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Evaluating AI-Driven Mental Health Solutions: A Hybrid Fuzzy Multi-Criteria Decision-Making Approach

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Abstract: Background: AI-driven mental health solutions offer transformative potential for improving mental healthcare outcomes, but identifying the most effective approaches remains a challenge. This study addresses this gap by evaluating and prioritizing AI-driven mental health alternatives based on key criteria, including feasibility of implementation, cost-effectiveness, scalability, ethical compliance, user satisfaction, and impact on clinical outcomes. Methods: A fuzzy multi-criteria decision-making (MCDM) model, consisting of fuzzy TOPSIS and fuzzy ARAS, was employed to rank the alternatives, while a hybridization of the two methods was used to address discrepancies between the methods, each emphasizing distinct evaluative aspect. Results: Fuzzy TOPSIS, focusing on closeness to the ideal solution, ranked personalization of care (A5) as the top alternative with a closeness coefficient of 0.50, followed by user engagement (A2) at 0.45. Fuzzy ARAS, which evaluates cumulative performance, also ranked A5 the highest, with an overall performance rating of Si = 0.90 and utility degree Qi = 0.92. Combining both methods provided a balanced assessment, with A5 retaining its top position due to high scores in user satisfaction and clinical outcomes. Conclusions: This result underscores the importance of personalization and engagement in optimizing AI-driven mental health solutions, suggesting that tailored, user-focused approaches are pivotal for maximizing treatment success and user adherence.

Keywords: AI-driven mental health solutions; hybrid fuzzy multi-criteria decision-making (MCDM); fuzzy TOPSIS and fuzzy ARAS methods; personalization of care; user engagement

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1. Introduction

The current trend in global industrialization is tilting towards the use of Artificial Intelligence (AI) in most human activities. The application of AI in healthcare services has existed since the beginning of the 1950s when doctors of that era tried to increase their level of productivity by identifying the nature and causes of an illness through the employment of computer programs [1,2]. Since then, there has been increased adoption of AI in healthcare services up until recent years. This is due to the advancement and sophistication of modern computing devices and the increased availability of data [3]. The application of AI in healthcare services is slowly bringing modifications into the practice of medicine [4]. The objective of AI is to imitate human intellectual routines and procedures [5].

There is rapid progress in the model of adopting AI in the area of healthcare activities which is triggered by the increasing access to healthcare data and the significant growth in the methods of performing analysis for healthcare activities [6]. In spite of all these, there has been very little or intermediate levels of applications of AI in mental healthcare situations, while it has gained significant use in the areas of dermatology, oncology, and radiology [7]. Other areas of applications of AI in healthcare include diagnosis and decision-making [4]. Due to the large amount of morbidity and mortality tendencies in patients with mental illness, in addition to the huge gap created by the unavailability of mental healthcare workers, it is therefore urgently necessary to adopt AI to assist in the identification of individuals that have very high risk tendencies of mental illness. This will prompt early professional action against partial or total mental health diseases. Recent studies have shown that the application of AI in medicine to improve mental healthcare services to patients is encouraging [8].

The influence of mental illness on several millions of people globally is significant [9]. With the sophistication of AI technology, the multi-criteria decision-making (MCDM) method is a major suitable tool for the analysis of mental health. The MCDM tool has been widely applied in the field of mental health [10]. The MCDM tool is increasingly being used in the healthcare sector to put into practice healthcare decisions which have more than one criteria that are incompatible [11]. Decision-making in the healthcare sector is being performed from the perspective of different aspects of complex problems that are being linked to medical, economic, technological, ethical, social, and environmental factors [12]. The MCDM places special attention on the application of hybrid interdependent decisions [10]. Most MCDM techniques use the adoption of weights or indices to represent the level of relevance of a particular criterion [13]. The ranking and selection of the alternatives are performed in accordance with their obtained composite values [14]. The MCDM techniques operate in a regular, ordered procedure and are sophisticated enough to solve problems of mental health [15]. Though several authors have performed different research in MCDM for healthcare activities while adopting different techniques, there is gross insufficiency in the area of the adoption of MCDM techniques for the implementation of mental health interventions using AI. The aim of this study was to identify critical success factors for the implementation of AI-driven mental health interventions using MCDM. The implementation was performed using the Fuzzy Additive Ratio Assessment (fuzzy ARAS) method of MCDM.

2. Literature Review

Healthcare analysis can be achieved using a variety of tools. These tools are very important in good decision-making in the healthcare sector. Adopting the required decision-making tools is very germane in making critical mental healthcare decisions in healthcare. As a result of the state-of-the-art cutting-edge AI technology, there are several decision-making choices that can be used for implementation in mental health. There are examples of AI technologies that can be used in mental healthcare; these includes chatbots and some diagnostic tools. Obtaining the most appropriate decisions and their success rate requires an assessment of several criteria. This segment evaluates previous studies that have been performed which are pertinent to the objective of this study. There are various researchers that have worked on the advancement of different AI technologies and the different methods of ranking and selecting the best decision-making processes regarding mental health interventions using different MCDM approach.

Guptal et al. [16] proposed a theory to obtain a technology which will assist organizations in the selection of the best technology to increase its utilization by people of interest in their respective healthcare fields. The study investigated the challenges of the use of AI in the healthcare sector. The DELPHI and the focus group discussions (FGDs) were used for the analysis of about 250 technology-related challenges, then reducing this number to the 16 most pertinent challenges. Further analysis was performed using the cross-impact matrix multiplication applied to classification (MICMAC) and the interpretive structural modeling (ISM) approach to categorize the challenges into several levels of intensity and pertinence. The results of the MICMAC and ISM approaches were used to portray that AI has an unrealized ability to analyze cybersecurity susceptibility and the lack of infrastructure with the relevant enabling laws, which are the major challenges obstructing the use of AI in healthcare. Suha et al. [17] investigated the potential of 15 major sustainability indexes in integrating AI applications in the decision-making processes of the healthcare sector. The study performed an ordered procedure of examination to rank and select the indexes that are most important to the healthcare sector. Deductions were obtained from knowledgeable professionals, and quantitative outcomes were converted to quantitative data, which were then processed in terms of relevance and non-relevance. In addition, the indexes were grouped into three, via two methods of clustering. The study proposed that practitioners in the healthcare sector will find its results a good source of information during the use of AI decision-making processes in the healthcare sectors of developing countries.

Joshi et al. [18] simulated the adoption of AI for more than one level of analysis using the MCDM method. The study highlighted the challenges associated with making future decisions. The study provided an important understanding of the use of AI in general healthcare facilities. Hsu et al. [10] presented the building of structures for these critical factors by the addition of chatbots into the military's services for mental health. The methodologies adapted were into four stages: the first stage or initial stage; the second stage, which was the confirmation stage using the fuzzy Delphi approach; the third stage, which was the creation stage; and the fourth stage, which was the establishment stage. The study revealed three major discoveries as follows: Firstly, a major achievement was identifying twenty-one indexes and four dimensions; secondly, the twenty-one indexes and four dimensions exhibited self-standing associations, which manipulate one another; and thirdly, from the study, the four dimensions include boundaries, activities, goals, and technology. Chakraborty et al. [19] addressed the challenge of mental health issues via the development of a web portal for the timely prediction and prevention of mental health issues in persons. The study adopted the random forest classifier methodology to determine the amount of stress needed from an examination that is question and answer-based for a person's internal physiological response to reflect on the person's face. These results are brought together to estimate the likely mental health status of the individual.

Rane et al. [20] used blockchain technology to improve awareness in medicine through open data allotment. The study examined the barriers to the realization of a healthcare metaverse while considering factors such as the interaction of technology, privacy of data, and ethics. The study approached these barriers and proffered a solution for its reduction, putting into consideration the importance of the working together of multiple fields and their regulation structure. The study provided a platform for integrating AI into the evolving nature of the healthcare metaverse. The outcome of this research will serve as a reference with which to plan for the changing overlap of healthcare and metaverse technologies. Akhtar et al. [21] researched the integration of digital technologies into healthcare. In this study, there were ten major facilitators to assist in achieving the desired outcome. The relevance of these facilitators was examined using the fuzzy MARCOS and fuzzy TOPSIS multicriteria analysis methods. A quantitative structure for healthcare decision-making was proposed through the results of this study. The confirmation of the outcome of the study was achieved through the use of sensitivity analysis.

