0.806563	0.449086
NFR08	0.3705	0.5	0.806563	0.376188

Table 6: Criteria weights

Criteria	COST(C1)	RISK(C2)	VALUE(C3)	DETRIMENT(C4)
Weight	0.2784002`	0.2545674	0.1567372	0.3102951

5.1.1. Comparative Analysis of Weight Assessment

Two distinct objective weighing methods determined the criteria weights and analysis. CRITIC and Entropy were the strategies for weight selection. The suggested methodology's weights were compared for correctness and efficiency. This comparison evaluated the weights. The comparative analysis results are fully reported in this subsection. The comparison was carried out here.

Fermatean Fuzzy CRITIC and Entropy:

The CRITIC technique calculates criteria weights in multi-criteria decision-making. This method uses an inter-criteria correlation matrix to determine each criterion's relevance. The CRITIC technique can process both quantitative and qualitative data. The entropy method is another option for selecting criterion weights. With this approach, weights are assigned under how much uncertainty or unpredictability there is in the data. When a decision-making problem comprises several criteria and the decision-makers have no background information or expertise with the criteria, the entropy method is especially helpful. The criteria weights derived from the proposed MEREC approach were compared with those obtained from previously existing methodologies, particularly CRITIC and Entropy, to gauge its efficacy. Table 8 displays the findings of this comparison together with the related Pearson correlation coefficients (r). These weights are also graphically depicted in Figure 3 With a significance level of = 0.05 (confidence level of 95%), the values of r in Table 8's last row represent the degree of correlation between the findings from the MEREC technique and those from the other methods that were taken into consideration. The reliability of the MEREC approach in comparison to other techniques is determined by these correlation coefficients, which offer insight into the degree of agreement between the various methods.

These results show that the suggested MEREC technique generates credible and trustworthy criteria weights for MCDM issues. As a result, the current study effectively shows the effectiveness of the suggested strategy in contrast to other widely utilized strategies. The comparison analysis's findings demonstrate how well the FF- MEREC-WISP method produces reliable and consistent rankings of the requirements. The suggested methodology can be viewed as a trustworthy and useful method for identifying the most important software needs in practical applications.

Fermatean Fuzzy TOPSIS:

We performed a comparison analysis with existing decision-making methods. This was to validate our proposed methodology. Fermatean fuzzy sets are relatively new in decision-making, so we compared

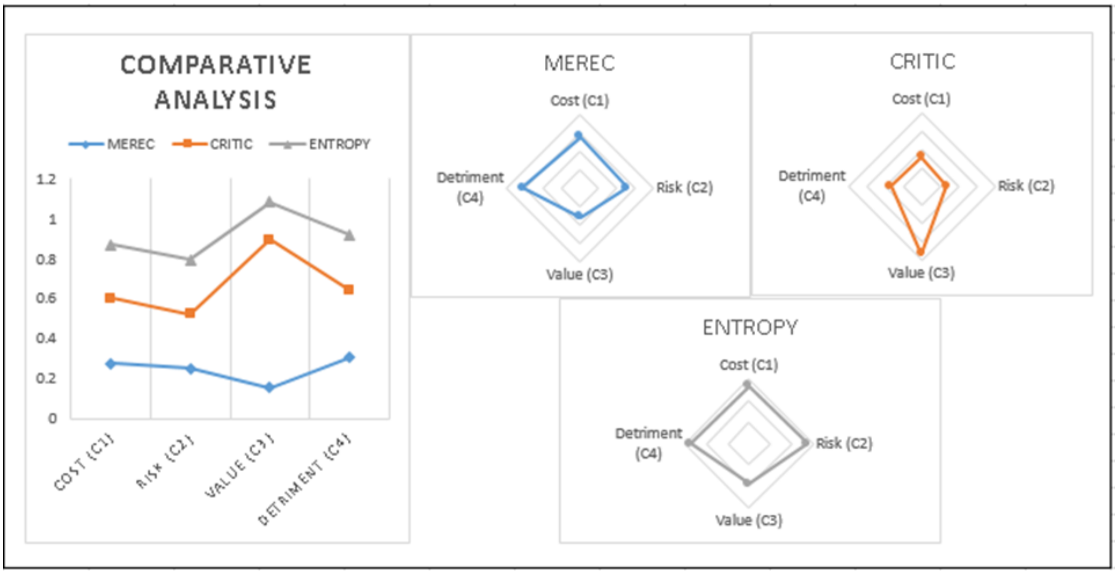

Figure 3: The results of criteria weights (case study: UpFlex)

