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A Fuzzy Multi-Criteria Decision-Making Approach to Personalised Treatment in Neuroscience

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Abstract: Personalised treatment approaches have become increasingly important in the field of neuroscience, aiming to improve healthcare quality and patient satisfaction. This study contributes to the development of personalised treatment strategies by integrating fuzzy multi-criteria decision-making (FMCDM) techniques. Given the uncertainties and multidimensional criteria involved in treatment evaluations, FMCDM provides a robust framework to enhance decision-making in healthcare. The primary objectives of this study are to manage uncertainties in treatment evaluations, to develop an integrated decision-making approach for patient monitoring, and to evaluate treatment criteria on an individual patient basis. The prioritization of treatment criteria for each patient was performed using Fuzzy Logarithm Methodology of Additive Weights (FLMAW), while personalised treatment approaches were evaluated with Fuzzy Ranking of Alternatives with Weights of Criteria (FRAWEC) method. The results demonstrated that the criteria for Patient A and Patient B, as recommended by the expert team, were distinct, leading to different personalised treatment approaches for each. The proposed model integrates FLMAW and FRAWEC methods to optimise personalised treatment strategies by addressing uncertainties and evaluating key factors such as biometric data, treatment response, and psychosocial aspects. By prioritising treatment criteria and ranking interventions based on individual patient profiles, the model facilitates tailored treatment plans that address both physical and psychological health needs. This study discusses practical implications for healthcare professionals and management strategies for implementing these innovative approaches. Future research highlights the need for broader expert collaboration and the continuous integration of advanced technologies to update monitoring criteria.

Keywords: personalised treatment approach; fuzzy MCDM; LMAW RAWEC; patient monitoring.

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1. Introduction

Patient monitoring in the field of neuroscience plays a critical role in optimising treatment processes by continuous evaluation of individual health status. Since each patient's neurological and psychological characteristics are unique, it is of paramount importance to develop personalised monitoring strategies (Griñán-Ferré et al., 2024).

Multi-criteria decision-making (MCDM) is a process that helps decision-makers determine the best option by considering multiple conflicting criteria. Today, complex decision-making situations are influenced not only by economic factors but also by environmental, social, and technical factors. Therefore, MCDM methods allow for a systematic evaluation of different criteria (Ferreira et al., 2023).

MCDM methods generally consist of three main stages: (1) defining the decision problem and determining the relevant criteria; (2) evaluating and scoring alternatives; (3) analysing and ranking alternatives. This process enables decision-makers to better understand complex situations and produce appropriate solutions (Samanlioglu, 2019). However, in real-world clinical scenarios, especially in neuroscience, decision-making is often complicated by high levels of uncertainty and imprecise information. Expert judgements may involve vagueness, data may be incomplete, and patient conditions may evolve in unpredictable ways. To address these challenges, fuzzy MCDM (FMCDM) methods have been developed. These methods extend traditional MCDM by incorporating fuzzy logic, which allows for the modelling of ambiguity and subjectivity in human reasoning (Van Thanh, Hai, & Lan, 2022). There are several reasons why FMCDM methods are preferred for this study:

- **Uncertainty and Complexity:** In patient monitoring and personalised treatment approaches, various criteria and uncertainties must be assessed concurrently. FMCDM provides an effective framework for managing these uncertainties.
- **Integration of Expert Opinions:** Gathering the opinions of different experts is essential in the development of personalised treatment recommendations. FMCDM allows experts to express their assessments in a flexible format, thus achieving a more robust consensus.
- **Consideration of Different Criteria:** In neuroscience, it is necessary to evaluate social, psychological, and biometric factors together in patient monitoring. FMCDM manages these multidimensional decision-making processes more effectively.

FMCDM methods allow patient data to be analysed dynamically and flexibly, offering the potential to create more effective decision support systems (Wubineh, Deriba, & Woldeyohannis, 2024). This study aims to reveal the potential of FMCDM methods in patient monitoring processes. The main objectives are:

- **Use of FMCDM:** Effective management of uncertainties and multidimensional criteria in the evaluation of personalised treatment options;
- **Intelligent Support Provision:** Development of decision support systems for patient monitoring in the field of neuroscience, thus determining the most appropriate treatment recommendations for the patient's situation;
- **Personalised Approaches:** Increasing treatment adherence by evaluating the criteria for each patient by experts.

These approaches contribute to optimising personalised treatment processes and serve as an initial effort to enhance the effectiveness of patient monitoring in neuroscience. The primary aim of this paper is to develop a personalised treatment model integrating Fuzzy Logarithmic Methodology of Additive Weights (FLMAW) and Fuzzy Ranking Alternatives with Weights of Criterion (FRAWEC) methods to improve healthcare decision-making. The study specifically targets the management of uncertainties in treatment evaluation, the prioritisation of treatment criteria according to individual patient profiles, and the recommendation of tailored therapeutic strategies. By integrating these two FMCDM methods, the model enhances the decision-making process through systematic evaluation of key decision criteria, thereby supporting more precise and patient-specific care planning.

2. Literature Review

The literature review is divided into two main sections. The first part explores current studies in neuroscience, highlighting methods and findings related to patient monitoring. The second part examines research involving LMAW and RAWEC methods, evaluating their application domains and benefits.

2.1. Current Studies in the Field of Neuroscience

Understanding the cognitive aspects of decision-making is becoming increasingly important. Decision-makers must assess multiple conflicting criteria, making it essential to consider their preferences, biases, and reasoning patterns. To support this need, advanced decision support systems are required, incorporating cognitive insights, data-driven analytics, and intelligent algorithms. These systems assist in structuring problems, prioritising criteria, and identifying optimal solutions, leading to more informed, transparent, and effective decision-making. The FITradeoff method is an MCDM approach developed for preference modelling based on partial knowledge in this area, and the user-friendly, flexible nature of the method has been evaluated in several studies (de Almeida, Frej, & Roselli, 2021). This method offers a powerful tool for analysing and improving decision-making behaviours, with a particular focus on elements such as cognitive load and effort.

De Lima Da Silva, Cabral Seixas Costa, and de Almeida (2024) used electroencephalography (EEG) and eye-tracking tools to examine cognitive elements in the selection process of the FITradeoff method. In this study, the flexible and interactive nature of the method had significant effects on decision-making behaviours, and it was observed that it increased decision efficiency by reducing cognitive load. In particular, it has been stated that as the number of preferred criteria increases, decision-makers strategically strive to minimise cognitive load. Similarly, Roselli and de Almeida (2023) introduced the 'success-based decision rule' to enable flexible determination of scaling constants in the FITradeoff method. This rule has been proposed to improve the holistic evaluation by leveraging the benefits of graphical aids to decision-makers. This rule, supported by neuroscience experiments, provides the decision-maker with information about the probability of success of graphs and makes the selection process more understandable.

De Almeida et al. (2023) sought to enhance flexibility by integrating the holistic and decomposition approaches of the FITradeoff method. This approach aimed to improve decision-makers' efficiency by reducing their cognitive load. By combining these two modelling paradigms in decision-making with partial information, the study increased the consistency of decision processes and offered greater flexibility in implementation.

Roselli et al. (2020), on the other hand, conducted a neuroscience experiment to understand the behaviour of decision-makers during the Tradeoff Elicitation Procedure. In this experiment, EEG and eye-tracking data were analysed, and it was determined that the cognitive efforts of decision makers increased at the points where they encountered difficulties. This analysis of decision-maker behaviours is a guide for making decision support systems user-friendly based on the FITradeoff method.

Finally, in another neuroscience experiment conducted by Roselli, de Almeida, and Frej (2019), it was found that data visualisation in the FITradeoff method contributed to the decision process. Decision-makers were able to demonstrate higher cognitive effort and provide consistency in their preferences with these visual aids. These aspects of the method guide the intuitive judgements of decision makers and reveal the benefits of supporting the FITradeoff method with neuroscience tools in decision support processes.

2.2. Research Carried out with LMAW/FLMAW and RAWEC/FRAWEC Methods

LMAW is a new MCDM method used in both criteria weighting and ranking of alternatives. The method's integration with the Bonferroni Addition Operator offers a powerful solution to group decision-making problems. This operator increases the fairness of the decision-making process by ensuring that individual contributions are taken into account in a more balanced way in the

evaluation of alternatives. Therefore, this method is considered an important tool in MCDM applications. Some of the studies using LMAW and FLMAW methods are summarised in Table 1.

Table 1. Studies with LMAW/FLMAW methods

Authors	Year	Topic
Ünsal et al.	2024	Application of Z-number-based FMCDM in solar power plant location selection
Fernández-Portillo et al.	2024	Prioritising sustainable development goals in the Dominican Republic with FLMAW
Karakuş	2024	Assessment of ecotourism potential using geographic information system (GIS)-based FLMAW for resource management
Nasution et al.	2024	Government AI Readiness Index using FLMAW and Schweizer-Sklar Weighted Framework
Darıcı et al.	2024	Assessing unemployment risks in the communication sector due to AI with FMCDM
Asadi et al.	2023	Blockchain implementation in SMEs' supply chains based on the FLMAW method.
Pamučar et al.	2023	Decision analysis model for smart mobility under a circular economy approach.
Tešić et al.	2023	Development of FLMAW-GREY Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) model for dump truck selection.
Božanić et al.	2022	Modification of LMAW with triangular fuzzy numbers in MCDM.
Pamučar et al.	2021	A new LMAW methodology application in logistics.