El-Douh et al. [22] performed a review to examine the different areas that are critical for a sustainable healthcare system using the COVID-19 pandemic as a case study. The study revealed the need for adequate access to a good healthcare system, mental healthcare, international collaboration, adequate communication, and preparation. The MCDM was used to perform an analysis of the extent of sustainability of healthcare systems using the weights and their various criteria. A comparison was performed amongst the criteria while the neutrosophic process was performed to make a comparison of the indistinct data. Ahmad et al. [23] examined the effect of social distancing on human psychology to obtain the ranking and selection of these psychological factors to ascertain their level of importance. Two fuzzy MCDM approaches were used to perform the multicriteria analysis, namely the fuzzy best–worst method (f-BWM) and fuzzy technique for order of preference by similarity to ideal solution (fuzzy TOPSIS). The result revealed that five important psychological factors were highly ranked to have the potential to affect people as a result of the pandemic. These psychological factors are namely panic, anxiety, frustration, stress, and insomnia. Further multicriteria analysis was performed using the fuzzy weighted sum method (f-WSM) and fuzzy multi attributive border approximation area comparison (f-MABAC) to rank and select the psychological factors for validation. A comparison was performed between the earlier and later multicriteria methods for validation. Sensitivity analysis was also performed by the study. The outcome of the research showed that the psychological factors were ranked in line with the highest, average, and lowest psychological factors.

The literature has reviewed the performance of studies in the area of AI implementation for healthcare activities. All the literature examined considered AI and/or MCDM approaches for decision-making. All these approaches in the considered studies had the basic intention to improve the efficiency of healthcare decision-making and its processes. Most of the considered literature worked on the healthcare system as a broad entity, with insignificant contributions to the area of mental health interventions. The knowledge gap in mental health and related interventions was not explored in all the available literature when a critical search was performed for the existing literature. This study will contribute to the body of knowledge using the MCDM for the identification of critical success factors for the implementation of AI-enabled mental health interventions.

3. Materials and Methods

This section presents the methodology used in this study. It presents the basic principles of fuzzy sets, the technique for order of preference by similarity to ideal solution (TOPSIS), and the fuzzy additive ratio assessment (fuzzy ARAS) method. The methodology used for implementing this research is presented in Figure 1.

This section discusses the basics of fuzzy quantities, triangular fuzzy numbers, the fuzzy analytic hierarchy process (Fuzzy AHP), the technique for order of preference by similarity to ideal solution (TOPSIS), and the fuzzy additive ratio assessment (fuzzy ARAS) method. Also, the data collection methods and case study descriptions are presented in this section.

3.1. Fuzzy Quantities

A fuzzy set is a mathematical technique that allows for partial membership in a set and is used to describe imprecision and vagueness. The concept of a fuzzy set was presented by Zadeh in 1965 to extend the theory of classical set theory, where membership was limited to binary function [24,25].

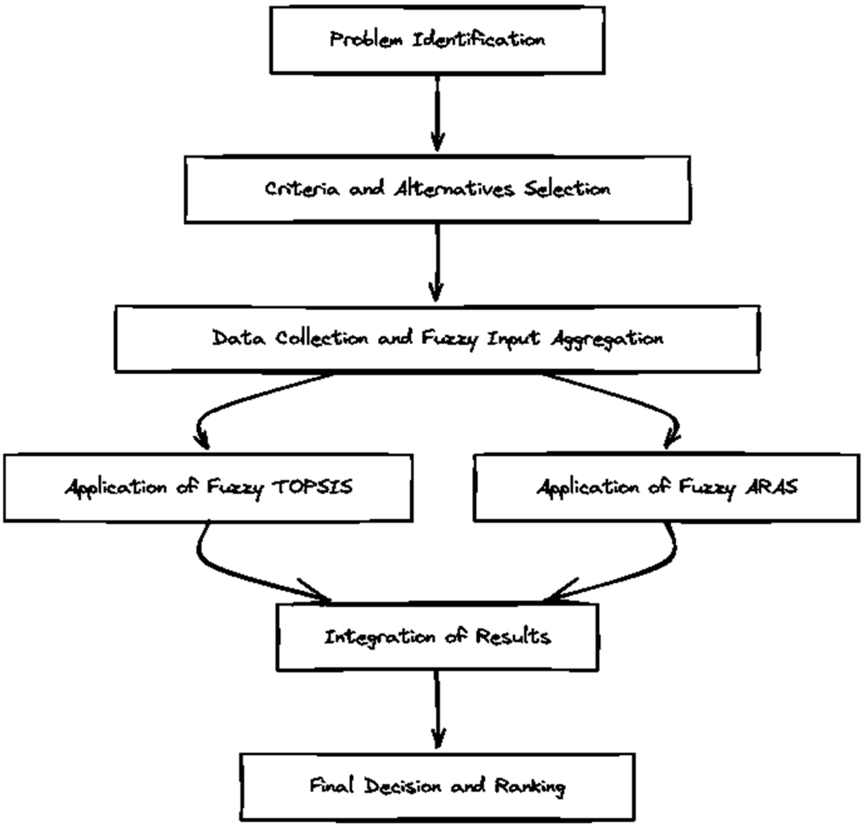

Figure 1. Methodology of the study.

3.2. Triangular Fuzzy Quantity

A triangular fuzzy quantity (TFQ) $\overline{L}$ is determined on a real number set $\mathbb{Y}$ and is presented by a membership function $\mu_{\overline{L}}(\varkappa)$: $\mathbb{Y} \to [0,1]$. This membership function is expressed as Equation (1):

$$\mu_{\overline{L}}(\varkappa) = \begin{cases} \frac{x-\alpha}{\beta-\alpha} & \alpha \leq x \leq \beta \\ \frac{\gamma-x}{\gamma-\beta} & \beta \leq x \leq \gamma \\ 0, & otherwise \end{cases} \tag{1}$$

α, β, and γ represent the bottom-, middle-, and higher-level bounds of the fuzzy quantity, respectively (Figure 2). They make up the triangular representation. The TFQ is represented as $\overline{L}$ and expressed as $\overline{L} = (\alpha, \beta, \gamma)$

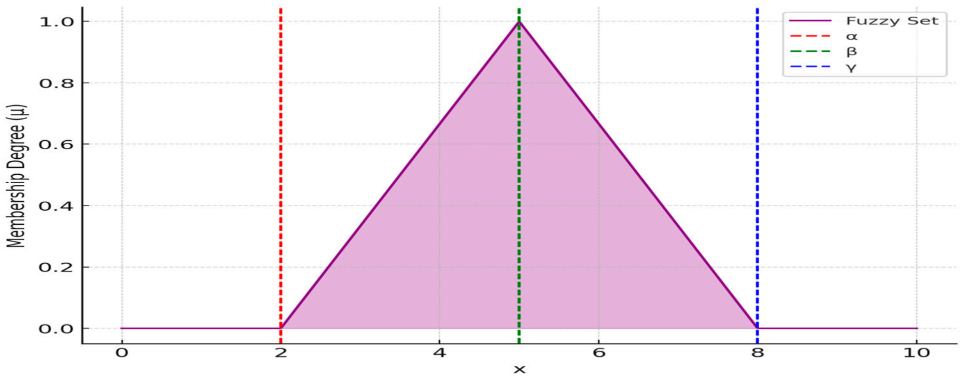

Figure 2. Triangular fuzzy quantity.

In this study, a triangular 10-point linguistic scale is used to collect the opinions of the experts that participated in this study (Figure 3).

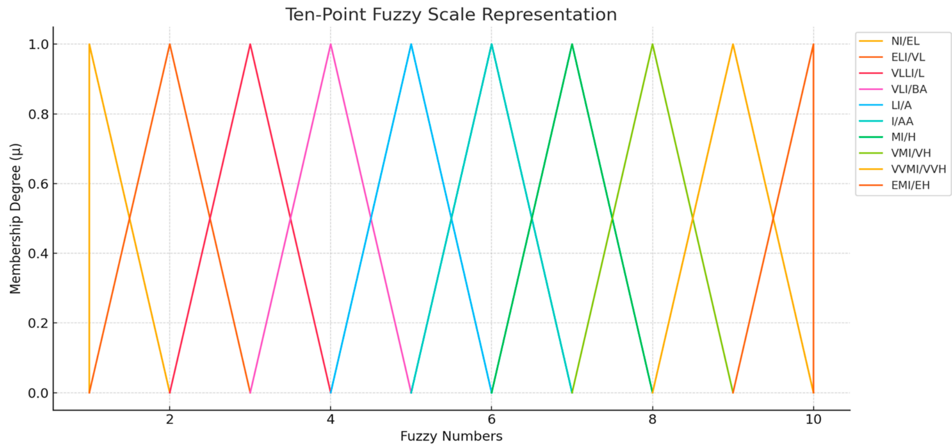

Figure 3. Triangular 10-point linguistic scale used in this study [26].

From Figure 3, NI/EL represents Not Important (NI)/Extremely Low (EL), ELI/VL is Extremely Less Important (ELI)/Very Low (VL), VLLI/L is Very Very Less Important (VLLI)/Low (L), VLI/BA is Very Less Important (VLI)/Below Average (BA), LI/A is Less Important (LI)/Average (A), I/AA is Important (I)/Above Average (AA), MI/H is More Important (MI)/High (H), VMI/VH is Very More Important (VMI)/Very High (VH), VVMI/VVH is Very Very More Important (VVMI)/Very Very High (VVH), and EMI/EH is Extremely More Important (EMI)/Extremely High (EH).