Table 7: Final ranking by using MEREC-WISP integration with extended FFS

Criteria	**COST(C1)**	**RISK(C2)**	**VALUE(C3)**	**DETRIMENT(C4)**			
Weight	0.2784002`	0.2545674	0.1567372	0.3102951			
MEREC-WISP Integration							**TOPSIS Ranking**
REQ_ID	**WSD**	**WPR**	**SSD**	**PPR**	**UI**	**Ranking**	
FR01	-0.27406144	0.33071250	0.7815829	0.8038493	0.7927161	11	20
FR02	-0.32783466	0.26504933	0.7236879	0.7641839	0.7439359	21	24
FR03	-0.33432231	0.23834928	0.7167029	0.7480551	0.7323790	22	21
FR04	-0.28839341	0.26620345	0.7661524	0.7648811	0.7655167	16	15
FR05	-0.34747831	0.23039617	0.7025385	0.7432508	0.7228947	23	22
FR06	-0.45293495	0.15510457	0.5889985	0.6977691	0.6433838	26	26
FR07	-0.41217198	0.13727861	0.6328860	0.6870009	0.6599434	25	25
FR08	-0.31197355	0.25006010	0.7407648	0.7551293	0.7479470	20	19
FR09	-0.40186700	0.15725056	0.6439809	0.6990654	0.6715231	24	23
FR010	-0.28897984	0.27781345	0.7655210	0.7718944	0.7687077	14	17
FR11	-0.65454826	0.07453074	0.3719312	0.6490965	0.5105138	28	28
FR12	-0.25766787	0.24085784	0.7992331	0.7495704	0.7744017	12	7
FR13	-0.19215279	0.38091440	0.8697700	0.8341750	0.8519725	8	9
FR14	-0.30299440	0.24564545	0.7504322	0.7524625	0.7514473	18	16
FR15	-0.25766787	0.24085784	0.7992331	0.7495704	0.7744017	13	8
FR16	-0.54982680	0.11009242	0.4846797	0.6705784	0.5776290	27	27
FR17	-0.15582316	0.44790842	0.9088843	0.8746444	0.8917644	5	5
FR18	-0.16577190	0.43265766	0.8981730	0.8654318	0.8818024	6	10
FR19	-0.28950908	0.25246253	0.7649512	0.7565805	0.7607658	17	14
FR20	-0.12541954	0.48524368	0.9416184	0.8971976	0.9194080	2	1
NFR01	-0.17412653	0.43748036	0.8891780	0.8683450	0.8787615	7	11
NFR02	-0.29595253	0.28545183	0.7580138	0.7765085	0.7672612	15	18
NFR03	-0.14630535	0.46354001	0.9191317	0.8840870	0.9016094	3	4

NFR04	-0.21976194	0.27450003	0.8400446	0.7698928	0.8049687	10	3
NFR05	-0.07119443	0.65542531	1.0000000	1.0000000	1.0000000	1	2
NFR06	-0.29015794	0.21981648	0.7642526	0.7368599	0.7505562	19	13
NFR7	-0.15142751	0.45499455	0.9136169	0.8789249	0.8962709	4	6
NFR08	-0.22074176	0.36414998	0.8389896	0.8240480	0.8315188	9	12

