A Fuzzy Decision System for Providing Emotional Support to College Students via Customization

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Abstract: *Emotional and psychological difficulties are common among college students and can harm both their health and their ability to study. These complicated concerns are not adequately addressed by traditional assistance systems that use single-criterion approaches. For this, the research introduces Emotional Customization Support using Fuzzy Multicriteria Decision (EMOTICS-FMD) system, which integrates multiple criteria in both quantitative and qualitative manners to provide customized emotional support for college students. The EMOTICS-FMD involves three phases, with an initial application of the Fuzzy Analytic Hierarchy Process (FAHP) to dynamically adjust the weights of the criteria based on gathered student feedback. Secondly, to rank the available support alternatives for each scenario, the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) has been used. Thirdly, the Mamdani inference system is utilized to address the inherent uncertainty in emotional assessment and support provision, leading to more accurate decision-making and an engaging, effective support system for students. The model has been validated using a publicly available Kaggle dataset comprising over 102 college students from diverse academic backgrounds. The quantitative factors, such as age, year of study, and Cumulative Grade Point Average (CGPA), along with qualitative variables, including students' self-reported emotional state and the level of difficulty of their courses, serve as input criteria. The performance results show that, compared to standard single-criterion methods, the EMOTICS-FMD system significantly enhances the accuracy and customization of emotional support recommendations.*

Keywords: *Fuzzy multicriteria decision-making, emotional support, customization, mamdani fuzzy inference.*

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1. Introduction

Emotional support is a significant aspect closely related to the mental and physical wellness of college students, which can increase motivation, lead to better learning outcomes, and reduce stress [5]. Students' learning effectiveness can be improved by using a customized and dynamic learning model, along with an additional analysis of emotional support, to facilitate effective decision-making [16]. Enhancing the creation of a customized educational platform that takes into account students' preferences and adjusts to meet their emotional needs is recommended [7]. Several emotional factors in students can be analyzed through their behavior, as captured on video, while solving a code, including frustration, fear, disgust, happiness, neutrality, sadness, and surprise [8]. The existing customization scenario for college students lacks content understanding, student discontinuity, language barriers, and the selection of study materials, among other issues. By developing a dynamic and interactive learning environment, the students gain support and targeted guidance [6].

Research provides students with various psychological evaluations that they can use to gain insight into their own emotional health and skill level, including tests of emotional regulation, self-esteem, and social interaction [20]. Earlier learning models focused on the cognitive status of students, and later, researchers recognized the use of adaptive learning systems for identifying students' affective conditions, which has been applied using fuzzy expert systems [12]. Learner satisfaction is highly impacted by customized emotional features and distinct preferences [21]. The diverse and stressed student strengths currently present harm to student improvement and well-being. Hence, customization is needed to target student success [2]. The evaluation of student satisfaction regarding the impact of personalized experiences is analyzed using fuzzy logic [18].

The psychological curve metric considers both past and future performance of college students to assess their level of satisfaction with the unique learning requirements and determine whether those demands are being met successfully [13]. Fuzzy logic is ideal for creating knowledge-based support systems that preserve the inherent fuzziness in student models, as it mimics human thinking and facilitates decision-making in the face of uncertain student characteristics [9]. the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) is used as a heuristic decision-making method to analyze student learning parameters in terms of multiple criteria [24]. However, the precise technique that links emotional support to students' satisfaction with learning remains uncertain, and this uncertainty affects decision-making [17]. For this, the Fuzzy Analytic Hierarchy Process (FAHDP) is applied to provide relative importance weights for the student profile as criteria [19]. The multiple criteria are analyzed to provide customized support for each student, utilizing a fuzzy algorithm to enhance decision accuracy [23].

The research highlights are staged as:

1) To develop an EMOTIonal Customization Support using Fuzzy Multicriteria Decision (EMOTICS-FMD) system, for college students that accurately addresses their individual needs.
2) To dynamically adjust the weights of the criteria based on feedback from students using FAHP.
3) To rank the available decision support for each scenario using the FTOPSIS.
4) To handle the inherent uncertainty in emotional assessment and customization provision, using the Mamdani inference system results in more accurate decision-making and practical recommendations.

The upcoming sections of the manuscript are organized as follows: section 2 provides a literature summary, and section 3 presents a detailed description of the Kaggle student mental health data analysis. Section 4 details the proposed EMOTICS-FMD algorithm, including the flow of integrated algorithms for weighting, ranking, and ultimately creating a customized decision support system. Section 5 validates the performance of EMOTICS-FMD against existing models using various metrics, and section 6 concludes the work.