The classification of fuzzy importance values in this study was based on a ten-point fuzzy linguistic scale widely referenced in previous fuzzy multi-criteria decision-making (MCDM) studies [26]. The linguistic variables used, such as "Not Important", "Very Important", and "Extremely Important", were mapped to corresponding triangular fuzzy numbers (TFNs). These mappings followed a standardized approach, ensuring consistency and comparability with the existing literature. Thresholds for importance values were determined using established benchmarks from previous studies [27], where each linguistic term corresponded to a specific range within a triangular fuzzy number set. For instance, "Not Important" (NI) was mapped to (1, 1, 2), while "Extremely Important" (EMI) was represented as (9, 10, 10). This standardized approach allowed for the systematic conversion of qualitative expert opinions into quantitative fuzzy numbers.

3.3. Arithmetic Operations with TFQs

TFQs permit the combination or comparison of fuzzy numbers in a number of ways during operations on them. If two TFQs are represented as [27] $\overline{L}_1 = (\alpha_1, \beta_1, \gamma_1)$ and $\overline{L}_2 = (\alpha_2, \beta_2, \gamma_2)$, then addition, multiplication, subtraction, division, and reciprocals can be performed. The basic arithmetic operations with TFQs are given as follows:

Addition

$$\overline{L}_1 \bigoplus \overline{L}_2 = (\alpha_1 + \alpha_2, \beta_1 + \beta_2, \gamma_1 + \gamma_2) \tag{2}$$

Multiplication (with an assumption that all bounds are positive)

$$\overline{L}_1 \bigotimes \overline{L}_2 = (\alpha_1 \times \alpha_2, \beta_1 \times \beta_2, \gamma_1 \times \gamma_2) \tag{3}$$

Subtraction

$$\overline{L}_1 \ominus \overline{L}_2 = (\alpha_1 - \gamma_2, \beta_1 - \beta_2, \gamma_1 - \alpha_2) \tag{4}$$

Division (with an assumption that all bounds are positive)

$$\overline{L}_1 \oslash \overline{L}_2 = \left(\frac{\alpha_1}{\gamma_2}, \frac{\beta_1}{\beta_2}, \frac{\gamma_1}{\alpha_2}\right) \tag{5}$$

In the case of reciprocal

$$L_1^{-1} = \left(\frac{1}{\gamma_1}, \frac{1}{\beta_1}, \frac{1}{\alpha_1}\right) \tag{6}$$

3.4. Fuzzy Analytic Hierarchy Process (Fuzzy AHP)

The analytic hierarchy process is a popular decision analysis technique for prioritizing a collection of choices based on several criteria. However, in practical situations, experts are prone to uncertainty when attempting to precisely quantify the relative importance of attributes via pairwise comparisons. To address this challenge, the fuzzy analytic hierarchy process (Fuzzy AHP) integrates fuzzy logic into traditional AHPs, enabling decision makers to express judgments using fuzzy numbers rather than precise values. The following steps are taken when adopting the process:

Step 1: Construct a Pairwise Comparison Matrix

The first step is the construction of a pairwise construction matrix $\overline{C}$ where criteria are compared in pairwise form to determine their relative importance. The comparative values are represented as fuzzy quantities using Equation (7):

$$\overline{C} = \begin{bmatrix} 1 & \overline{c}_{12} & \cdots & \overline{c}_{1n} \\ 1/\overline{c}_{12} & 1 & \cdots & \overline{c}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/\overline{c}_{1n} & 1/\overline{c}_{2n} & \cdots & 1 \end{bmatrix} \tag{7}$$

where $\overline{c}_{ij}$ represents the comparison between fuzzy criterion i and fuzzy criterion j. For instance, $\overline{c}_{12}$ is used to represent how relevant criterion 1 is when compared to criterion 2.

Step 2: Calculation of the Geometric Means and Weights

The next step is to compute the geometric means of the individual criterion. The geometric mean $\overline{g}_i$ for i criterion is calculated using Equation (8):

$$\overline{g}_i = \left(\overline{c}_{i1} \bigotimes \times \overline{c}_{i2} \bigotimes \cdots \bigotimes \overline{c}_{in}\right)^{\frac{1}{n}} \tag{8}$$

The summation of the pairwise comparison is carried out to form a fuzzy number for the individual criterion.

$$\overline{w}_i = \frac{\overline{g}_i}{\overline{g}_1 \oplus \overline{g}_2 \bigoplus \cdots \bigoplus \overline{g}_n} \tag{9}$$

This represents the comparative weight of the individual criterion. The weights are represented using triangular fuzzy numbers as follows:

$$\overline{w}_i = \{\alpha_{wi}, \beta_{wi}, \gamma_{wi}\}$$

where α_{wi} is the bottom-level bound of the weight, β_{wi} is the middle bound of the weight, and γ_{wi} is the higher-level bound of the weight.

3.5. Multi-Criteria Decision-Making (MCDM) Problem Formulation

The MCDM method involves the assessment of a set of alternatives using a number of criteria, whereby an individual criterion may have different levels of significance. The performance of the individual alternative in comparison to the individual criterion is expressed as a fuzzy number. The following steps are taken in implementing the approach [27,28]:

Step 1: Construction of the Fuzzy Decision Matrix

In this step, the construction of the fuzzy decision matrix $\overline{X}$ is implemented. The individual element $\overline{X}_{ij} = (\alpha_{ij}, \beta_{ij}, \gamma_{ij})$ represents the fuzzy performance of alternative A_i in comparison to criterion B_j. This is performed using Equation (10):

$$\overline{X} = \begin{bmatrix} \overline{X}_{11} & \overline{X}_{12} & \cdots & \overline{X}_{1n} \\ \overline{X}_{21} & \overline{X}_{22} & \cdots & \overline{X}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \overline{X}_{m1} & \overline{X}_{m2} & \cdots & \overline{X}_{mn} \end{bmatrix} \tag{10}$$

$\overline{X}_{ij}$ is a triangular fuzzy number that reflects the performance of alternative A_i under criterion B_j.

Step 2: Normalization of the Decision Matrix

For the beneficial criteria where high values are desirable, the normalization process entails dividing the individual element by the maximum of the corresponding criterion using Equation (11):

$$\overline{N}_{ij} = \left(\frac{\alpha_{ij}}{\gamma_j^*}, \frac{\beta_{ij}}{\gamma_j^*}, \frac{\gamma_{ij}}{\gamma_j^*} \right) \tag{11}$$

For the cost criteria, it is better to have a low value, and the normalization procedure is represented as Equation (12):

$$\overline{N}_{ij} = \left(\frac{\alpha_j^-}{\gamma_{ij}}, \frac{\alpha_j^-}{\beta_{ij}}, \frac{\alpha_j^-}{\alpha_{ij}} \right) \tag{12}$$

where

γ_j^* is the maximum value of the j criterion;

α_j^- is the minimum value of the j criterion.

3.6. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

The TOPSIS method uses the ranking approach to rank alternatives by their distance from an ideal solution, which minimizes costs and maximizes benefits. The following steps are taken in adopting the process [27]:

Step 1: Calculation of the Weighted Normalized Matrix

The weighted normalized decision matrix $\overline{W}_{ij}$ is calculated by performing the multiplication of the individual element of the normalized matrix with the corresponding weight for the individual criterion using Equation (13):

$$\overline{W}_{ij} = \overline{N}_{ij} \bigotimes v_j \tag{13}$$

where v_j is the fuzzy weight of B_j criterion.

Step 2: Identification of the Ideal Solutions

The positive ideal solution (PIS) and negative ideal solution are obtained using Equations (14) and (15):

$$\text{PIS} = \overline{P}^+ = \left(\overline{W}_1^+, \overline{W}_2^+, \cdots \overline{W}_n^+ \right) \text{ where } \overline{W}_j^+ = max_i \overline{W}_{ij} \tag{14}$$

$$\text{NIS} = \overline{P}^{-} = \left(\overline{W}_1^{-}, \overline{W}_2^{-}, \cdots \overline{W}_n^{-}\right) \text{ where } \overline{W}_j^{-} = min_i \overline{W}_{ij} \tag{15}$$

Step 3: Calculation of the Distances to the Ideal Solution

The distance between the individual alternative and positive ideal solution or negative ideal solution is calculated using a Euclidean distance measurement of Equations (16) and (17):

$$d_i^{+} = \sum_{j=1}^{n} \left(\overline{W}_{ij} - \overline{W}_j^{+}\right)^2 \tag{16}$$

$$d_i^{-} = \sum_{j=1}^{n} \left(\overline{W}_{ij} - \overline{W}_j^{-}\right)^2 \tag{17}$$

Step 4: Calculation of the Closeness Coefficient

The alternative closeness coefficient CC_i for each criterion is calculated using Equation (18):

$$CC_i = \frac{d_i^{-}}{d_i^{-} - d_i^{+}} \tag{18}$$

The closeness coefficient is used to measure the closeness of the individual alternative to the ideal solution. A higher value of a closeness coefficient will give a better alternative.