Table 8: The criteria weight and correlation coefficient of comparative analysis

	Case Study: UpFlex		
Weights	**CRITIC**	**Entropy**	**MEREC**
Cost (C1)	0.325788	0.2671615	0.2784002
Risk (C2)	0.2720224	0.270068	0.2545674
Value (C3)	0.7388815	0.1880928	0.1567372
Detriment (C4)	0.3376856	0.2746776	0.3102951
R	**0.889 (p-value < 0.05)**	**0.953 (p-value < 0.05)**	

our method with the Fermatean fuzzy TOPSIS method. This comparison aimed to showcase the effectiveness and efficiency of our suggested solution against others. TOPSIS managed to handle interpersonal uncertainties from participants' varied and conflicting views. It did this by collectively considering all responses and choosing the best option from multiple possibilities. When comparing WISP and TOPSIS using Fermatean fuzzy data, WISP outperformed TOPSIS. It was better at handling uncertainties and provided more reliable and robust solutions. To tackle uncertainty and imprecision in decision-making, WISP considers how much each option fits into the fuzzy set of optimal solutions. A weight modification mechanism is also used by WISP to change the weights of the criteria based on how significant they are in the decision-making process. In contrast, TOPSIS evaluates the alternatives using predetermined weights, which may not be appropriate in all circumstances.

We analyzed the results and discovered that WISP assigns twenty requirements the highest priority which is 1 and eleventh requirements the least priority which is 28. Figure 4 also shows the visual

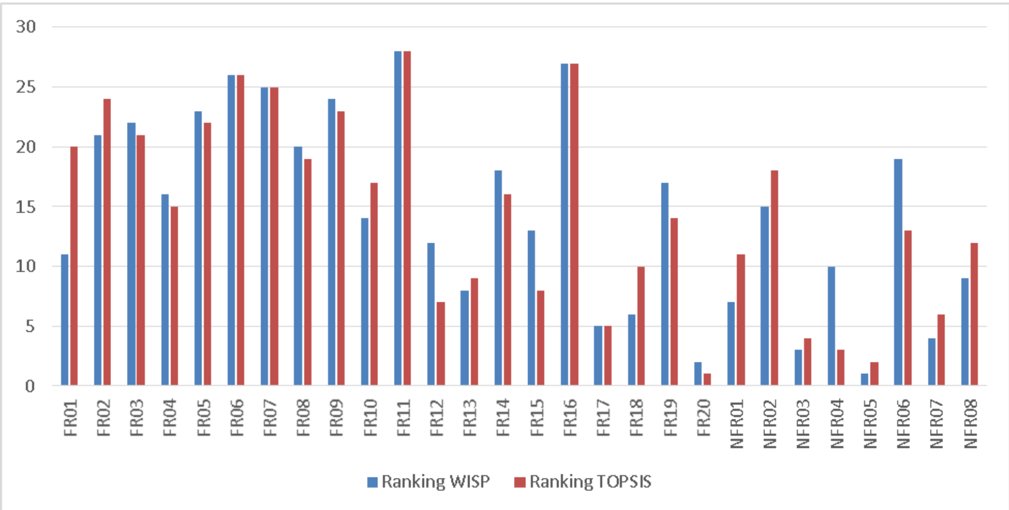

Figure 4: Comparative Analysis of Ranking (Case study: UpFlex)

representation of the comparative analysis of Priorities using the WISP and TOPSIS methods.

5.2. Sensitivity Analysis

A sensitivity analysis was done on the suggested model to confirm its validity and dependability as a decision-making tool. The sensitivity analysis pattern involved modifying two criteria's values while maintaining the values of all the other criteria. Systematically, criterion C1 was switched with the C2 criteria, then with the other criteria shown in Table 9. For each swap, the rankings were recalculated to see how the new criteria weights affected the final standing. The results of the final ranking after swapping are shown in Table 10.