2. Related Works

Nguyen [14] examined the correlation between emotional ability and collaboration consequences among 372 Vietnamese university students using an 18-item scale. The four dimensions of emotional intelligence measured were awareness of emotions, usage, understanding, and control. The results show that emotional intelligence has a positive effect on collaboration performance, highlighting the importance of cultivating emotional support in colleges. The cross-sectional investigation design, particularly in limiting causal inference, is a limitation, as is the small sample size and the potential for self-reported data bias.

The existing online learning grading systems heavily rely on test averages. Krouska *et al*. [10] presented a two-tier fuzzy controller that considers the social behavior of learners when determining their final scores. The first level determines the extent to which students are actively involved, and the second level recommends grading changes that more properly represent students' total performance. The research increased student engagement but also improved the accuracy and fairness of grading. However, the model may need substantial data collection and validation for refinement.

Sargazi Moghadam *et al*. [15] introduced an Artificial Intelligence-based decision-making system for online educational programs that detects and suggests micro-break activities based on students' emotional characteristics, utilizing an Adaptive Genetic Algorithm (AGA). The framework was adjusted to meet the emotional requirements and preferences of 40 ESL students in a case study, resulting in improved learning performance. The outcomes demonstrated that the suggested exercises were successful in raising the spirits of students and raising their grades. A small number of participants and the necessity for additional validation in varied educational environments are two drawbacks of the study.

Bellarhmouch *et al*. [3] presented a method for adapting student models in learning systems that integrates different types of student input utilizing Fuzzy Logic with Decision Support System (FLDSS), similarity approaches, and stereotype procedures. By efficiently handling uncertainty, the method enhances customization and accuracy through the analysis of learning styles and emotions, thereby improving decision-making support. Although it demonstrates enhanced student model inception and updating, there are a few drawbacks to consider, including the potential complexity of implementation and the need for thorough validation.

Labbaf *et al*. [11] utilized a dataset of twenty-one college students from Southern California, who were included, with multimodal data collected before, during, and after the COVID-19 lockdown. A pulse oximeter, an inertial measurement unit, pressure sensors, and questionnaires assessing mood/mental health/lifestyle changes are all employed in it. Limitations, such as sample size limitations and data collection variability, are a focus of key analyses that center on longitudinal patterns in health indicators, physical activity, and emotional well-being.

Xu [22] introduced a Fuzzy Cluster Analysis Technique with a Star Discrete Analysis (FCA-SDA) model and evaluated college students' engagement with mental health support services. The method allows for better management of high-dimensional data and enhances data tracking and matching to meet the diverse needs of students. The results demonstrated that the performance analysis is efficient and the data coupling is more accurate. Possible implementation complexity and reliance on high-quality data for reliable results are limitations.

Bharath and Lakshmi [4] proposed an optimized ensemble sentiment analysis system utilizing fuzzy logic and deep learning methods along with efficient feature selection and feature extraction methods. The proposed model successfully handles linguistic uncertainty and therefore achieves the accuracy in classification of sentiment with better performance than some of the traditional methods. However, its reliance on training data with labels and sentiment classification restrict its usage in adaptive decision-support environments.

The existing research suggests that there are different ways to help college students emotionally and academically, and each of these approaches has its own set of advantages and disadvantages. A limited sample size and self-report bias were problems with one study that showed emotional intelligence had a favorable effect on teamwork. Despite the need for more varied validation, an AI-based method successfully enhanced student attitude and grades. However, the use of a fuzzy logic model improved decision support; however, it was challenging to implement in practice. Problems with data variability and sample size plagued an emotional support data study. Although it performed well overall, a sophisticated fuzzy algorithm struggled with bias and handling data in real-time. To overcome these obstacles, the EMOTICS-FMD system incorporates emotional support, integrates extensive data sources, adapts to students' needs in real-time, and includes fuzzy AHP and FTOPSIS mechanisms for continuous validation and customization, resulting in a stronger and more customized decision support.

Table 1. Summary of related works in emotion-aware decision support.