Step 5: Ranking of the Alternatives

The ranking and selection of the alternatives are dependent on their closeness coefficient. The optimal system is the alternative that has the highest closeness coefficient CC_i.

3.7. Fuzzy Additive Ratio Assessment (Fuzzy ARAS) Method

The fuzzy ARAS method is implemented using the following steps [29]:

Step 1: Determine the linguistic terms for criteria weights and performance ratings.

The linguistic variable is designated based on the literature to constitute the relevance of criteria and the performance ratings of the alternatives. The linguistic expressions are allocated fuzzy numbers.

Step 2: Transform the opinion of the experts to interval-valued triangular fuzzy numbers.

The views of individual experts are transformed to an interval-valued triangular fuzzy number:

$$\overline{Q}_k = (\alpha_k, \beta_k, \gamma_k)$$

where α_k is the bottom-level bound, β_k is the value at the middle, and γ_k is the higher-level bound of the k-th expert's view. The sum of all the fuzzy numbers from all the experts are calculated using Equations (19)–(23):

$$\alpha = \min_k (\alpha_k) \tag{19}$$

$$\alpha' = \left(\prod_{k=1}^{k} \alpha_k\right)^{\frac{1}{K}} \tag{20}$$

$$\beta = \left(\prod_{k=1}^{k} \beta_k\right)^{\frac{1}{K}} \tag{21}$$

$$\gamma' = \left(\prod_{k=1}^{k} \gamma_k\right)^{\frac{1}{K}} \tag{22}$$

$$\gamma = \min_k (\gamma_k) \tag{23}$$

From the sum of the interval-valued triangular fuzzy number, $\overline{Q}_k = \{(\alpha.\alpha'), \beta, (\gamma', \gamma)\}$ is obtained from the expert assessment.

Step 3: Decision matrix formulation

The construction of the decision matrix Z is carried out. Z_{ij} represents the performance rating of the i-th alternative in comparison to the j-th criterion, as in Equation (24):

$$Z = \{Z_{ij}\}_{m\times n} \tag{24}$$

where m is the quantity of alternatives and n is the quantity of criteria. The criteria vector weight is given as Equation (25):

$$W = \{w_j\} \tag{25}$$

where w_j is the j-th criterion's weight. The decision matrix for each decision maker k is given as Equation (26):

$$Z_k = \left\{Z_{kij}\right\}_{m\times n} \tag{26}$$

In the same way, the weight of the vector provided by each maker is given as Equation (27):

$$W_k = \left\{w_{kj}\right\}_{n\times k'} \tag{27}$$

where k is the quantity of decision makers participating.

Step 4: Obtain the Optimal Performance Rating for the Individual Criterion

The optimal performance rating Z_{oj} for each criterion j is computed based on whether the criterion is a beneficial or cost criterion using Equation (28):

$$Z_{oj} = \begin{cases} max_i\, Z_{ij}, & if\ j \in\ \Omega_{max}\ (benficial\ criterion) \\ min_i\, Z_{ij}, & if\ j \in\ \Omega_{min}\ (cost\ criterion) \end{cases} \tag{28}$$

The equation for fuzzy quantities is as given in Equation (29):

$$\overline{Z}_{oj} = \left\{\left(\alpha_{oj}, \alpha'_{oj}\right), \beta_{oj}, \left(\gamma'_{oj}, \gamma_{oj}\right)\right\} \tag{29}$$

where Ω_{max} is the beneficial criteria and Ω_{min} is the cost criteria.

Step 5: Normalization of the Decision Matrix

The normalization of the decision matrix is performed by dividing the element by the aggregate of all the values for that criterion, which is achieved using Equation (30):

$$\overline{Z}_{ij} = \frac{Z_{ij}}{\sum_{i=0}^{m} Z_{ij}} \tag{30}$$

Considering the cost criteria, normalization is carried out, where lower-level values are comparatively better; this is performed using Equation (31):

$$Z_{ij} = \frac{1}{Z^*_{ij}} \tag{31}$$

where

Z^*_{ij} is the most favorable value of the criterion.

Normalization for the fuzzy performance rating is given as Equation (32):

$$r_{ij} = \begin{cases} \left(\frac{a_{ij}}{c_{+j}}, \frac{a'_{ij}}{c_{+j}}, \frac{b_{ij}}{c_{+j}}, \frac{c'_{ij}}{c_{+j}}, \frac{c_{ij}}{c_{+j}}\right), & j\ \in\ \Omega_{max} \\ \left(\frac{1}{a_{ij}/a_{-j}}, \frac{1}{a'_{ij}/a_{-j}}, \frac{1}{b_{ij}/a_{-j}}, \frac{1}{c'_{ij}/a_{-j}}, \frac{1}{c_{ij}/a_{-j}}\right), & j\ \in\ \Omega_{min} \end{cases} \tag{32}$$

where

c_{+j} is equal to $\sum_{i=0}^{m} c_{ij}$ for the beneficial criteria and a_{-j} is equal to $\sum_{i=0}^{m} \frac{1}{a_{ij}}$ for the cost criteria.

Step 6: Application of Weights to the Normalized Decision Matrix

The individual element of the normalized decision matrix is multiplied by the corresponding weight of the individual criterion. This is performed using Equation (33):

$$V_{ij} = w_j \times r_{ij} \tag{33}$$

where

V_{ij} is the weighted normalized performance rating of the i-th alternative in comparison with the j-th criterion.

Step 7: Calculation of the Overall Fuzzy Performance Rating

The total performance rating S_i for the individual i is computed by the addition of all the weighted normalized values over all the criteria. This is performed using Equation (34):

$$S_i = \sum_{j=1}^{n} V_{ij} \tag{34}$$

Step 8: Defuzzification of the Performance Rating

Defuzzification is performed to make a comparison of the fuzzy performance ratings through the use of the geometric mean of the triangular fuzzy numbers. This is performed using Equation (35):

$$gm(Q) = \frac{\alpha + \alpha' + \beta + \gamma' + \gamma}{5} \tag{35}$$

where

$Q = \{(\alpha, \alpha'), \beta, (\gamma', \gamma)\}$ is the fuzzy performance rating for an alternative.

Step 9: Calculation of the Degree of Utility.

The degree of utility U_i for the individual alternative is computed in comparison to the most favorable alternative S_0. This is performed using Equation (36):

$$U_i = \frac{S_i}{S_0} \tag{36}$$

This value represents the level of closeness of the individual alternative to the optimal solution.

Step 10: Ranking of the Alternatives

The ranking of the alternatives is performed based on the values of their degree of utility U_i. The alternatives are ranked from the highest to the lowest. The alternative with the highest utility values is ranked as the most favorable alternative with other alternatives in that sequence.

3.8. Data Collection

A questionnaire (Appendix A) was designed and adopted to obtain the views of the experts on the weights of the chosen criteria in identifying the critical success factors for the implementation of AI-driven mental health interventions using the MCDM. The questionnaire design was informed by an extensive literature review focusing on fuzzy multi-criteria decision-making (MCDM) approaches within healthcare and AI-driven mental health solutions. Key evaluation criteria and alternatives were identified and refined through iterative discussions with pilot participants to ensure relevance and comprehensiveness. To ensure the selection of competent and highly knowledgeable experts, specific criteria were applied. Experts selected for this study demonstrated substantial academic and professional qualifications, including advanced degrees and extensive experience in the relevant fields. The selection process prioritized diversity in professional backgrounds to ensure a balanced perspective from academia, healthcare practice, and research institutions.

The panel consisted of five experts with varied expertise. Expert 1 holds an MSc in healthcare and has over a decade of experience, with a focus on clinical outcomes. Expert 2 possesses a Ph.D. in academics with significant contributions to clinical research. Expert 3 has a Ph.D. and works in a research institution, focusing on feasibility studies for AI implementation. Expert 4, with an MSc in private healthcare practice, prioritized user satisfaction in their evaluation. Expert 5 holds a Ph.D. in healthcare, with extensive experience focusing on clinical outcomes. The questionnaire included both quantitative and qualitative components, with linguistic terms mapped to triangular fuzzy numbers to systematically capture subjective expert opinions. This approach ensured consistency and reliability across all evaluations, contributing to the robustness of the aggregated fuzzy decision matrix.

The experts were notified that the response was voluntary before they provided the required information. Also, the experts were informed that the information that they provided would be used solely for the purpose of research and that they would be kept anonymous. The questionnaire was filled in and returned by the experts with their consent for the information in it to be utilized for this study.