Table 9: Swapping the Criteria Weights for Sensitivity Analysis (Case Study: UpFlex)

Criteria's	COST(C1)	RISK(C2)	VALUE(C3)	DETRIMENT(C4)
Weight (Baseline)	0.2784	0.254567	0.156737	0.310295
C1 to C2	0.254567	0.2784	0.156737	0.310295
C1 to C3	0.156737	0.254567	0.2784	0.310295
C1 to C4	0.310295	0.254567	0.156737	0.2784
C2 to C3	0.2784	0.156737	0.254567	0.310295
C2 to C4	0.2784	0.310295	0.156737	0.254567
C3 to C4	0.2784	0.310295	0.254567	0.156737

Table 10: Results after Appling Sensitivity Analysis (Case Study: UpFlex)

	BASELINE	C1 TO C2	C1 TO C3	C1 TO C4	C2 TO C3	C2 TO C4	C3 TO C4
FR01	11	11	10	11	10	11	10
FR02	21	21	20	18	19	18	12
FR03	22	22	23	22	22	22	20
FR04	16	15	14	15	14	15	14
FR05	23	23	22	23	23	23	22
FR06	26	26	25	26	26	26	26
FR07	25	25	26	25	25	25	25
FR08	20	20	16	21	20	19	19
FR09	24	24	24	24	24	24	24
FR10	14	14	12	14	13	14	13
FR11	28	28	28	28	28	28	28

FR12	12	12	17	12	15	12	15
FR13	8	8	8	8	8	8	8
FR14	18	18	19	19	18	20	21
FR15	13	13	18	13	16	13	16
FR16	27	27	27	27	27	27	27
FR17	5	5	5	5	4	5	6
FR18	6	6	4	7	7	7	7
FR19	17	17	15	17	17	16	17
FR20	2	2	2	2	2	2	3
NFR01	7	7	6	6	6	7	5
NFR02	15	16	13	16	11	17	18
NFR03	3	3	3	4	3	4	4
NFR04	10	10	11	10	12	10	11
NFR05	1	1	1	1	1	1	1
NFR06	19	19	21	20	21	21	23
NFR07	4	4	7	3	5	3	2
NFR08	9	9	9	9	9	9	9