Reference	Approach / Method	Key results	Limitations
Nguyen [14]	Emotional intelligence study with survey (Vietnam, 372 students)	Found positive correlation between emotional intelligence and collaboration	Limited by cross-sectional design, small sample, and self-report bias
Krouska *et al*. [10]	Two-tier fuzzy controller for online grading	Improved engagement, accuracy, and fairness in grading	Requires extensive data collection and validation
Sargazi Moghadam *et al*. [15]	AGA for micro-break recommendations	Boosted learning performance and mood in English as a second language students	Small participant group; limited generalizability
Bellarhmouch *et al*. [3]	FLDSS - Fuzzy logic decision support integrating learning styles and emotions	Enhanced customization and decision-making accuracy	Complex to implement; needs wider validation
Labbaf *et al*. [11]	Multimodal sensing (oximeter, inertial measurement unit, pressure sensors, surveys during COVID)	Provided longitudinal insights into health, activity, and emotions	Very small sample; variability in data collection
Xu [22]	Heuristic Fuzzy C-Means with Fuzzy Cognitive Maps (HFC-FCM)	Achieved >95% accuracy in cognitive progress, engagement, prediction	Algorithmic bias risk; lacks real-time validation
Bharath and Lakshmi [4]	FCA-SDA	Improved efficiency in high-dimensional data management for mental health support	Implementation complexity; depends on high-quality input data

State of the Art and Gaps. Fuzzy rule-based models, AI-driven adaptive frameworks, and multimodal clustering techniques all have expanded existing research on emotion-aware decision assistance for students. These approaches each have advantages in terms of interpretability, customization, and richer signal detection. These methods, however, are primarily distinct, restricted to limited datasets, and frequently depend on static weighting systems that are unable to adjust to evolving student feedback. Furthermore, there are gaps in real-time application and long-term academic or emotional consequences because scalability and long-term impact are rarely evaluated. It addresses these problems by combining FTOPSIS for robust multi-criteria ranking, FAHP for dynamic weighting, and Mamdani fuzzy inference for interpretable recommendations. This creates an end-to-end adaptive pipeline that connects academic support and emotional stability over the long term with short-term engagement. Table 1 shows the summary of related works in emotion aware decision support.

3. Data Analysis

An analysis of college students' emotional wellness in relation to their academic status, including Cumulative Grade Point Average (CGPA), year of study, course intensity, and emotional wellness, has been collected using a Google Forms survey on the Kaggle platform [1]. The data originated from the Malaysia University, with an input of 102 student records. Table 2 contains information about one hundred students, the majority of whom are female (71%). Their majors courses span 1-4 years for different fields, including engineering, computer science, law, business, psychology, the arts, sciences, and the humanities. The students range in age from 18 to 24 and are spread out across the first four years of the course. Fifteen pupils have disclosed suffering from mental health issues; twenty-five have reported emotional states like depression, twenty-eight have stated anxiety, and twenty-five have reported panic attacks. A large portion of the student body has chosen not to seek professional assistance for their mental health issues, while only 5 students have sought specialized therapy despite these worries.

4. Research Idea

The research aims to develop the EMOTICS-FMD system to address the psychological and emotional issues that college students encounter more effectively than standard support systems, which only consider one factor. The system employs FAHP and FTOPSIS to deliver customized support by combining quantitative variables, such as students' ages, years in school, and CGPA, with qualitative variables, including students' self-reported emotional states and the difficulty of the course. Emotional support recommendations are made more accurate and customized by the Mamdani inference system, which further improves decision-making under uncertainty. This research focuses on multicriteria decision-making problems, as they often involve uncertainty and imprecise information. The research aims to address this challenge by utilizing fuzzy decision techniques. This study proposes a linguistic decision process to resolve multiple-criteria decision support within a fuzzy environment, where college students face a challenge in providing emotional support using customized recommendations. In this decision system, the evaluation of alternatives is conducted using linguistic variables identified through multiple students' input criteria related to their mental health. The integrated FTOPSIS model presented in this paper facilitates the measurement of distance between two fuzzy trapezoidal numbers and extends the FTOPSIS procedure to the fuzzy environment.