3.9. Case Study Description

A case study focused on evaluating and ranking the most effective AI-powered mental health solutions that can enhance mental health therapy is presented. Based on communication with experts and a literature review, five AI-based intervention strategies, including personalization of care, user engagement, integration with healthcare systems, data security and privacy, and clinical outcomes, were identified (Table 1). Furthermore, the case study identified six important criteria, which include feasibility of implementation, cost-effectiveness, scalability, ethical compliance, user satisfaction, and impact on clinical outcomes.

Table 1. Description of the criteria and alternatives considered in this study.

Criteria	
Criteria	**Definition**
Feasibility of Implementation [30]	The practicality and ease with which an AI-driven mental health solution can be developed, integrated, and maintained within existing healthcare systems.
Cost-Effectiveness [31]	The economic efficiency of the solution, considering both initial development and ongoing operational costs relative to the benefits achieved in mental health outcomes.
Scalability [32]	The ability of the solution to be expanded and adapted to serve a larger population without compromising performance or effectiveness.
Ethical Compliance [33]	Adherence to ethical standards, including patient confidentiality, informed consent, and the responsible use of AI in mental healthcare.
User Satisfaction [34]	The degree to which users find the AI-driven solution acceptable, engaging, and helpful in addressing their mental health needs.
Impact on Clinical Outcomes [35]	The effectiveness of the solution in improving mental health conditions, as evidenced by measurable changes in clinical assessments.

Table 1. *Cont.*

Alternatives	
Alternatives	**Definition**
Clinical Outcomes [36]	The measurable changes in patients' mental health status resulting from the use of the AI-driven solution.
User Engagement [37]	The level of interaction and participation by users with the AI-driven solution, indicating its usability and appeal.
Integration with Healthcare Systems [38]	The ability of the solution to seamlessly connect with existing healthcare infrastructure and processes.
Data Security and Privacy [39]	The measures taken to ensure the confidentiality and security of patient data in compliance with legal and ethical standards.
Personalization of Care [40]	The extent to which the solution can adapt to the unique needs and preferences of individual patients.

Expert opinions were collected from five professionals with experience in mental health intervention and expertise on the functionalities of AI using linguistic terms (see Figure 3) mapped to triangular fuzzy numbers to capture uncertainties. Fuzzy TOPSIS and fuzzy ARAS methods were used to evaluate the AI-driven mental health solutions. To further enhance the results, the two methods were harmonized using the normalized geometric mean. Fuzzy TOPSIS emphasized the proximity to the ideal solution, while fuzzy ARAS assessed the overall performance across all criteria. Missing data were addressed using the Ignore Missing Values approach, ensuring that only available ratings contributed to the aggregated results. The hierarchical structure of the problems considered in this study is presented in Figure 4.

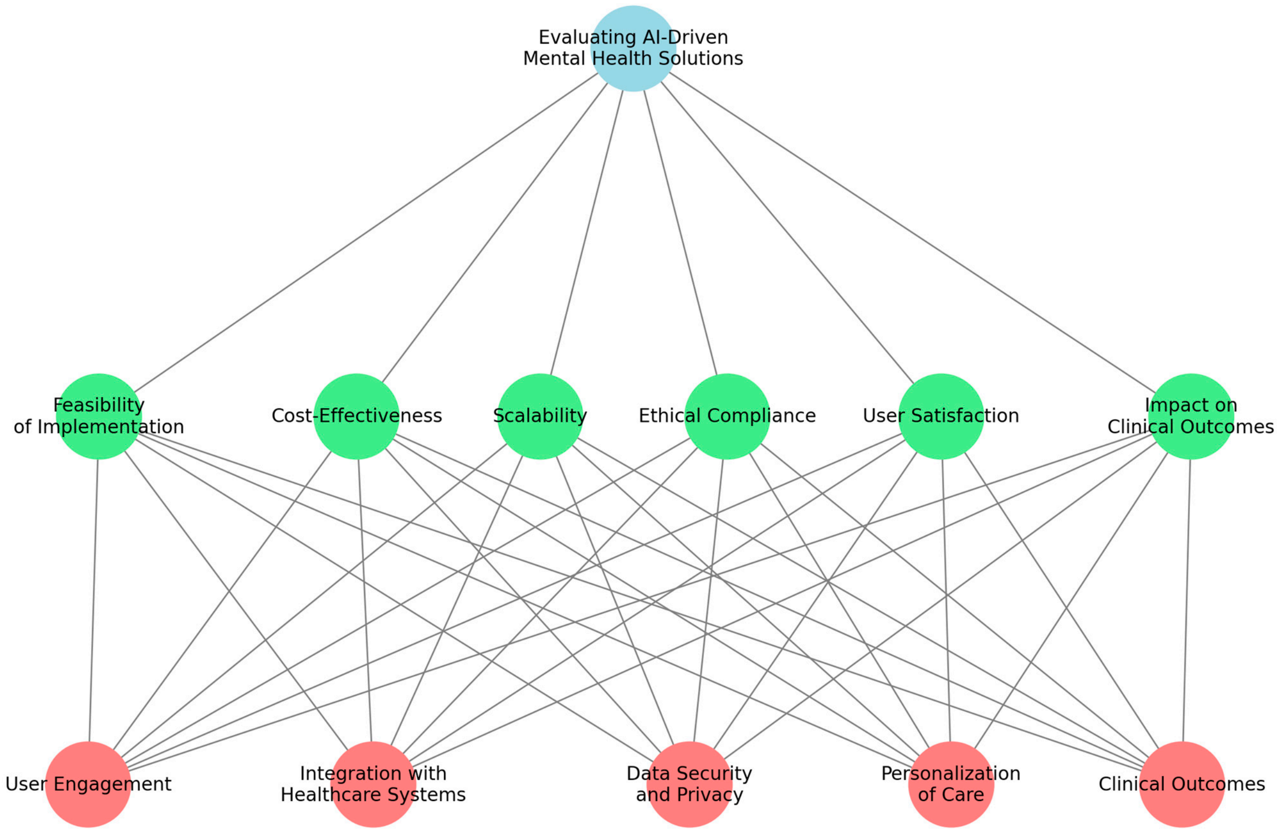

Figure 4. The hierarchical structure of the problems considered in this study.

3.10. Ethical Considerations in the Decision-Making Framework

Ethical principles played a fundamental role in guiding this study's design, expert selection, data handling, and decision-making processes (Figure 5). Ensuring transparency, fairness, and adherence to established ethical standards was prioritized throughout the study. Experts were chosen based on their academic qualifications, professional expertise, and the relevance of their research to AI-driven healthcare solutions. Care was taken to ensure representation from diverse sectors, including academia, healthcare, and research institutions, to reduce bias and improve inclusivity. Participants were informed of their voluntary participation, and it was explicitly stated that their responses would be used solely for research purposes while ensuring their anonymity. By returning completed questionnaires, respondents provided implicit consent to participate. As the study did not involve any physical or psychological intervention, formal ethical approval from an institutional review board was not required. However, the research adhered to the ethical principles outlined in the Declaration of Helsinki and complied with relevant data protection regulations to ensure confidentiality and proper data management.

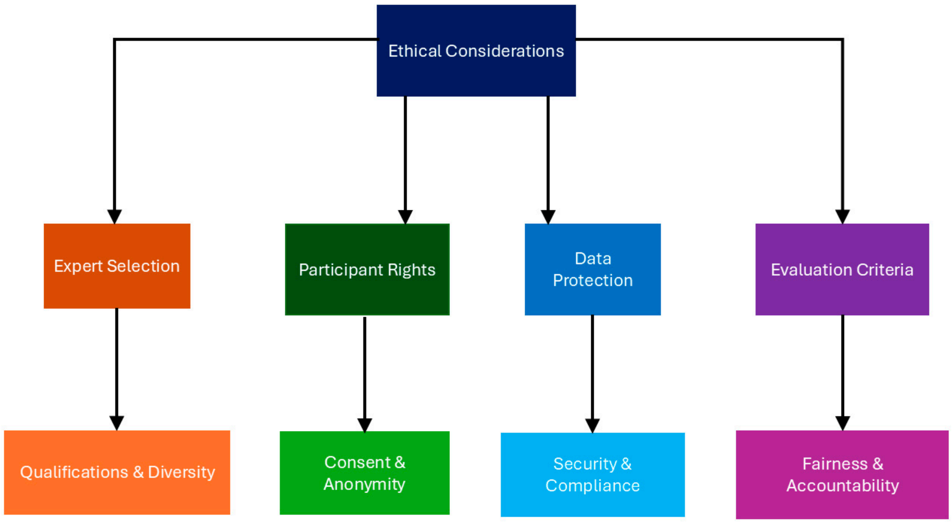

Figure 5. Ethical perspectives considered in this study.