Table 1 reflects the progression and application of LMAW/FLMAW methodologies in various contexts, highlighting their versatility and relevance in contemporary research. Table 2 presents the application of the newly developed RAWEC method within MCDM frameworks.

Table 2. Studies with RAWEC/FRAWEC methods

Authors	Year	Topic	Methods Used
Puška et al.	2024a	Selection of agricultural distribution center locations	RAWEC, LMAW
Nedeljković et al.	2024	Selection of agricultural product sales channels	Fuzzy DOUBLE MEthod based on the Removal Effects of Criteria (MEREC), FRAWEC
Puška et al.	2024b	Agricultural sustainability through renewable energy integration	FMCDM, RAWEC
Mohamed, Salam, and Ye	2024	Selection of sustainable material for the drone aerodynamic wing	Neutrosophic RAWEC
Sandra et al.	2025	Selection of drilling techniques for heat extraction from geothermal reservoirs	Fuzzy-rough approach
Do	2024	Ranking of the top ten universities in Vietnam	RAWEC, Proximity Index Value (PIV), Root Assessment Method (RAM), Simple Ranking Process (SRP)
Akbulut & Aydın	2024	Multidimensional performance measurement of Turkish banks	Modified Standard Deviation (MSD), Modified Preference Selection Index (MPSI), RAWEC
Petrovic et al.	2024	Multicriteria sustainability assessment of transport modes	RAWEC, Standard Deviation (SD), ENTROPY, FANMA
Nedeljković et al.	2024	Selection of agricultural product sales channels	Fuzzy Double MEREC and FRAWEC

Table 2 presents various studies focusing on sustainability and optimisation issues in different areas. The use of innovative approaches such as RAWEC and fuzzy methods shows that

MCDM techniques adapt to complex decision-making scenarios such as agriculture, education, banking, and transportation.

2.3. Identified Gaps

Highlighting research gaps is crucial to emphasise the original contribution of the study. In this context, a general review of existing studies on personalised treatment approaches in neuroscience patient monitoring can be presented as follows:

- **Neglect of Patient-Specific Criteria Differentiation:** Most current studies focus on treatment recommendations within a general framework, lacking tailored multi-criteria decision-making approaches that adapt to individual patient conditions. This gap provides a significant opportunity to develop a decision support system which incorporates personal health conditions and biometric data.
- **Limited Application of Fuzzy Logic Approaches:** In neuroscience, the comprehensive use of FMCDM methods in patient monitoring remains limited. Most studies employ traditional decision-making methods that may not fully capture uncertainties or the importance of expert opinions.
- **Insufficiency of Dynamic and Updatable Treatment Processes:** Current studies often lack flexibility in adapting the treatment process dynamically. However, real-time monitoring of patients and offering optimised treatment plans based on this data could enhance patient compliance and yield more effective outcomes.

2.4. Contributions

The paper addresses critical shortcomings in existing studies concerning personalised treatment approaches in neuroscience, particularly regarding patient monitoring. Despite the increasing recognition of the necessity for individualised treatment strategies, much of the current literature still adheres to standardised protocols that overlook the specific needs of patients. This study introduces a novel framework for personalised treatment recommendations through the integration of FMCDM methodologies. By doing so, it not only bridges the gap in the literature regarding the application of advanced decision support systems in healthcare but also highlights the essential role of expert evaluations and patient-specific data in enhancing treatment efficacy.

Moreover, this research responds to the pressing need for dynamic and adaptable models in patient management. The proposed approach aims to provide a robust solution for continuous patient monitoring, ensuring that treatment plans remain relevant and effective in the face of evolving patient conditions. Thus, the findings will significantly contribute to the enhancement of personalised healthcare practices, offering valuable insights that may inform future research and applications within the field.

- **Need for personalised treatments suited to patient characteristics:** Modern healthcare practices increasingly aim for more individualised treatment strategies, moving away from standard approaches. By developing a system that provides personalised treatment recommendations for patient monitoring in neuroscience, this study is expected to increase patient satisfaction and compliance. The absence of comprehensive research in this direction underscores the study's unique value.
- **Lack of fuzzy logic-based decision support systems:** Most decision support system research in the literature is limited in its use of techniques like fuzzy logic to manage uncertainties. This study advocates for the application of FMCDM methods to handle uncertainty and make more accurate decisions within neuroscience patient monitoring processes.
- **A rapidly responsive and adaptable model to patient needs:** The main goal is to develop a model that can be continuously updated and respond promptly to patient conditions. The lack of an effective system in the current literature that addresses this need and makes patient monitoring dynamic is evident. This approach aims to bridge this gap.

3. Materials and Methods

This section outlines the fundamental mathematical concepts of the proposed FMCDM model.

3.1. Fuzzy Set Theory

Zadeh (1965) established fuzzy set theory, which is a system that represents uncertainty while also allowing decision makers to make judgements using linguistic variables. Fuzzy numbers can exist in theory and practice in a variety of forms. These are idioms used to represent unknown numbers. However, triangular fuzzy numbers are the most widely used form. Triangular fuzzy numbers have been used in various studies to translate qualitative comments into quantitative ones. Triangular fuzzy numbers portray each number as three numbers. The first, second, and third integers that characterise a fuzzy number represent the lowest, most likely, and biggest possible values, respectively.

Suppose $\tilde{A} = (a_l, a_m, a_u)$ and $\tilde{B} = (b_l, b_m, b_u)$ are two triangular fuzzy numbers. The mathematical computations for these integers are described in Eqs. (1)-(4).

$$\tilde{A} + \tilde{B} = (a_l + b_l, a_m + b_m, a_u + b_u) \quad (1)$$

$$\tilde{A} - \tilde{B} = (a_l - b_u, a_m - b_m, a_u - b_l) \quad (2)$$

$$\tilde{A} \times \tilde{B} = (a_l b_l, a_m b_m, a_u b_u) \quad (3)$$

$$\frac{\tilde{A}}{\tilde{B}} = \left(\frac{a_l}{b_u}, \frac{a_m}{b_m}, \frac{a_u}{b_l} \right) \quad (4)$$

Triangular fuzzy numbers can be converted to crisp numbers using a variety of formulae. In this study, Eq. (5) is used to defuzzify a fuzzy integer, such as $\tilde{A} = (a_l, a_m, a_u)$.

$$A = \frac{a_l + 4a_m + a_u}{6} \quad (5)$$

3.2. FLMAW Method for Prioritisation of Criterion

In the MCDM environment, fuzzy logic-based methods have been developed to effectively handle uncertainty, enabling decision-makers to incorporate both subjective and objective assessments. Within this framework, methods like Fuzzy AHP, Fuzzy SWARA, Fuzzy CRITIC, and Fuzzy LMAW offer distinct approaches for the criteria weighting process. Table 3 presents a comparative evaluation of these methods, highlighting their key characteristics, capabilities in managing uncertainty, differences in data types, computational complexities, and respective advantages and disadvantages.

Table 3. Comparison of Fuzzy AHP, Fuzzy SWARA, Fuzzy CRITIC, and Fuzzy LMAW Methods

Feature	Fuzzy AHP	Fuzzy SWARA	Fuzzy CRITIC	Fuzzy LMAW
Core Approach	Fuzzy pairwise comparisons with a hierarchical structure	Stepwise fuzzy prioritisation of criteria	Objective weighting based on fuzzy data	Fuzzy logarithmic computation combined with Bonferroni aggregator
Uncertainty Handling	Incorporates uncertainty using triangular/trapezoidal fuzzy numbers	Uses linguistic terms and fuzzy intervals	Fuzzification of data variance and correlation	Fuzzy modelling of both criteria weights and alternative evaluations
Data Type	Subjective (expert opinion + uncertainty)	Subjective (flexible expert assessment)	Objective (uncertain data sets)	Hybrid (subjective + objective + uncertainty)

Complexity	High (fuzzy matrix computations)	Medium (simplified fuzzy steps)	Medium (data normalisation and fuzzification)	High (logarithmic operations and fuzzy integration)
Advantages	- Manages uncertainty in hierarchical models - Consistency check	- Flexible expert input - Quick implementation	- Maintains objectivity - Tolerant to low-quality data	- Handles both subjective and objective uncertainty - Rank consistency
Disadvantages	- Computationally intensive - Relies on expert input	- Limited scalability - Risk of inconsistency in linguistic scales	- Challenges in processing fuzzy data - Ignores subjective factors	- Mathematically complex - Requires both expert judgment and data

The LMAW method, introduced by Pamučar et al. (2021), is used in this study to determine the weights of evaluation criteria. Its selection is grounded in both theoretical justification and practical advantages, as supported by the findings of Pamučar et al. (2021) and Darıcı et al. (2024). One of the key strengths of the LMAW method is its ability to maintain a consistent mathematical structure regardless of the number of criteria or alternatives, ensuring scalability and adaptability to various decision contexts. It is particularly effective in managing large-scale and complex decision problems involving multiple criteria and alternatives. LMAW generates clear and interpretable quantitative scores, which improve transparency and facilitate informed decision-making. Moreover, it allows the integration of both qualitative and quantitative data within a single framework, enabling comprehensive evaluations. The method avoids the rank reversal problem, ensuring reliable rankings even when the number of alternatives changes. It also demonstrates robustness by producing stable results across different datasets and remaining resistant to parameter fluctuations. The use of the Bonferroni aggregator provides a flexible mechanism for incorporating diverse expert opinions. Furthermore, the method's compatibility with sensitivity analysis further enhances its value by offering deeper insights into the impact of varying criteria weights and methodological parameters. The procedural steps of this method are presented below (Božanić et al., 2022):

Step 1: Prioritising criteria

The identified experts prioritise the criteria using the linguistic terms given in the fuzzy scale in Table 4.