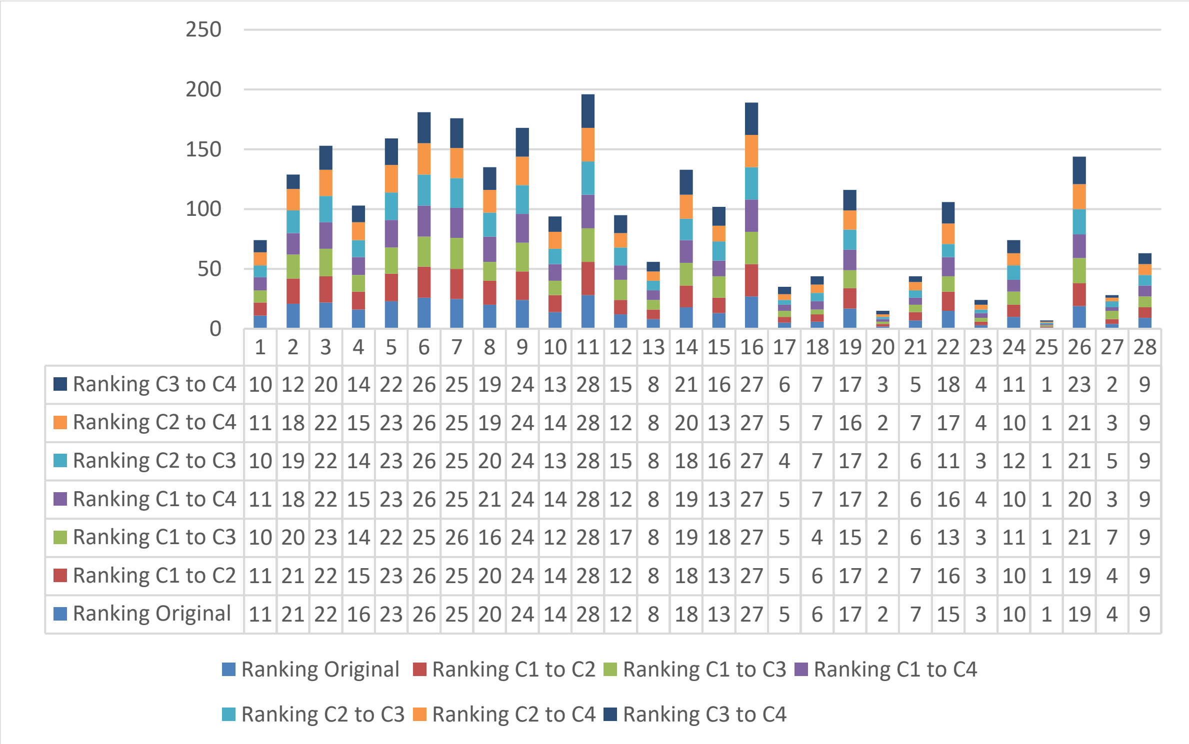

Figure 5: Results of Sensitivity Analysis (Case study: UpFlex)

Each case study's sensitivity analysis results showcased the robustness of the proposed decision-making model. It showed that the model's rankings weren't affected by small changes in criteria weights. The model's robustness level is high, indicating its applicability in real-world scenarios with varied inputs. The model can give precise, consistent outcomes. The FFS-MEREC-WISP model backs the final solution choice. Sensitivity analysis results are shown in Figure 5. The model's ranking consistency is evident. The sensitivity analysis provides robustness insights. It shows the model's ability to be accurate in different situations. This confirms the decision-making method proposed. A real-world case study tested the model. It focused on software requirements prioritization. The model proved effective in prioritizing software requirements. The ranking matched the decision-makers' preferences. This showed the model's practicality in a real-world scenario. The model was also applied to another real-world case study. It effectively prioritized software requirements. The ranking aligned with the decision-makers' preferences. This demonstrated its real-world effectiveness and practicality.

6. Conclusions and Future Direction

This section provides a detailed analysis of the research activities. It emphasizes the contributions made to achieve the study goals. We share our discoveries and discuss their addition to the existing body of knowledge. We also offer a comprehensive account of any validity risks encountered during the study.

6.1. Summary

We introduced FF-MEREC-WISP, a new method, in our study. It merges MEREC and WISP, using Fermatean fuzzy sets. This improves the prioritization process. Our goal was to present a new approach based on Fermatean fuzzy sets. It tackles the current limitations in requirements prioritization methods. A Literature Review helped us identify these gaps. It emphasized the need for a more reliable, accurate strategy. We reviewed existing prioritization methodologies extensively. Their flaws were identified. We compared them, highlighting the need for a better strategy. We developed a methodology to achieve our research goals. It encompassed data collection, pre-processing, analysis, and evaluation. A case study was conducted to validate our proposed strategy. It was compared with current methods like TOPSIS and WISP. Our strategy proved to be more reliable and accurate. Pearson correlation coefficients were used to define our proposed method thoroughly. It was compared with existing methods. A strong correlation was found between the weights from FF-MERECWISP and those from CRITIC, Entropy, and TOPSIS. The results were credible and reliable. We shared our case study results. We demonstrated how FF-MEREC-WISP outperformed other options. For each case study, we provided a visual comparison between FF-MEREC-WISP and TOPSIS. This study's results have significant implications for requirements engineering practitioners and researchers. Our work highlights the shortcomings of current prioritization techniques. It emphasizes the need to prioritize both functional needs (FRs) and non-functional requirements (NFRs). Our research contributes significantly to the body of knowledge. It suggests a novel strategy that addresses these limitations. It provides a viable solution to the challenges faced by requirements engineers in this field.

6.2. Limitations and Future Directions

Our proposed approach was evaluated in an academic environment, not an industrial one. This is a significant limitation. Consequently, the study's results may not fully apply to real-world scenarios. We also used just three decision-makers to establish the baseline. This might not fully represent the expertise and diverse perspectives of a larger expert group. Future studies could involve more decision-makers for a more comprehensive and accurate baseline. Despite these limitations, our study significantly contributes to the requirements prioritization field. It provides a strong foundation for further research.

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