To minimize cognitive biases, expert responses were aggregated using fuzzy linguistic scales, ensuring the equitable representation of all expert opinions in the final analysis without being disproportionately influenced by any single perspective. Data privacy and security were prioritized, with robust protocols implemented to protect the integrity and confidentiality of the collected responses. All electronic data were encrypted and securely stored, aligning with regulations such as the General Data Protection Regulation (GDPR). Ethical principles were explicitly considered in the weighting and prioritization of evaluation criteria. Factors such as data security, privacy, fairness, and accountability were emphasized during the prioritization and evaluation phases, ensuring that ethical considerations were adequately reflected in the final decision matrix.

By embedding these ethical principles into each stage of the research process, the study ensured transparency, accountability, and respect for participants' contributions. Future research can build upon these principles to further enhance the integration of ethical considerations in AI-driven healthcare decision-making frameworks.

4. Results

This section presents the results of the study. The expert responses on AI-driven clinical solutions in mental health reflect diverse educational, experiential, and organizational backgrounds. Respondents, ranging from MSc to PhD holders, represent healthcare, academia, private practice, and research institutions, with experience spanning 6 to 20 years. Healthcare professionals prioritize clinical outcomes, academics focus on innovation, researchers emphasize feasibility, and private practitioners highlight user satisfaction. Key prioritization criteria include clinical impact, feasibility of implementation, and user satisfaction, demonstrating a balanced focus on both operational efficiency and user experience. All experts unanimously stress the importance of human–AI collaboration, recognizing AI as a complementary tool that enhances efficiency and decision-making without replacing the essential human touch in mental healthcare. These insights collectively emphasize the need for tailored AI strategies that address educational, experiential, and sector-specific factors while prioritizing measurable outcomes and ethical implementation.

4.1. Weights Determination and Decision Matrix Aggregation

Table 2 provides the linguistic responses from the experts on the weights attached to the criteria and the aggregated weights obtained using the fuzzy AHP for weights. Table 3 presents a summary of all criteria and their importance with respect to AI-based mental health solutions; these responses depict the different opinions of experts, using a range of triangular fuzzy membership functions, and provide an insight into which features are given greater importance.

Table 2. Fuzzy weight assigned by the experts.

Criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
Feasibility of Implementation (C1)	I	VMI	VVMI	VVMI	EMI
Cost-Effectiveness (C2)	MI	MI	VVMI	EMI	VVMI
Scalability (C3)	VMI	VVMI	VVMI	VVMI	VVMI
Ethical Compliance (C4)	VMI	VVMI	VMI	VMI	VMI
User Satisfaction (C5)	EMI	VVMI	VMI	VVMI	EMI
Impact on Clinical Outcomes (C6)	MI	VVMI	VMI	VVMI	VVMI

Table 3. Fuzzy AHP for weights determination.

Criteria	Low	Medium	High
Feasibility of Implementation (C1)	7.43	8.41	9.35
Cost-Effectiveness (C2)	7.43	8.41	9.26
Scalability (C3)	7.87	8.78	9.35
Ethical Compliance (C4)	7	8	9
User Satisfaction (C5)	8	9	9.43
Impact on Clinical Outcomes (C6)	7.43	8.41	9.26

The results (Table 3) show that user satisfaction (C5) is the most important criterion, with a high fuzzy importance of (8.0, 9.0, 9.43). This strongly suggests that user satisfaction is right at the top when evaluating AI-driven mental health solutions. Its consistent top values in all three dimensions (low, medium, and high) also point out its importance. This is particularly relevant given that mental health interventions tend to be more effective when they cater to user needs and preferences, which in turn makes the user more involved in adherence to better treatment outcomes. Scalability (C3) is second, with major fuzzy importance (7.87, 8.78, 9.35). In AI-driven mental health solutions, large-scale scalability is an inevitable requirement. Under such circumstances, a solution is expected to address the need of a variety of clients without a compromise in performance. The high score for scalability shows that there are pressing needs for solutions that can be expanded efficiently to benefit a wider audience, ensuring that access to interventions is not limited by resource constraints. While user satisfaction and scalability are critical to the success of AI-powered mental health interventions, the feasibility of implementation (C1) is also relevant, with a fuzzy weight of (7.43, 8.41, 9.35). A well-designed solution that encounters obstacles arising from technology or logistics would not deliver the expected impact to patients. In terms of cost-effectiveness (C2), its weight of (7.43, 8.41, 9.26) shows the importance of establishing a compromise among factors related to performance and impact with cost, especially in a resource-constrained environment. For this study, experts indicated that the widespread adoption of AI-powered mental health solutions can only be attained if they are cost-effective. Cost-effectiveness does not only precipitate clinical efficacy, but it also contributes to the economic viability and effective diffusion of solutions.

The experts attributed a moderate weight (7.00, 8.00, 9.00) for ethical compliance (C4) compared to other criteria. While ethical considerations must remain a priority, the experts' scores propose that ethical adherence is seen more as a baseline necessity rather than a distinguishing aspect. This could indicate that moral issues, though fundamental, are not viewed as the main determining factor unless a specific solution presents notable ethical difficulties. Finally, impact on clinical outcomes (C6), with a geometric mean of (7.43, 8.41, 9.26), is closely aligned with both user satisfaction and feasibility. The experts' assessments emphasize that the proposed solution must accomplish its intended health benefits, a core objective for any mental health intervention. The high scores suggest that the experts recognize the necessity for AI-driven approaches to have a tangible and quantifiable impact on users' mental well-being, whether through decreased symptoms, enhanced quality of life, or other clinical metrics.

The fuzzy numbers in Table 3 suggest that experts prioritize user-focused outcomes, particularly satisfaction, alongside the ability to scale solutions for broader impact. At the same time, they acknowledge the need for feasible, cost-effective, and ethically sound solutions that drive meaningful clinical outcomes. The consistently high ratings across most criteria indicate that any AI-driven mental health solution must holistically address these aspects to be considered viable by experts. The inclusion of ethical compliance and cost-effectiveness as critical, yet somewhat secondary, considerations reflect a pragmatic approach, emphasizing that solutions must first be effective and scalable before fine-tuning aspects like cost and ethical considerations.

4.2. Aggregated Fuzzy Decision Matrix

The aggregated fuzzy decision matrix (Equation (37)) provides a comprehensive view of expert evaluations on various AI-driven mental health solutions across multiple criteria. Each entry in the matrix represents a triangular fuzzy number (l, m, u) which reflects the aggregated opinions of five experts regarding the importance and performance of each alternative under specific criteria. The use of triangular fuzzy numbers captures uncertainty and variability in expert opinions, offering a more nuanced view than single-point estimates. The presence of X values for certain entries, such as in cost-effectiveness (C2) for A4, indicates instances where expert feedback was not provided. These were handled using the Ignore Missing Values approach, ensuring that the aggregated results for each criterion remain representative of available expert input.

From the matrix, A5 (personalization of care) consistently shows high values across all criteria, particularly in user satisfaction (C5) and impact on clinical outcomes (C6), suggesting that experts view personalization as critical for successful outcomes in AI-driven mental health solutions. This alternative's high ratings highlight its potential effectiveness in delivering tailored mental health interventions. A2 (user engagement) also receives favorable scores, especially in scalability (C3) and ethical compliance (C4), underscoring the importance of user engagement in building adaptable and ethically responsible solutions. Meanwhile, A3 (integration with healthcare systems) and A4 (data security and privacy) have moderate ratings, reflecting their roles as supportive yet less prioritized factors.

$$\check{D}_{aggregated} = \begin{bmatrix} (7.6, 8.2, 9.0) & (8.4, 9.1, 9.8) & (7.1, 8.0, 9.0) & (8.5, 9.2, 9.9) & (9.0, 9.5, 10.0) \\ (4.4, 5.6, 6.2) & (6.3, 7.2, 8.0) & (X) & (8.1, 9.0, 9.7) & (8.6, 9.1, 9.7) \\ (7.2, 8.0, 8.9) & (8.3, 9.1, 9.7) & (8.4, 9.0, 9.8) & (8.6, 9.2, 9.9) & (8.5, 9.0, 9.8) \\ (7.1, 8.0, 9.0) & (X) & (8.3, 9.0, 9.6) & (8.9, 9.3, 9.8) & (7.9, 8.5, 9.1) \\ (8.5, 9.2, 9.9) & (8.1, 9.0, 9.7) & (8.6, 9.3, 9.8) & (9.3, 9.7, 10.0) & (8.1, 8.9, 9.6) \end{bmatrix} \quad (37)$$

4.3. Fuzzy TOPSIS

The values of the closeness coefficient given in Figure 6 indicate the closeness of each alternative to the fuzzy positive ideal solution (FPIS) and distance from the fuzzy negative ideal solution (FNIS). Usually, the most preferred solution is the alterative with the highest closeness coefficient. The result shows that A5 (personalization of care) is the most preferred among the five alternatives, with a closeness coefficient equal to 0.50 (Figure 6). This reinforces that AI-powered solutions require a high level of customization to be effective and should be tailored to the needs of individuals receiving mental healthcare. This is a very desirable attribute of AI-driven mental health technologies as it can lead to an increase in user engagement and better clinical outcomes, while it also helps ensure that the solutions are personalized and customizable so that individual needs are met.