Table 4. *Prioritisation Scale*

Fuzzy Linguistic Descriptive	Abbreviation	Fuzzy Number
Absolutely low	AL	(1,1,1)
Very low	VL	(1,1.5,2)
Low	L	(1.5,2,2.5)
Medium	M	(2,2.5,3)
Equal	E	(2.5,3,3.5)
Medium-high	MH	(3,3.5,4)
High	H	(3.5,4,4.5)
Very high	VH	(4,4.5,5)
Absolutely high	AH	(4.5,5,5)

Source: (Božanić et al., 2022)

Using the fuzzy linguistic scale, significant values are assigned to the criteria of greater importance, and conversely. For each specialist, the priority vectors are obtained individually $\tilde{P}^e = (\tilde{\gamma}_{C_1}^e, \tilde{\gamma}_{C_2}^e, \dots, \tilde{\gamma}_{C_n}^e)$ $\tilde{P}^e = (\tilde{\gamma}_{C_1}^e, \tilde{\gamma}_{C_2}^e, \dots, \tilde{\gamma}_{C_n}^e)$.

Step 2: Determination of the fuzzy absolute anti-ideal point $(\tilde{\gamma}_{AIP})$ $(\tilde{\gamma}_{AIP})$

This fuzzy number is established by experts. It is smaller than the smallest value in the whole collection of priority vectors. Those who brought the method to the literature used it as $\tilde{\gamma}_{AIP} = \tilde{\gamma}_{AIP} = (0.5, 0.5, 0.5)$.

Step 3: Determination of the fuzzy relationship vector $(\tilde{R}^e \tilde{R}^e)$

The connection between the components of the priority vector and the exact opposite ideal point is computed using Eq. (6).

$$\tilde{\eta}_{C_n}^e = \left(\frac{\tilde{\gamma}_{C_n}^e}{\tilde{\gamma}_{AIP}} \right) = \left(\frac{\gamma_{C_n}^{(l)e}}{\gamma_{AIP}^{(r)}}, \frac{\gamma_{C_n}^{(m)e}}{\gamma_{AIP}^{(m)}}, \frac{\gamma_{C_n}^{(r)e}}{\gamma_{AIP}^{(l)}} \right) \quad (6)$$

Step 4: Computing the vectors $(w_j^e w_j^e)$ of weight coefficients

Eq. (7) is utilised to acquire the fuzzy score of the weight coefficients of the criteria of every expert.

$$\tilde{w}_j^e = \left(\frac{\ln(\tilde{\eta}_{C_n}^e)}{\ln(\prod_{j=1}^n \tilde{\eta}_{C_n}^e)} \right) = \left(\frac{\ln(\eta_{C_n}^{(l)e})}{\ln(\prod_{j=1}^n \eta_{C_n}^{(r)e})}, \frac{\ln(\eta_{C_n}^{(m)e})}{\ln(\prod_{j=1}^n \eta_{C_n}^{(m)e})}, \frac{\ln(\eta_{C_n}^{(r)e})}{\ln(\prod_{j=1}^n \eta_{C_n}^{(l)e})} \right) \quad (7)$$

The weight factors of all experts are acquired in the shape of $w_j^e = (\tilde{w}_1^e, \tilde{w}_2^e, \dots, \tilde{w}_n^e)^T$ $w_j^e = (\tilde{w}_1^e, \tilde{w}_2^e, \dots, \tilde{w}_n^e)^T$.

Step 5: Calculating combined fuzzy vectors of weight coefficients.

The combined fuzzy vectors of the weight coefficients are determined by utilising the Bonferroni aggregator relying on Eq. (8) $w_j = (\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_n)^T$ $w_j = (\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_n)^T$.

$$\tilde{w}_j = \left(\frac{1}{k(k-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^k \tilde{w}_i^{e(p)} \tilde{w}_j^{e(q)} \right)^{\frac{1}{p+q}} =$$

$$\left\{ \left(\frac{1}{k(k-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^k w_i^{(l_e)p} w_j^{(l_e)q} \right)^{\frac{1}{p+q}}, \left(\frac{1}{k(k-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^k w_i^{(m_e)p} w_j^{(m_e)q} \right)^{\frac{1}{p+q}}, \left(\frac{1}{k(k-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^k w_i^{(r_e)p} w_j^{(r_e)q} \right)^{\frac{1}{p+q}} \right\}$$

$$\left\{ \left(\frac{1}{k(k-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^k w_i^{(l_e)p} w_j^{(l_e)q} \right)^{\frac{1}{p+q}}, \left(\frac{1}{k(k-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^k w_i^{(m_e)p} w_j^{(m_e)q} \right)^{\frac{1}{p+q}}, \left(\frac{1}{k(k-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^k w_i^{(r_e)p} w_j^{(r_e)q} \right)^{\frac{1}{p+q}} \right\} \quad (8)$$

Step 6: Computation of the ultimate value of the weighted criteria.

The final values of the criteria's weight coefficients are obtained through clarification based on $w_j = (w_1, w_2, \dots, w_n)^T$ $w_j = (w_1, w_2, \dots, w_n)^T$, as illustrated in Eq. (5).

3.3. FRAWEC Method for Ranking Alternatives

Several methods are widely employed to rank alternatives in MCDM problems. Among them, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VIšekriterijumsko KOmpromisno Rangiranje (VIKOR), and Preference Ranking Organisation Method for Enrichment Evaluation (PROMETHEE) are well-established. On the other hand, the RAWEC method, introduced by Puška et al. (2024a), which ranks alternatives based on weighted deviations, has recently gained increasing attention. RAWEC offers several advantages, including its simple, low-step computational structure, which makes it more efficient than other methods. It uses a dual normalisation approach to handle benefit and cost criteria separately, ensuring balanced data treatment. RAWEC is also adaptable to dynamic decision matrices, avoiding rank reversal issues often encountered in other MCDM methods. The method supports both quantitative and qualitative criteria, allowing for a comprehensive evaluation process. It also proves robust in sensitivity analysis, maintaining ranking consistency despite changes in criteria weights, and presents results on a standardised scale from -1 to +1, ensuring clarity and transparency. To address uncertainty and imprecision in expert judgements and real-world data, fuzzy extensions of these methods, including fuzzy RAWEC, have been developed. These fuzzy adaptations improve the model's capability to incorporate vague and uncertain information in decision-making. Table 5 offers a comparative analysis of fuzzy versions of TOPSIS, VIKOR, PROMETHEE, and RAWEC, and focuses on their theoretical foundations, data requirements, uncertainty-handling strategies, computational complexities, advantages, and limitations.

Table 5. Comparison of Fuzzy Versions of TOPSIS, VIKOR, PROMETHEE, and RAWEC Methods

Feature	Fuzzy TOPSIS	Fuzzy VIKOR	Fuzzy PROMETHEE	Fuzzy RAWEC
Core Approach	Fuzzy distance to ideal and anti-ideal solutions	Fuzzy group utility and regret for compromise solutions	Fuzzy preference functions and outranking flow analysis	Double normalisation + fuzzy weighted deviation calculation
Uncertainty Handling	Triangular/Trapezoidal fuzzy numbers for data uncertainty	Linguistic terms and fuzzy intervals	Fuzzification of preference functions	Fuzzification of both criterion weights and the alternatives
Data Type	Quantitative + Qualitative (with uncertainty)	Quantitative + Qualitative (for compromise scenarios)	Qualitative (based on preference functions)	Mixed (quantitative + qualitative + dynamic data)
Complexity	Moderate (ideal solution computation)	High (optimisation of group utility and regret)	High (multiple preference functions)	Moderate (double normalisation and deviation analysis)
Advantages	- Clear ideal point reference - Relatively simple computation	- Effective for compromise solutions - Suitable for group decisions	- Flexible preference functions - Partial dominance analysis	- Adaptable to dynamic data - Rank consistency
Disadvantages	- Subjectivity in defining the ideal point - Challenging with high-dimensional data	- Complex optimisation steps - Expert dependency	- Computational intensity - Critical selection of the preference function	- Limited literature support for a novel method

In this study, the RAWEC method is fuzzified using triangular fuzzy numbers.