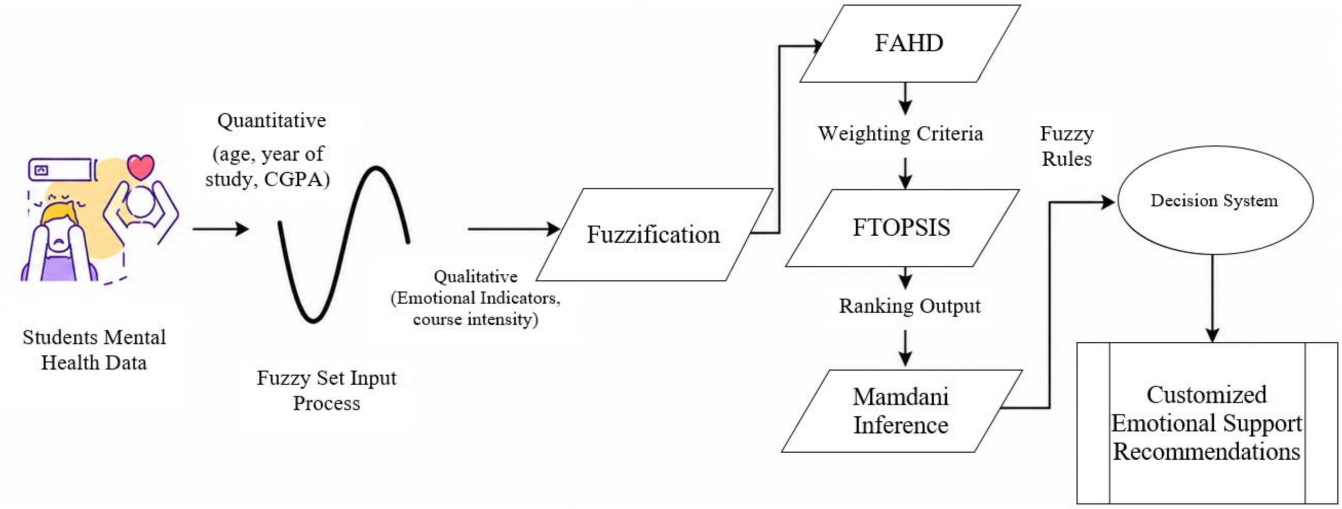

Figure 1. Graphical illustration of EMOTIOCS-FMD system.

With the use of fuzzy logic approaches, the EMOTICS-FMD system, depicted in Figure 1, works by an integrated approach that satisfies students' emotional demands, taking into account both their quantitative and qualitative requirements. The system's incorporation of and dynamic weighting using FAHP, alternative ranking from FTOPSIS, and Mamdani fuzzy inference, allows for more precise and customized recommendation making, which improves students' mental health and academic achievement.

4.1. Fuzzy Set Input Process

The fuzzification includes membership functions for the fuzzy sets "very young" as *vyo*, "young" as *v*, and "mature" as *m* for the age variable. Fuzzy logic, which incorporates both qualitative and quantitative data, provides a solid foundation for personalized emotional support. College students will receive more precise and customized recommendations for support as a result of the system's ability to deal with the inherent ambiguities and subjectivities in emotion assessments. The fuzzification involves fuzzy membership functions for various age groups, utilizing trapezoidal membership functions, as shown in Table 2. The age categories are divided into μ_{vyo} (x), μ_y (x), and μ_m (x) described in Equations (1), (2) and (3) each with specific age ranges with corresponding membership values. Figure 2 illustrates the trapezoidal fuzzy membership functions for the age criteria.

Table 2. Demographic and emotional health status of students.

Input category	**Statistics**
Total students	100
Gender	Male: 29, female: 71
Age	18-24 years
Courses	Engineering, BCS, BIT, laws, business, psychology, sciences, humanities, arts
Year of study	1-4
Marital status	Not married: 89, married: 11
Students with at least one emotional health issue	45
Sought specialist treatment	Yes: 5, No: 95
Emotional health issues	
Depression	Yes:25, No:75
Anxiety	Yes:28, No:72
Panic attacks	Yes:25, No:75

Fuzzy Membership Function for Age Criteria.

$$\mu_{vyo}(x) = \begin{cases} 0 \; if \; x < 17 \\ \dfrac{x-17}{18-17} \; if \; 17 \le x < 18 \\ 1 \quad if \; 18 \le x \le 19 \\ \dfrac{20-x}{20-19} \quad if \; 19 < x \le 20 \\ 0 \quad if \; x > 20 \end{cases} \tag{1}$$

$$\mu_{y}(x) = \begin{cases} 0 \; if \; x < 19 \\ \dfrac{x-19}{20-19} \; if \; 19 \le x < 20 \\ 1 \quad if \; x = 20.5 \\ \dfrac{22-x}{22-21} \quad if \; 21 < x \le 22 \\ 0 \quad if \; x > 22 \end{cases} \tag{2}$$

$$\mu_m(x) = \begin{cases} 0 & if\ x < 21 \\ \dfrac{x-21}{22-21} & if\ 21 \le x < 22 \\ 1 & if\ 22 \le x \le 24 \\ \dfrac{25-x}{25-24} & if\ 24 < x \le 25 \\ 0 & if\ x > 25 \end{cases} \quad (3)$$