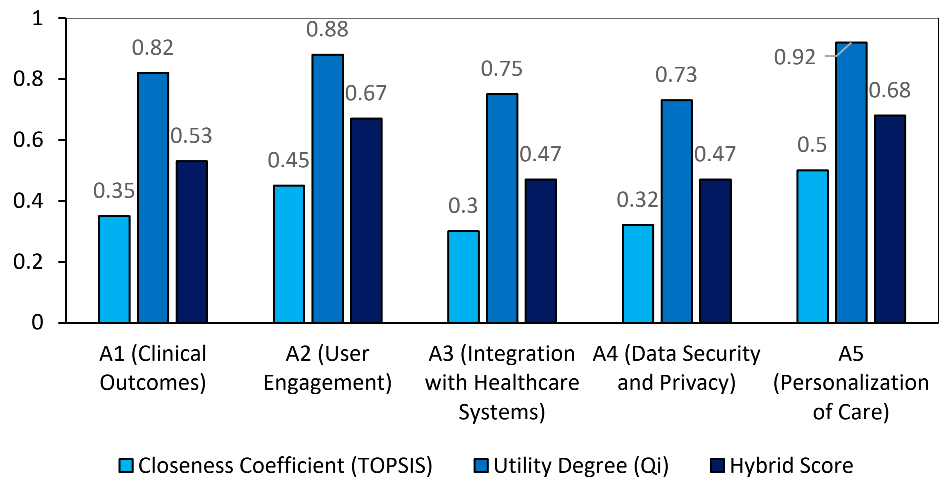

Figure 6. Closeness coefficient, utility degree, and hybrid score for the alternatives.

A2 (user engagement), with a closeness coefficient of 0.45, is the second most preferred (Figure 7) alternative, indicating that user engagement in AI-powered mental health solutions is a major area that should receive attention (Table 3). The more these AI-driven tools can meaningfully engage with patients, the higher their potential of supporting users in adhering to treatments and increasing overall satisfaction. This also corresponds with the high weighting of user satisfaction in fuzzy AHP analysis, which reiterates that user-focused mental health interventions are highly significant. A1 (clinical outcomes), with a closeness coefficient of 0.35, ranks third. While clinical outcomes are essential for the evaluation of AI-driven mental health solutions, achieving positive results appears to be less impactful than personalized care and sustained user involvement. Interestingly, this implies that even though progressing clinical outcomes are necessary, specialists may see meeting individual needs and maintaining engagement as more crucial determinants of a program's success. A one-size-fits-all approach may be sub-optimal; instead, tailoring support for diverse circumstances and maintaining an open dialog over the long term may hold the greatest promise for progress.

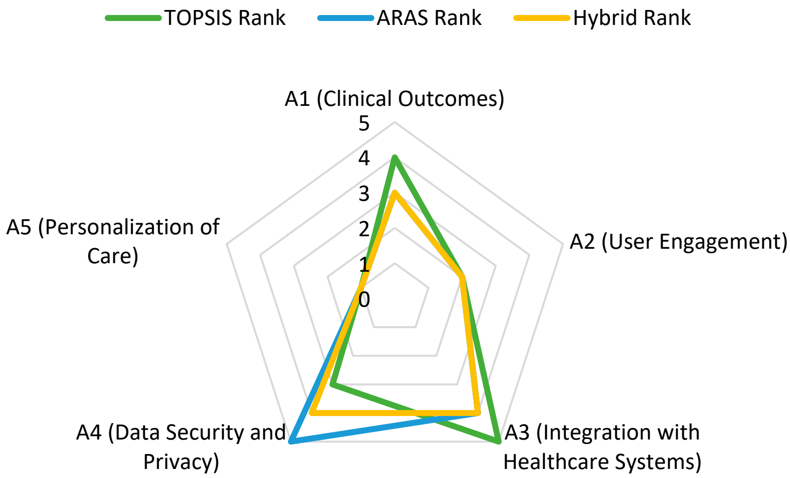

Figure 7. Rank for TOPSIS, ARAS, and hybrid rank methods.

A3 (integration with healthcare systems) and A4 (data security and privacy) have the lowest closeness coefficients of 0.30 and 0.32, respectively. This indicates that experts see these factors as less critical determinants for AI effectiveness in mental healthcare solutions. Thes factors are seen as supporting indicators rather than as primary factors. This result implies the direct interplay between "person" and "platform" through customization and involvement. It should also be noted that integration and privacy remain highly important and should not be understated, as without the proper handling of such relationships, personal information can be compromised.

4.4. Fuzzy ARAS

Fuzzy ARAS results showed A5 (personalization of care) as the best optimal alternative with highest utility degree (Qi = 0.92) and overall fuzzy performance score (Si = 0.90) (Figure 6). The findings align with the outcome of the fuzzy TOPSIS method where Alternative 5 attained the closest proximity to the ideal solution with the highest closeness coefficient. The consistent top ranking of A5 across both methods highlights the importance of tailoring mental health solutions to individual user needs to enhance engagement and treatment outcomes. In both fuzzy ARAS and fuzzy TOPSIS, A2 (user engagement) stands out as the second rank, underscoring the importance of engaging users in mental healthcare solutions. When an AI-assisted mental healthcare system promotes interaction and connection, it improves therapeutic outcomes for users. In the fuzzy ARAS analysis, A1 (clinical outcomes) ranks third with a utility degree of Qi = 0.82, while in fuzzy TOPSIS, it ranks slightly lower. This discrepancy suggests that while clinical outcomes are essential, they are prioritized just below user-centric features like personalization and engagement in optimizing AI-driven mental health solutions. As shown by the fuzzy ARAS assessment A3 (integration with healthcare systems) and A4 (data security and privacy) ranked on the lower side with utility degrees of Qi3 = 0.75 and Qi4 = 0.73, respectively. These results suggest that, although integration and data security are important foundational elements, they are not seen as differentiators for the success of AI-driven mental health solutions. Experts may consider these factors as essential, but not as critical as personalization, user engagement, and clinical outcomes in the decision-making process.

4.5. Hybrid Fuzzy TOPSIS-ARAS Model

The results obtained from applying fuzzy TOPSIS and fuzzy ARAS revealed substantial differences in the ranking of some alternatives, highlighting the distinct viewpoints of these two methodologies. Fuzzy TOPSIS prioritizes how close each alternative is to the ideal solution across all criteria, prioritizing proximity to optimality. In contrast, fuzzy ARAS evaluates alternatives based on their aggregate performance relative to the defined criteria, focusing on the cumulative contribution rather than proximity to an ideal point. For example, A1 (clinical outcomes) placed fourth using fuzzy TOPSIS, but achieved third with fuzzy ARAS. Similarly, A4 (data security and privacy) ranked higher, with TOPSIS in third but lower and with ARAS in fifth. These divergences stem from the inherent variances in the computational logic and priorities of the two approaches. A Combined Score approach was applied to address these inconsistencies using the geometric mean of the normalized results from both methods. This strategy successfully balanced the unique perspectives of fuzzy TOPSIS and fuzzy ARAS, merging the emphasis on ideal proximity and aggregate performance.

In the proposed hybrid model, the closeness coefficients obtained from the fuzzy TOPSIS and the utility degrees from the fuzzy ARAS are normalized using min-max normalization (Equations (38) and (39)), while the Geometric mean is used to combine the results (Equation (40)). The alternative with the highest hybrid score is indicated as the most preferred.

$$Normalized\ TOPSIS = \frac{CC - \min(CC)}{\max(CC) - \min(CC)} \tag{38}$$

$$Normalized\ ARAS = \frac{Q_i - \min(Q_i)}{\max(Q_i) - \min(Q_i)} \tag{39}$$

$$Hybrid\ Score = \sqrt{Normalized\ TOPSIS \times Normalized\ ARAS} \tag{40}$$

The Combined Score approach merges these insights, offering a balanced view that integrates both proximity-to-ideal (TOPSIS) and overall performance (ARAS) assessments. A5 (personalization of care) ranks first across all methods, with a Combined Score of 0.68 (Figures 6 and 7), underscoring the importance of personalized care as a primary factor in AI-driven mental health solutions. This consistency reflects that personalization resonates strongly with both ideal proximity and overall performance perspectives.