Step 1: Construction of the initial decision matrix

The identified experts prioritise the criteria using the linguistic terms given in the fuzzy scale in Table 4.

The combined decision matrix ($\tilde{X}$) is obtained using Eq. (9).

$$\tilde{X} = [\tilde{x}_{ij}]_{k \times n} = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{k1} & \cdots & \tilde{x}_{kn} \end{bmatrix} \quad (9)$$

$\tilde{x}_{ij} = (x_{ij}^l, x_{ij}^m, x_{ij}^u)$ represents fuzzy value of criterion j in alternative i .

Step 2: Creating the normalisation matrix ($\tilde{N}$)

When normalising the initial decision matrix, double normalisation is performed with Eq. (10) for the benefit normalisation ($\tilde{n}_{ij}$) and Eq. (11) for the cost normalisation ($(\tilde{n}_{ij})'$).

$$\tilde{n}_{ij} = (n_{ij}^l, n_{ij}^m, n_{ij}^u) = \frac{\tilde{x}_{ij}}{\max(\tilde{x}_{ij})} = \left(\frac{x_{ij}^l}{\max(x_{ij}^u)}, \frac{x_{ij}^m}{\max(x_{ij}^u)}, \frac{x_{ij}^u}{\max(x_{ij}^u)} \right) \quad (10)$$

and

$$(\tilde{n}_{ij})' = (n_{ij}^l, n_{ij}^m, n_{ij}^u) = \frac{\min(\tilde{x}_{ij})}{\tilde{x}_{ij}} = \left(\frac{\min(x_{ij}^l)}{x_{ij}^u}, \frac{\min(x_{ij}^l)}{x_{ij}^m}, \frac{\min(x_{ij}^l)}{x_{ij}^l} \right) \quad (10)$$

$$\tilde{n}_{ij} = (n_{ij}^l, n_{ij}^m, n_{ij}^u) = \frac{\min(\tilde{x}_{ij})}{\tilde{x}_{ij}} = \left(\frac{\min(x_{ij}^l)}{x_{ij}^u}, \frac{\min(x_{ij}^l)}{x_{ij}^m}, \frac{\min(x_{ij}^l)}{x_{ij}^l} \right) \quad (11)$$

and

$$(\tilde{n}_{ij})' = (n_{ij}^l, n_{ij}^m, n_{ij}^u) = \frac{\tilde{x}_{ij}}{\max(\tilde{x}_{ij})} = \left(\frac{x_{ij}^l}{\max(x_{ij}^u)}, \frac{x_{ij}^m}{\max(x_{ij}^u)}, \frac{x_{ij}^u}{\max(x_{ij}^u)} \right) \quad (11)$$

Step 3: Calculating the deviation from the criterion weight

First, the deviations of the normalised data from the maximum values represented by the number 1 are calculated, and the deviation is multiplied by the weights of the criteria, and the total deviation from the weight of the criteria is obtained by Eqs. (12) and (13).

$$\tilde{\vartheta}_{ij} = \left(\sum_{i=1}^n [(1 - n_{ij}^u) * w_j^l], \sum_{i=1}^n [(1 - n_{ij}^m) * w_j^m], \sum_{i=1}^n [(1 - n_{ij}^l) * w_j^u] \right) \quad (12)$$

$$(\tilde{\vartheta}_{ij})' = \left(\sum_{i=1}^n [(1 - (n_{ij}^u)') * w_j^l], \sum_{i=1}^n [(1 - (n_{ij}^m)') * w_j^m], \sum_{i=1}^n [(1 - (n_{ij}^l)') * w_j^u] \right) \quad (13)$$

Step 4: Calculation of the value of the RAWEC method

The final score of the RAWEC method, obtained by Eq. (14), takes a value between (-1,1).

$$\tilde{Q}_i = \frac{(\tilde{\vartheta}_{ij})' - \tilde{\vartheta}_{ij}}{(\tilde{\vartheta}_{ij})' + \tilde{\vartheta}_{ij}} = \left(\frac{(\vartheta_{ij}^l)' - \vartheta_{ij}^u}{(\vartheta_{ij}^u)' + \vartheta_{ij}^u}, \frac{(\vartheta_{ij}^m)' - \vartheta_{ij}^m}{(\vartheta_{ij}^m)' + \vartheta_{ij}^m}, \frac{(\vartheta_{ij}^u)' - \vartheta_{ij}^l}{(\vartheta_{ij}^l)' + \vartheta_{ij}^l} \right) \quad (14)$$

The superiority of an alternative is determined by how high the value of the method of that alternative is. The alternative with the highest value represents the ideal choice.

4. Case Study

The specialists selected as the decision-makers in patient monitoring and treatment processes are people with different areas of expertise. A total of seven experts participated in the study. The areas of expertise and roles of the proposed group of seven experts are shown in Table 6.

Table 6. Profiles of the Experts

Area of Expertise	Role
Neurologist (E1)	Assesses neurological conditions
Psychologist/Psychiatrist (E2)	Provides psychological support and evaluations
Nurse (E3)	Assists in patient monitoring and treatment applications
Nutritionist (E4)	Develops individualised nutrition plans
Physiotherapist (E5)	Implements physical rehabilitation programs
Genetic Counselor (E6)	Provides information on genetic testing and results
Data Analyst (E7)	Analyses collected data to contribute to the decision support system

The experts in Table 6 contribute to patient monitoring and treatment processes by working in various health institutions and multidisciplinary teams.

4.1. Criteria That Can Be Used to Monitor the Condition of Patients

Patient monitoring involves the systematic observation of clinical and physiological parameters to assess the effectiveness of treatment and the patient's well-being. This continuous observation helps healthcare providers make informed decisions, increase patient safety, and improve health outcomes. By analysing various criteria, clinicians can detect potential problems early and ensure timely intervention. Effective patient monitoring promotes personalised care, supports adherence to treatment plans, and optimises healthcare resources. Patient monitoring criteria determined by the expert group, their explanations, and importance are given in Table 7.

Table 7. Patient Monitoring Criteria

Criterion	Description	Importance
Neuropsychological status (C1)	Assesses cognitive and emotional health.	Identifies challenges affecting treatment adherence and outcomes.
Biometric data (C2)	Includes physiological measures like heart rate, blood pressure, etc.	Monitors real-time health changes crucial for patient management.
Behavioural observations (C3)	Evaluates changes in behaviour or mood.	Recognises treatment efficacy or psychological issues.
Treatment response (C4)	Measures how well a patient responds to treatment.	Guides adjustments in treatment plans based on effectiveness.
Quality of life (C5)	Assesses the patient's overall well-being and life satisfaction.	Provides a holistic view of treatment success and patient comfort.
Genetic data (C6)	Information on genetic predispositions.	Supports personalised treatment approaches tailored to genetic factors.
Medication history (C7)	Records previous and current medications taken by the patient.	Prevents adverse interactions and informs treatment choices.
Physical activity level (C8)	Measures the patient's level of physical activity.	Influences recovery rates and overall health improvement.
Nutritional habits (C9)	Evaluates dietary practices and preferences.	Adjusts dietary recommendations for better health outcomes.
Social support level (C10)	Assesses the availability and quality of social support.	Recognises the importance of support networks in recovery processes.

Together, the criteria in Table 7 provide a comprehensive framework for patient follow-up, improving the overall effectiveness of health interventions.

4.2. Personalised Treatment Approaches

Personalised treatment approaches are designed to address the unique needs and circumstances of individual patients, particularly in complex fields like neuroscience. These strategies integrate various methods, including emotional support programs, tailored treatment plans, and advanced monitoring systems, ensuring comprehensive care. Personalised treatment

approaches improve the effectiveness of treatments by focusing on specific aspects such as genetic profiles, behavioural observations, and lifestyle choices. This individualised care model promotes better patient adherence, treatment adherence, and ultimately better health outcomes. The personalised treatment approaches identified and described by the expert team are given in Table 8.

Table 8. Personalised Treatment Approaches

Approach	Definition	Importance
Emotional support programs (A1)	Initiatives providing psychological assistance to patients to enhance emotional well-being.	Crucial for mental health, helping patients cope with stress and emotional challenges during treatment.
Individual treatment plans (A2)	Tailored strategies based on the specific needs and conditions of the patient.	Ensures that interventions are effective and relevant, increasing the likelihood of successful outcomes.
Neurological monitoring systems (A3)	Technologies designed to track neurological health and changes in real-time.	Important for early detection of issues and timely interventions, improving patient management.
Alternative and complementary therapies (A4)	Non-conventional treatments that complement standard medical care.	Provide holistic options that can enhance traditional treatments and improve patient satisfaction.
Education and information (A5)	Programs aimed at informing patients about their conditions and treatment options.	Empowers patients to make informed decisions, fostering active participation in their healthcare.
Genetic testing and counselling (A6)	Assessing genetic predispositions to tailor treatment approaches.	Enables personalised treatment based on genetic factors, improving treatment effectiveness and safety.
Individual drug therapy (A7)	Customised medication plans based on the patient's unique health profile.	Optimises drug efficacy and minimises adverse effects by considering individual reactions to medications.
Physical rehabilitation (A8)	Programs designed to restore function and improve physical health post-treatment.	Essential for recovery, enhancing mobility and quality of life after neurological interventions.
Diet and nutrition plans (A9)	Customised dietary guidelines to support overall health and specific medical conditions.	Supports treatment efficacy, enhances recovery, and improves overall health through proper nutrition.
Social interaction programs (A10)	Initiatives promoting social engagement and support networks among patients.	Vital for emotional well-being, reducing isolation, and fostering community support for better health outcomes.