The observation that A5 (personalization of care) consistently achieved the highest rank across both fuzzy TOPSIS and fuzzy ARAS is supported by the existing literature, which emphasizes the importance of personalization in digital mental health interventions. Research by Hornstein et al. (2023) [41] highlights that personalization strategies, including user choice, provider choice, and rule-based adaptations, significantly improve adherence, satisfaction, and clinical outcomes. These findings suggest that tailored interventions not only align closely with an ideal solution (proximity-to-ideal), but also deliver cumulative benefits across multiple performance criteria, aligning with aggregate performance perspectives. Similarly, Malik et al. (2022) [42] found that users of AI-driven mental health applications reported higher satisfaction and engagement when interventions were personalized to their specific needs. The study demonstrated that tailored responses and adaptive coping mechanisms resulted in increased trust and long-term adherence to mental health solutions. This evidence reinforces the dual role of personalization in optimizing both the immediate fit (as emphasized in TOPSIS) and cumulative contributions to overall performance (as emphasized in ARAS).

The ranking of A1 (clinical outcomes) in third place suggests that while achieving positive clinical outcomes remains a central goal of AI-driven mental health solutions, it is often viewed as an outcome that emerges indirectly from other critical factors, such as user engagement and personalization. Experts acknowledged that successful clinical outcomes are closely linked to high levels of user engagement and tailored care experiences, highlighting the interconnected nature of these criteria. This explains why clinical outcomes, despite their significance, were slightly deprioritized compared to the more immediate impact of user-centered factors. A4 (data security and privacy) ranked fourth, indicating that while data protection measures are foundational to successfully deploying AI-driven health solutions, they are often perceived as baseline requirements rather than differentiating factors. Experts viewed compliance with security standards and privacy protocols as essential but insufficient on their own to drive user adoption or improve therapeutic outcomes. Similarly, A3 (integration with healthcare systems) ranked fifth, reflecting its role as a critical but secondary enabler in the overall success of AI-driven mental health interventions. Integration with existing healthcare infrastructure, including interoperability with electronic health records (EHRs), was seen as technically vital but less impactful in influencing immediate user-centered outcomes. The combined model thus reconciles differences between TOPSIS and ARAS, affirming personalization, engagement, and clinical outcomes as priorities while acknowledging the supporting roles of data security and integration.

4.6. Challenges and Limitations

One limitation of this study is the reliance on five experts to evaluate AI-driven mental health solutions. While these experts were carefully selected based on their extensive experience, diverse professional backgrounds—including healthcare, academia, private practice, and research institutions—and their familiarity with AI and mental health solutions, the small sample size may restrict the breadth of perspectives and potentially introduce bias. The use of fuzzy MCDM methods, however, helps mitigate some of these limitations by allowing linguistic variables mapped to triangular fuzzy numbers to represent expert opinions. This approach reduces the impact of subjective variations and enhances the robustness of the aggregated results. Future studies could include a larger and more geographically diverse group of experts to improve the representativeness and generalizability of findings. Additionally, further research could explore potential biases in expert selection and their implications on decision-making outcomes.

Additionally, the criteria selected, though comprehensive, may not encompass all factors relevant to AI-driven mental health solutions in different contexts. For instance, operational efficiency, cultural adaptability, and financial considerations may influence the feasibility and effectiveness of these interventions, particularly in healthcare settings with unique resource constraints.

Another limitation is the study's use of a hybrid fuzzy MCDM model, which combines fuzzy TOPSIS and fuzzy ARAS. While this approach is effective for balancing ideal-proximity and aggregate performance, the results may vary if different decision-making methods are applied, potentially affecting the robustness of findings. Furthermore, the aggregation of fuzzy inputs to account for missing data may reduce the precision of the results. Finally, the generalizability of these findings is limited, as regulatory and operational factors specific to particular regions or healthcare systems may impact the broader application of the results. Future research should address these limitations by expanding the expert sample, exploring additional criteria, and testing the model across varied healthcare environments.

While this study evaluates the criteria independently using fuzzy TOPSIS and fuzzy ARAS, it is important to acknowledge the inherent interdependencies between some of these factors in real-world applications. For example, weak data security and privacy (A4) can undermine user trust, reducing user engagement (A2) and subsequently impacting clinical outcomes (A1). Similarly, poor integration with healthcare systems (A3) can affect the feasibility of implementation (C1) and scalability (C3) of the solution. Although the methods applied in this study do not explicitly account for such interdependencies, recognizing these relationships is crucial for understanding the broader dynamics of AI-driven mental health interventions. Future research could address this limitation by employing methods like Analytic Network Process (ANP) or Fuzzy Cognitive Mapping, which are well suited for analyzing and quantifying interdependencies among multiple criteria.

While this study employed fuzzy TOPSIS and fuzzy ARAS for evaluating AI-driven mental health solutions, it is acknowledged that Large Language Models (LLMs) and Generative AI (GenAI) hold potential for enhancing decision-making frameworks [43,44]. LLMs can play a role in multi-criteria decision-making (MCDM), but primarily as complementary tools rather than direct replacements for traditional MCDM frameworks like fuzzy TOPSIS or fuzzy ARAS. LLMs excel at processing unstructured data, such as textual expert opinions or qualitative insights, and are particularly valuable for criteria extraction, the aggregation of qualitative inputs, and the post hoc interpretation of results [43]. It can also be used in automating the process of decision-making [45]. However, the computational transparency, numerical rigor, and reproducibility offered by traditional fuzzy MCDM methods remain essential for structured decision analysis. Based on the advantages offered by LLMs, future research could explore hybrid approaches where LLMs handle qualitative pre-processing and post-analysis tasks, while fuzzy TOPSIS and fuzzy ARAS focus on the quantitative evaluation and ranking of alternatives. This synergy could combine the contextual reasoning and adaptive capabilities of LLMs with the mathematical robustness and transparency of fuzzy MCDM methods, resulting in a more dynamic and comprehensive decision-making framework.

5. Conclusions

This study reveals key factors for AI-driven mental health interventions through a hybrid MCDM approach that integrates fuzzy TOPSIS and fuzzy ARAS. Personalization of care consistently emerged as the top-ranked factor, underscoring the importance of tailored interventions that meet unique user needs. User engagement was also identified as critical, emphasizing that actively involving users enhances adherence and treatment outcomes. Together, these findings suggest that personalization and engagement are vital for AI-driven mental health solutions, supporting a user-centered approach as central to successful interventions.

Broader implications highlight that stakeholders should prioritize user satisfaction and engagement when developing AI mental health solutions. Practical recommendations include investing in secure, adaptive AI technologies that balance personalization with ethical standards. Future research should focus on expanding the criteria to include factors such as operational efficiency, adaptability to cultural nuances, and cost-effectiveness. Additionally, applying the MCDM framework in varied healthcare settings and increasing the diversity of the expert sample could strengthen the generalizability of the findings and ensure that AI interventions are optimized.

In practical terms, stakeholders—including healthcare providers, policymakers, and technology developers—can use these insights to design AI-driven mental health interventions with a stronger focus on personalization and engagement. Personalization, as identified in our study, stands out as the top-ranked factor because it tailors interventions to individual patient needs, enhancing trust, adherence, and therapeutic outcomes. Implementing personalization requires robust data analytics capabilities, continuous user feedback mechanisms, and adaptive AI algorithms that are capable of real-time adjustment based on user behavior and preferences. Similarly, fostering user engagement relies on designing intuitive user interfaces, incorporating interactive elements, and providing meaningful feedback loops within AI platforms. Engagement strategies must also consider cultural and demographic variations, ensuring inclusivity and relevance across diverse user groups.

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Institutional Review Board Statement: This study was conducted in accordance with the principles of the Declaration of Helsinki, and data were handled according to the General Data Protection Regulation.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data are contained within the article.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Sample Questionnaire

Table A1. Kindly rate the AI-driven mental health solutions (on their adoption in clinical practice) against the following criteria.

	Criteria						
	AI-Driven Mental Health Solutions	**Feasibility of Implementation (C1)**	**Cost-Effectiveness (C2)**	**Scalability (C3)**	**Ethical Compliance (C4)**	**User Satisfaction (C5)**	**Impact on Clinical Outcomes (C6)**
Alternatives	Clinical Outcomes (A1)	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
	User Engagement (A2)	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
	Integration with Healthcare Systems (A3)	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
	Data Security and Privacy (A4)	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.
	Personalization of Care (A5)	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.	Choose an item.

Table A2. Kindly click on the drop-down box to rate the importance of the following criteria on the selection of power system analysis software for teaching and learning.

Criteria	Importance Rating
Feasibility of Implementation (C1)	Choose an item.
Cost-Effectiveness (C2)	Choose an item.
Scalability (C3)	Choose an item.
Ethical Compliance (C4)	Choose an item.
User Satisfaction (C5)	Choose an item.
Impact on Clinical Outcomes (C6)	Choose an item.

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