Table 8 summarises the various personalised treatment approaches, defining each method and highlighting its importance. These approaches, such as emotional support programmes and individualised treatment plans, highlight the need for tailored health strategies that address unique patient needs. These methods' importance lies in their ability to increase treatment effectiveness, improve patient engagement, and promote overall well-being. By focusing on personalised care, healthcare providers can create more effective interventions that lead to better health outcomes and a higher quality of life for patients.

4.3. Data Collection and Analysis

To increase the effectiveness of personalised treatment approaches, two distinct patient profiles were proposed by the expert group. These profiles have been evaluated in detail to better understand individual needs and treatment responses. Out of respect for patient rights, the patients' names were described as Patient A and Patient B instead. Profiles, neuropsychological status, biometric data, behavioural observations, treatment responses, quality of life, genetic data, drug use history, physical activity levels, eating habits, and social support levels of these patients are presented in Table 9.

Table 9. Profiles of Patients A and B

Patient Name	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A	Moderate anxiety and depression	Normal blood pressure, overweight	Social withdrawal, low engagement in daily activities	Good response to medication	Moderate	Family history of similar illnesses	Regular use, no side effects	Light exercise twice a week	Irregular, unhealthy snacking	Low, limited family support
B	Mild anxiety and depression	Normal blood pressure, ideal weight	Reluctance in social interactions, low engagement in daily activities	Good response to medication	Moderate	Family history of similar mental illnesses	Regular use, no side effects	Light exercise once a week	Unbalanced, low intake of healthy foods	Low, limited friend circle

Table 9 is a composite table summarising the patient profiles of Patient A and Patient B and focusing on their characteristics to determine personalised treatment approaches.

4.3.1. Results of FLMAW Method Application

This analysis provides important information on how personalised treatment approaches can be optimised according to the individual characteristics of patients. Furthermore, this type of assessment helps healthcare professionals develop more effective and targeted treatment plans. The priority vectors obtained by the experts using the patient monitoring criteria of Table 3, paying attention to the profile related to Patient A, are presented in Table 10.

Table 10. Priority vectors of patient monitoring criteria for Patient A

Expert	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
E1	E	H	M	VH	E	MH	L	M	AH	VL
E2	MH	MH	E	VH	M	E	VL	L	VH	VL
E3	E	H	M	VH	E	MH	L	M	AH	VL
E4	E	MH	E	H	M	MH	M	E	VH	VL
E5	E	MH	E	H	E	E	L	M	VH	VL
E6	MH	MH	M	H	E	VH	L	M	VH	VL
E7	E	MH	E	H	E	E	L	M	VH	VL

Then, the value of the absolute fuzzy anti-ideal point was defined by the consumers as follows $\tilde{Y}_{AIP} = \tilde{Y}_{AIP} = (0.5, 0.5, 0.5)$. For example, the relationship between the priority vector elements defined by E1 and the absolute anti-ideal point is calculated as follows.

$$\tilde{\eta}_{C1}^{E1} = \left(\frac{2,5}{0,5}, \frac{3}{0,5}, \frac{3,5}{0,5} \right) = (5,6,7), \dots, \tilde{\eta}_{C10}^{E1} = \left(\frac{1}{0,5}, \frac{1,5}{0,5}, \frac{2}{0,5} \right) = (2,3,4).$$

Determination of the weight coefficients was done by applying Eq. (6). The computation of aggregated fuzzy vectors of the weight coefficients is done with the help of Eqs. (7) - (8) and (5). Weights of the patient monitoring criteria obtained for Patient A are given in Figure 1.

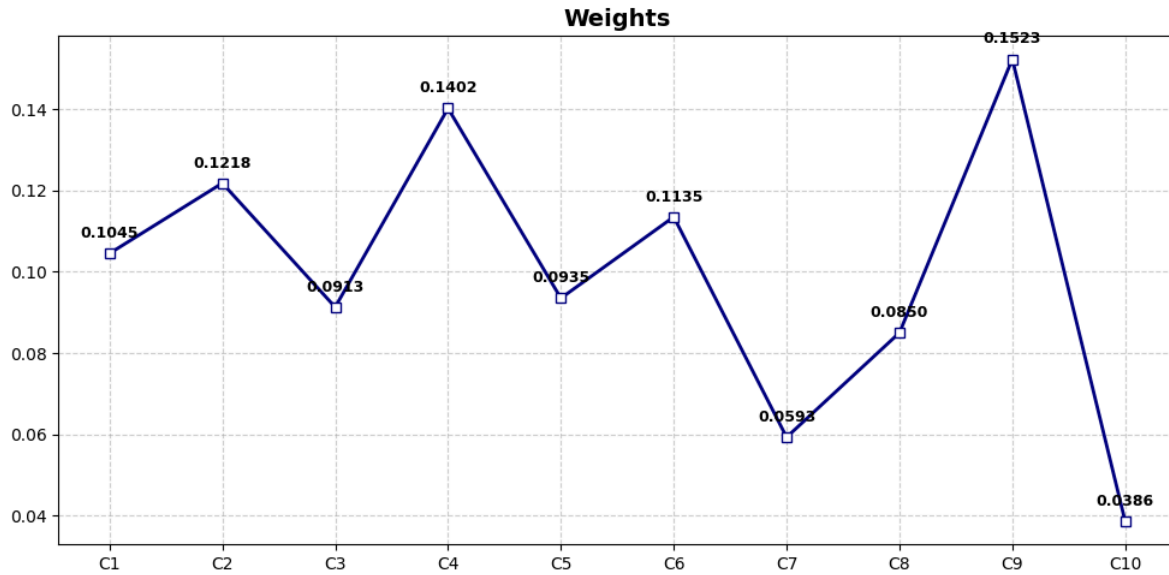


Figure 1. Priority of patient monitoring criteria for Patient A

Weighted evaluation of patient A's patient profile is an important tool in determining personalised treatment approaches. In this context, eating habits (C9=0.1523) and treatment response (C4=0.1402) have the highest weight and stand out as factors that directly influence the effect of the treatment process. Additionally, biometric data (C2) and genetic data (C6) provide important health indicators, suggesting that treatment strategies should be shaped according to these data. On the other hand, low weight values (e.g., social support level (C10)), although less critical, should not be ignored for general well-being. In this way, treatment plans for Patient A can be optimised based on individual characteristics, and an effective patient monitoring process can be ensured.

The priority vectors obtained by the experts using the patient monitoring criteria listed in Table 4, paying attention to the profile related to Patient B, are presented in Table 11.

Table 11. Priority vectors of patient monitoring criteria for Patient B

Expert	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
E1	H	VH	AH	E	MH	M	VH	E	E	3
E2	AH	H	MH	H	VH	E	H	M	L	MH
E3	MH	H	E	M	H	E	AH	VH	MH	E
E4	E	MH	E	M	MH	E	H	M	AH	E
E5	M	E	MH	E	H	M	MH	AH	E	L
E6	MH	E	M	E	MH	AH	E	M	M	VL
E7	E	MH	E	MH	E	E	VH	E	M	MH

Then, the value of the absolute fuzzy anti-ideal point was defined by the consumers as follows $\tilde{Y}_{AIP} = \tilde{Y}_{AIP} = (0.5, 0.5, 0.5)$. For example, the relationship between the priority vector elements defined by E1 and the absolute anti-ideal point is calculated as follows.

$$\tilde{\eta}_{C1}^{E1} = \left(\frac{3,5}{0,5}, \frac{4}{0,5}, \frac{4,5}{0,5} \right) = (7,8,9), \dots, \tilde{\eta}_{C10}^{E1} = \left(\frac{1,5}{0,5}, \frac{2}{0,5}, \frac{2,5}{0,5} \right) = (3,4,5).$$

Determination of the weight coefficients vector was done by applying Eq. (6). The computation of aggregated fuzzy vectors of the weight coefficients is done with the help of Eqs. (7)

- (8) and (5). The final values of the weight coefficients of the patient monitoring criteria obtained for Patient B are given in Figure 2.

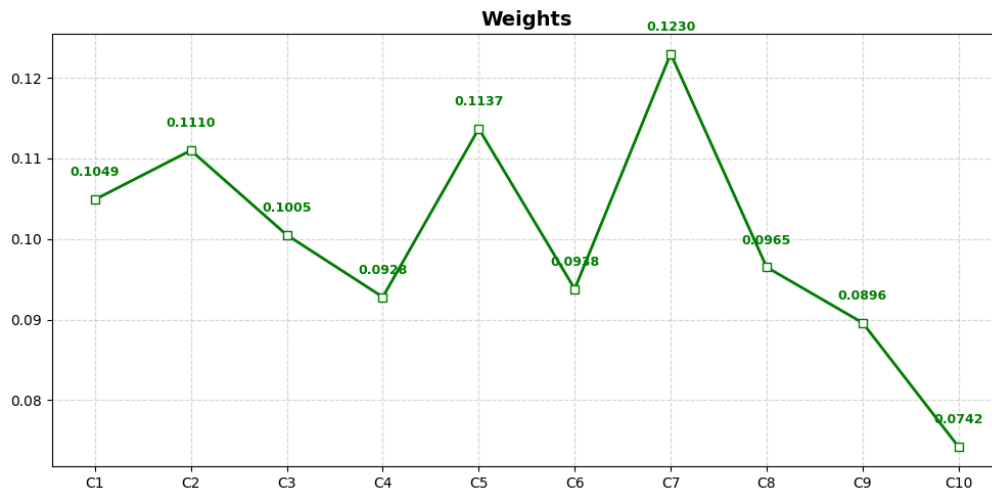


Figure 2. Priority of patient monitoring criteria for Patient B

The weighted assessment of the profile of patient B plays a decisive role in shaping personalised treatment approaches. According to tabular data, it has the highest weight with drug use history (C7=0.1230), which is a critical factor for the continuity and effectiveness of the treatment process. In addition, other high-weighted criteria such as quality of life (C5=0.1137) and biometric data (C2=0.1110) are important indicators for monitoring the general health status of Patient B. Criteria such as the level of social support (C10), which has a lower weight, should be taken into account in the treatment process, although it is less effective.

4.3.2. Results of FRAWEC Method Application

According to Table 4, each specialist evaluated their treatment strategy and personalised approaches for Patient A and Patient B. In these evaluations, the experts aimed to identify treatment modalities that are appropriate for each patient's specific health profile and individual needs. Thus, by adopting a patient-centered approach, the most appropriate treatment process has been optimised for both patients. Analyses of the FRAWEC method contribute to a comprehensive decision-making process aimed at improving treatment efficacy and taking into account individual differences. According to the experts, the evaluation of personalised treatment approaches for Patient A is presented in Table 12.

Table 12. Evaluation of personalised treatment approaches for Patient A

Patient A	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	H	E	MH	VH	H	M	E	MH	E	L
A2	VH	MH	E	AH	MH	E	VH	M	E	M
A3	AH	H	MH	VH	E	MH	AH	E	M	E
A4	MH	E	M	H	E	E	MH	H	E	MH
A5	E	VH	E	MH	H	MH	E	E	MH	M
A6	MH	MH	E	E	MH	AH	M	M	L	VL
A7	H	H	MH	AH	VH	E	H	E	M	E
A8	E	E	E	VH	MH	M	MH	AH	E	L
A9	M	MH	E	H	AH	E	H	MH	VH	M
A10	L	M	E	MH	E	L	E	E	M	MH

Table 12 serves as the initial decision matrix for Patient A, normalised decision matrices are obtained using Eq. (10) and Eq. (11). Then, the deviations from the criterion weights are obtained

by Eq. (12) and Eq. (13), and values of FRAWEC method are obtained by Eq. (14), as given in Table 13.

Table 13. Values of FRAWEC method for personalised treatment approaches

	$\tilde{\vartheta}_{ij}$			$(\tilde{\vartheta}_{ij})'$			$\tilde{Q}_i$			Q_i	Rank
A1	0.0240	0.0441	0.0726	0.0145	0.0277	0.0578	-0.4459	-0.2280	0.8787	-0.0799	5
A2	0.0252	0.0453	0.0732	0.0126	0.0244	0.0531	-0.4792	-0.2995	0.7379	-0.1566	6
A3	0.0276	0.0477	0.0755	0.0106	0.0197	0.0470	-0.5301	-0.4150	0.5094	-0.2801	10
A4	0.0218	0.0419	0.0702	0.0160	0.0295	0.0598	-0.4173	-0.1748	1.0069	-0.0183	3
A5	0.0264	0.0463	0.0747	0.0127	0.0251	0.0545	-0.4794	-0.2973	0.7184	-0.1583	7
A6	0.0154	0.0362	0.0641	0.0203	0.0355	0.0681	-0.3316	-0.0092	1.4755	0.1845	2
A7	0.0287	0.0488	0.0769	0.0104	0.0209	0.0485	-0.5302	-0.4001	0.5072	-0.2706	9
A8	0.0225	0.0427	0.0706	0.0161	0.0294	0.0596	-0.4181	-0.1846	0.9624	-0.0323	4
A9	0.0268	0.0470	0.0749	0.0124	0.0234	0.0520	-0.4925	-0.3354	0.6423	-0.1987	8
A10	0.0100	0.0343	0.0623	0.0224	0.0388	0.0760	-0.2889	0.0624	2.0395	0.3334	1

The analysis of Patient A's profile prioritises treatment strategies based on his specific needs. Social interaction programs (A10), ranked highest, focus on improving psychosocial well-being by addressing low social support, reducing isolation, and enhancing treatment adherence. Genetic testing and counselling (A6), ranked second, are crucial due to his family history, offering insights into genetic predispositions for more precise treatment planning. Alternative therapies (A4) and physical rehabilitation (A8) also rank high, supporting physical health, particularly in managing his overweight condition, and improving biometric and physical health metrics. Lastly, individual treatment plans (A2) and emotional support programs (A1) target his psychological state, addressing anxiety and depression. This prioritisation ensures a personalised, effective treatment plan, leading to improved care and health outcomes.

For performance analysis of the personalised treatment results for Patient A, the outcomes of the FRAWEC method are compared with those derived from FMARCOS, Fuzzy Compromise Ranking of Alternatives from Distance to Ideal Solution (FCRADIS), and FTOPSIS methods. These methods are selected based on their relatively simple processing steps, computational efficiency, and proven applicability across a wide range of decision-making problems in the current literature. Their structured yet flexible frameworks make them suitable for evaluating complex medical decisions involving both quantitative and qualitative criteria. The comparative results for Patient A, as determined by these methods, are presented in Figure 3 to evaluate the consistency, reliability, and alignment of FRAWEC with other established FMCDM methods.

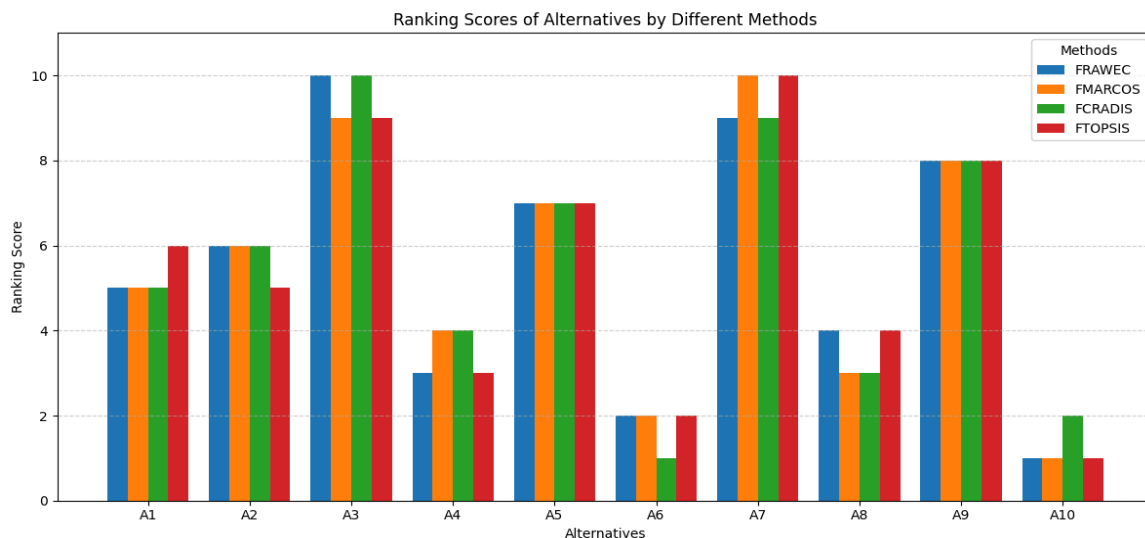


Figure 3. Ranking of personalised treatment approaches for Patient A with different methods

When comparing the rankings obtained from FRAWEC, FMARCOS, FCRADIS, and FTOPSIS methods for Patient A, it is observed that alternatives A9 and A5 occupied the same position across all methods, indicating complete consistency in the rankings. This consistency suggests a high level of agreement between the methods in evaluating the considered alternatives. For the remaining alternatives, only minor differences in the rankings are observed. These small changes can be attributed to normalisation processes inherent in these methods.

The evaluation of personalised treatment approaches for Patient B according to experts is presented in Table 14.

Table 14. Evaluation of personalised treatment approaches for Patient B

Patient B	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	VH	E	H	VH	MH	E	H	E	M	MH
A2	AH	MH	MH	VH	H	E	VH	M	E	E
A3	H	H	E	AH	MH	M	VH	E	M	M
A4	MH	E	MH	MH	E	E	E	MH	H	L
A5	MH	VH	MH	H	MH	E	MH	M	E	MH
A6	H	MH	M	E	MH	VH	M	L	M	VL
A7	VH	MH	E	AH	VH	E	H	M	M	E
A8	E	E	E	H	MH	M	MH	AH	AH	L
A9	M	E	E	MH	AH	E	MH	E	VH	M
A10	L	M	E	MH	E	L	E	M	M	MH

Following the establishment of table 14 as the initial decision matrix for Patient B, the normalised decision matrices are calculated using Eq. (10) and Eq. (11). Then, the deviations from the criterion weights are obtained by Eq. (12) and Eq. (13), and values of FRAWEC method are calculated with Eq. (14), as shown in table 15.

Table 15. Values of the FRAWEC method for personalised treatment approaches

	$\tilde{d}_{ij}$			$(\tilde{d}_{ij})'$			$\tilde{Q}_i$			Q_i	Rank
A1	0.0248	0.0447	0.0726	0.0116	0.0204	0.0502	-0.4969	-0.3731	0.6971	-0.2154	9
A2	0.0268	0.0467	0.0746	0.0104	0.0190	0.0485	-0.5214	-0.4220	0.5820	-0.2712	10
A3	0.0238	0.0437	0.0713	0.0126	0.0224	0.0529	-0.4728	-0.3227	0.7987	-0.1608	7
A4	0.0182	0.0383	0.0663	0.0177	0.0309	0.0641	-0.3727	-0.1082	1.2787	0.0789	3
A5	0.0241	0.0438	0.0719	0.0131	0.0234	0.0546	-0.4651	-0.3038	0.8214	-0.1431	6
A6	0.0118	0.0325	0.0607	0.0204	0.0350	0.0696	-0.3092	0.0365	1.7952	0.2720	1
A7	0.0248	0.0448	0.0725	0.0119	0.0216	0.0515	-0.4883	-0.3494	0.7265	-0.1932	8
A8	0.0207	0.0406	0.0682	0.0162	0.0278	0.0597	-0.4069	-0.1866	1.0583	-0.0159	4
A9	0.0224	0.0423	0.0698	0.0155	0.0261	0.0579	-0.4253	-0.2364	0.9368	-0.0723	5
A10	0.0143	0.0348	0.0622	0.0200	0.0327	0.0662	-0.3287	-0.0315	1.5169	0.1770	2

The analysis of Patient B's profile provides key insights into prioritised treatment approaches tailored to her specific needs. Genetic testing and counselling (A6) received the highest priority, reflecting the importance of understanding her family's history of mental health conditions to guide personalised treatment. Social interaction programs (A10) were assigned the second-highest priority, addressing her limited social support to enhance engagement and psychological well-being. Alternative and complementary therapies (A4) and Physical rehabilitation (A8) are also prioritised, supporting both mental and physical health. Diet and nutrition plans (A9), were positioned fifth, align with her need for improved dietary habits to promote overall health. Lower-priority strategies, such as Individual treatment plans (A2) and Emotional support programs (A1), are still relevant, but they may have less immediate impact compared to higher-ranked

interventions. This prioritisation enables a structured and individualised treatment plan to maximise Patient B's health outcomes.

For performance analysis, the results obtained from the FRAWEC method are compared with those derived from FMARCOS, FCRADIS, and FTOPSIS methods for Patient B, as illustrated in Figure 4. The comparison shows that alternatives A2 and A9 are ranked in the same positions across all methods, indicating complete alignment and a high level of consistency in the evaluation of these alternatives. For the remaining alternatives, only minor differences in rankings are observed. These slight variations are attributed to the different mathematical concepts used by these methods, and the different normalisation techniques involved.

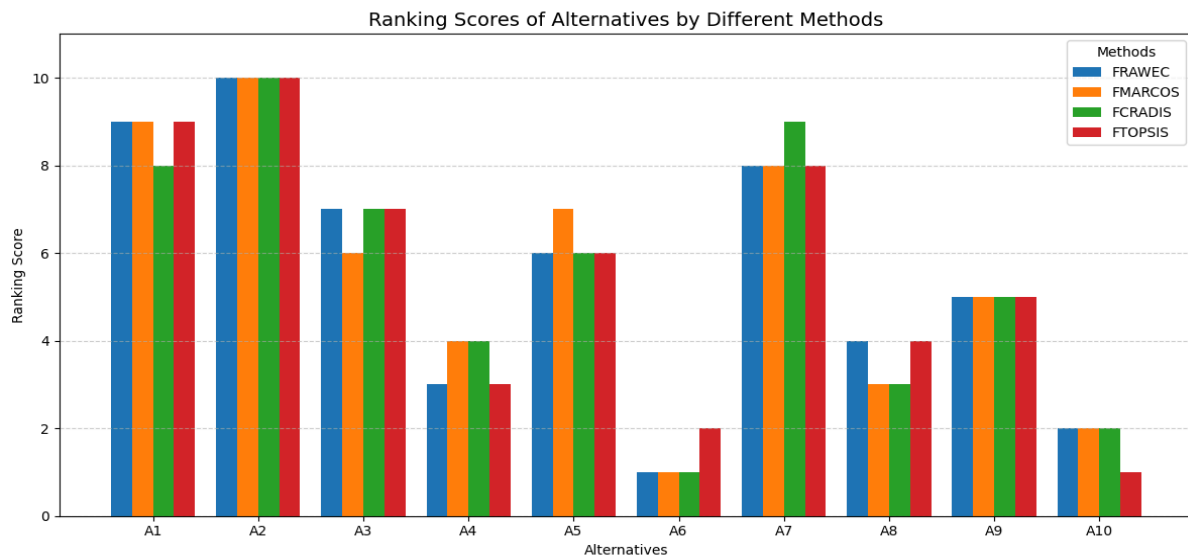


Figure 4. Ranking of personalised treatment approaches for Patient B with different methods

5. Discussion, Practical and Managerial Implications

5.1. Ranking Discussion

This study presents a multidisciplinary perspective by examining the effectiveness of personalised treatment approaches in patient monitoring and treatment processes. A fuzzy model is proposed to enhance the personalisation and effectiveness of treatment plans by integrating FLMAW and FRAWEC methods. By addressing the complexities and uncertainties involved in evaluating multiple treatment factors, the model enables the prioritisation of key criteria such as biometric data, treatment response, and psychosocial factors. It provides a structured approach to tailor treatment strategies for each patient, optimising both physical and psychological health outcomes. This approach ensures that treatments are customised to individual needs, improving patient care and supporting better decision-making in healthcare.

The FLMAW method was used to evaluate and prioritise treatment factors for Patient A and Patient B by assigning weights to key criteria such as biometric data, treatment response, and psychosocial factors. It effectively handled uncertainty and optimised treatment plans based on individual patient profiles. The FRAWEC method focused on ranking and evaluating personalised treatment strategies for each patient, emphasising factors like genetic testing, social support, and rehabilitation. This method helped in creating a tailored, comprehensive treatment plan that addressed both physical and psychological health needs.

With contributions from a group of experts, data obtained from the profiles of Patient A and Patient B helped identify the specific intervention needs tailored to each individual's health status. The findings highlight that personalised treatment approaches should be designed to align with each patient's individual needs and health profile. The emphasis on social interaction programs in Patient A's profile highlights the impact of low social support levels on Patient A's treatment process.

Social support directly influences the psychological well-being of individuals and increases their treatment adherence. In this context, it is concluded that establishing and strengthening a social support network plays a critical role in treatment processes. The evaluation based on Patient B's profile suggests that genetic testing and counselling should be prioritised as an intervention. This is considered a significant step in understanding the impact of Patient B's family history on mental health. Such information enables more targeted and effective interventions throughout the treatment process. Therefore, considering genetic factors is of vital importance in personalising treatment plans. A performance comparison has also been conducted by evaluating the rankings generated by the proposed FRAWEC method against those produced by FMARCOS, FCRADIS, and FTOPSIS methods. This comparison aims to assess the alignment and robustness of the results across different approaches. The consistency observed in the ranking trends demonstrates the reliability of the FRAWEC method and highlights its effectiveness in handling complex decision-making challenges in healthcare personalisation.

The applicability of personalised treatment approaches brings both opportunities and challenges for health management. Health administrators should adopt the following strategies to enhance the effectiveness of multidisciplinary teams and develop treatment plans tailored to patients' needs:

- **Education and Awareness:** Education programs should be organised for healthcare professionals to enhance the awareness and applicability of personalised treatment approaches. Experts should keep up with innovations in their fields and integrate this knowledge into patient care processes.
- **Data-Based Decision Making:** Using patient monitoring systems and data analytics enables a better evaluation of patients' health status. These systems provide healthcare professionals with crucial information to track individuals' responses to treatment and health progress. Continuous updating and analysis of data will contribute to creating effective treatment plans.
- **Policy Development:** Developing sustainable health policies is essential to support personalised treatment approaches. These policies can increase the flexibility of healthcare institutions, enhancing their capacity to respond to individuals' specific needs. Furthermore, supportive incentives should be provided to ensure the integrity and efficiency of the healthcare system.
- **Patient Participation:** Encouraging patients to actively participate in their treatment processes will improve treatment outcomes. Awareness programs allow patients to gain more insight into their health conditions and treatment options, increasing their engagement in decision-making processes. This develops patients' ability to manage their health and strengthens their commitment to treatment.
- **Multidisciplinary Collaboration:** Collaboration among healthcare professionals from various disciplines enhances the effectiveness of the treatment process. Diverse perspectives and experiences of experts aid in developing patient-centered treatment strategies. This cooperation enhances the quality of healthcare services, leading to better health outcomes.

This study provides significant insights into how personalised treatment approaches can be more effectively integrated into healthcare services. These approaches not only enhance patient well-being but also support the overall efficiency of the healthcare system, paving the way for more sustainable healthcare services.

5.2. Practical and Managerial Implications

The findings of this study provide significant practical and managerial insights regarding the implementation of personalised treatment approaches in healthcare. These insights can be categorised under several key areas:

- **Strengthening Patient-Centered Care:** The results emphasise the need for treatment plans to be tailored to individual patient profiles. Healthcare providers should develop

patient-centered care models that integrate each individual's unique needs, preferences, and conditions. This approach can enhance treatment adherence and improve health outcomes.

- **Interdisciplinary Collaboration:** The diversity of expert profiles highlights the importance of interdisciplinary collaboration. Healthcare institutions should encourage professionals from various specialties to come together and contribute to patient management and treatment planning. This collaboration can enhance the scope and effectiveness of care.
- **Use of Data Analytics:** The analysis of patient profiles underlines the importance of data-driven decision-making. Healthcare institutions should invest in advanced data analytics tools and systems to continuously monitor patient health data. This provides real-time data for timely interventions and updating treatment plans, ultimately improving patient outcomes.
- **Policy Development and Advocacy:** Policies that support personalised treatment strategies need to be developed. Healthcare administrators should advocate for policies that encourage innovation in treatment approaches, provide funding for research, and support the integration of personalised care. Such policies can create an enabling environment for the effective implementation of personalised interventions.
- **Training and Educational Programs:** Realising the potential of personalised treatment approaches requires adequate training for healthcare professionals. Institutions should invest in continuous training and education programs to inform healthcare workers about personalised medicine, data analytics, and patient-centered care. This can empower professionals to apply effective strategies in their practice.
- **Patient Engagement Strategies:** Ensuring patient participation in treatment processes is critical to improving adherence and satisfaction. Healthcare providers should develop strategies to actively involve patients, such as shared decision-making processes, educational resources, and support groups. When patients develop a sense of ownership in their care processes, they are more likely to adhere to treatment plans, resulting in better health outcomes.
- **Resource Allocation:** Successful implementation of personalised treatment approaches depends on proper resource allocation. Healthcare administrators must allocate adequate resources for developing and sustaining personalised treatment programs, covering staff, technology, and patient education. This investment can yield significant long-term benefits in patient care and outcomes.
- **Monitoring and Evaluation:** Continuous monitoring and evaluation of personalised treatment programs are necessary to determine their effectiveness. Institutions should establish metrics and benchmarks to systematically assess the success of these programs. This feedback loop can inform necessary adjustments and improvements in treatment strategies, ensuring continuous improvement in care quality.

The practical and managerial insights of this study underscore the need for a dedicated effort to integrate personalised treatment approaches into healthcare systems. By focusing on patient-centred care, strengthening interdisciplinary collaboration, using data analytics, and advocating for supportive policies, healthcare providers can enhance treatment effectiveness and improve overall patient well-being. The insights gained from this research lay a foundation for future advancements in personalised medicine, contributing to a more sustainable and effective healthcare system. The comparative analysis of alternative rankings using the FRAWEC, FMARCOS, FCRADIS, and FTOPSIS methods offers compelling evidence of the reliability and robustness of the FRAWEC method. The results show that FRAWEC can be confidently used in strategic decision-making for selecting personalised treatments, without concerns about instability or inconsistency. From a managerial perspective, this reliability enhances confidence in adopting FMCDM approaches, ensuring that personalised treatment strategies are based on consistent and dependable evaluations.

6. Conclusions, Limitations, and Future Directions

The main findings of this study indicate that personalised treatment approaches should be optimised based on individual patient profiles. Guided by the data provided by the expert group, various criteria were identified to enhance the effectiveness of treatment processes, emphasising the importance of these criteria in patient monitoring processes. Personalised treatment strategies are designed to consider not only medical conditions but also multidimensional factors such as patients' social support levels, quality of life, and individual needs. This approach improves both the success of treatment processes and the overall patients' quality of life. The findings offer valuable insights for managing healthcare services more effectively and integrating personalised medicine.

Nonetheless, the study has some limitations as well. Firstly, the number and diversity of the expert group are limited, with only seven experts involved, which may impact the generalisability of the results. Future studies should aim to expand and diversify the expert group. Specifically, including engineers who develop artificial intelligence-based health technologies, health policymakers, and hospital administrators in the process will enhance the decision support model alignment with real-world healthcare systems. Expanding the expert group in this way will improve the model's adaptability to various patient populations, healthcare systems, and clinical scenarios. Additionally, only specific criteria were considered in determining patient profiles, and working with a broader dataset could make the results more comprehensive. Since the data collection process relies on self-reports from participants, there is a risk of subjective biases and inaccurate reporting. Future studies should aim to overcome these limitations by using more extensive and diversified patient groups along with more comprehensive sets of criteria.

Future research can explore several key aspects to advance personalised treatment approaches. Expanding the participation of experts across multiple specialties can improve data quality by including diverse perspectives. The profiles of Patient A and Patient B were constructed to demonstrate the operation of the proposed model. However, future studies can conduct analyses with a larger number of anonymised real patient data as well as diversified synthetic scenarios to test the model's applicability in different clinical contexts. Additionally, integrating innovative technologies and data analytics can facilitate continuous updates to patient monitoring and treatment criteria. Advances in artificial intelligence and machine learning play a key role in optimising personalised treatment processes. These technologies have the potential to transform patient care by enabling faster and more effective decision-making. Developing specialised software to integrate personalised treatment approaches is a valuable step in healthcare. This software can include the following features:

- **Data Collection Module:** It should provide a user-friendly interface to systematically collect information such as patients' neuropsychological status, biometric data, treatment responses, quality of life, genetic data, and other health parameters. The collection of this data would assist healthcare professionals in the decision-making process.
- **Personalised Treatment Plan Generator:** It should include an algorithm capable of automatically generating personalised treatment plans based on patients' characteristics and needs. This algorithm should optimise treatment strategies by considering the criteria identified by experts.
- **Advanced Analytical Tools:** By using artificial intelligence and machine learning techniques for analysing the collected data, it should continuously monitor the effectiveness of the treatment process and make adjustments to treatment plans as needed.
- **FMCDM Methods:** It can integrate FMCDM methods in developing personalised treatment plans. These methods enable healthcare professionals to evaluate different treatment options based on patient profiles and manage uncertainties in the criteria. For example, numerous criteria such as patient health conditions, treatment responses, and side effects could be analysed using fuzzy logic to determine the most suitable treatment options.

- **Patient Monitoring System:** It should include a system capable of performing real-time data analysis to monitor treatment processes. This allows for continuous assessment of the treatment response and the patient's overall health.
- **Interaction and Feedback Mechanism:** It should offer an interactive platform to ensure patients' active participation in their treatment processes. Patients can provide feedback on their treatment plans and communicate with healthcare professionals.
- **Education and Information Module:** It should provide resources and educational materials to help patients learn more about their treatment processes. This would enhance patient engagement, supporting the success of treatment processes.
- **Interactive Reporting:** It offers users understandable and detailed reports about their treatment processes, helping them better understand their health status.
- **Community Support:** It provides community programs and social interaction opportunities to help users develop their social support networks.

In addition to the development of such systems, the methodological aspect of this study provides a valuable contribution to the literature. The comparative assessment of alternative rankings across the four FMCDM methods shows a high degree of consistency in prioritising patient profiles. This finding highlights the practical relevance of FMCDM methods in addressing complex and uncertain healthcare challenges, demonstrating their effectiveness in supporting informed decision-making in dynamic and evolving clinical environments.

Finally, the software should be continuously updated and adapted according to evolving healthcare needs. This software could enhance the quality of healthcare services and patient satisfaction by making personalised treatment approaches more effective. In future directions, the integration of such software will bring about significant change in healthcare systems and support individual health management.

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