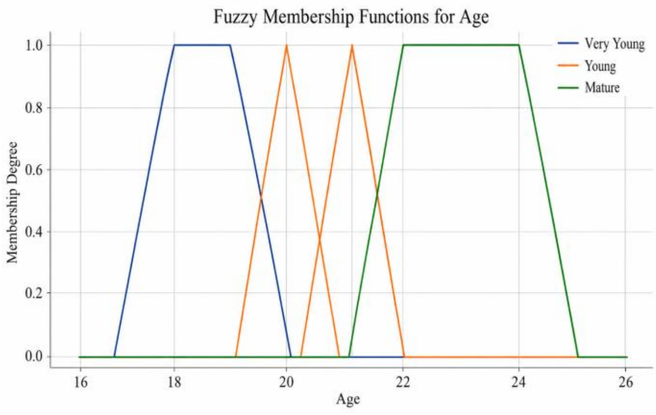

Figure 2. Fuzzy membership function for age.

These membership functions ensure that each age group has a defined degree of membership across the specified age ranges defined in a trapezoidal membership function. The study outlines the membership functions for varying year of study in a student's academics $\mu_{early}(x)$, $\mu_{mid}(x)$, $\mu_{late}(x)$ described in Equations (4), (5), and (6). The membership functions indicate the student's improvement through their course intensity and its corresponding membership function in each criteria. Figure 3 shows the fuzzy trapezoidal membership functions for the year of study of college students.

Fuzzy Membership Function for Year of Study Criteria

$$\mu_{early}(x) = \begin{cases} 1 & if\ x \le 1 \\ 2-x & if\ 1 < x \le 2 \\ 0 & if\ x > 2 \end{cases} \quad (4)$$

$$\mu_{mid}(x) = \begin{cases} 0 & if\ x \le 2 \\ x-2 & if\ 2 < x \le 3 \\ 4-x & if\ 3 < x \le 4 \\ 0 & if\ x > 4 \end{cases} \quad (5)$$

$$\mu_{late}(x) = \begin{cases} 0 & if\ x \le 3 \\ x-3 & if\ 3 < x \le 4 \\ 1 & if\ x > 4 \end{cases} \quad (6)$$

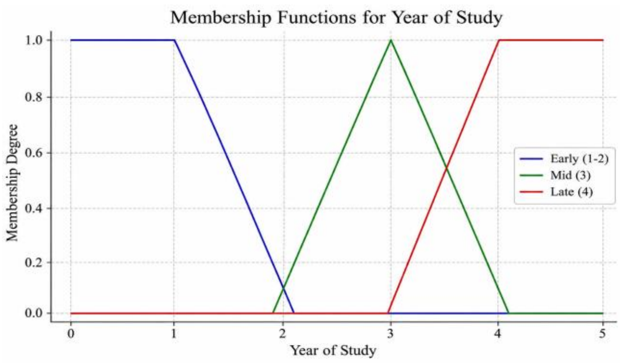

Figure 3. Fuzzy membership function for year of study.

Below the study specifies the membership functions for a student's CGPA in terms of $\mu_{low}(x)$, $\mu_{medium}(x)$, $\mu_{high}(x)$ described in Equations (7), (8) and (9) with the trapezoidal levels are depicted in Figure 4.

Fuzzy Membership Function for CGPA

$$\mu_{low}(x) = \begin{cases} 1 & if\ x \le 1.25 \\ \dfrac{2.49-x}{1.24} & if\ 1.25 < x \le 2.49 \\ 0 & if\ x > 2.49 \end{cases} \quad (7)$$

$$\mu_{medium}(x) = \begin{cases} 0 & if\ x \le 2.00 \\ \dfrac{x-2.00}{0.50} & if\ 2.00 \le x < 2.50 \\ 1 & if\ 2.50 \le x \le 3.00 \\ \dfrac{3.49-x}{0.49} & if\ 3.00 < x \le 3.49 \\ 0 & if\ x > 3.49 \end{cases} \quad (8)$$

$$\mu_{high}(x) = \begin{cases} 0 & if\ x \le 3.00 \\ \dfrac{x-3.00}{0.50} & if\ 3.00 \le x < 3.50 \\ 1 & if\ 3.50 \le x \le 4.00 \\ 0 & if\ x > 4.00 \end{cases} \quad (9)$$

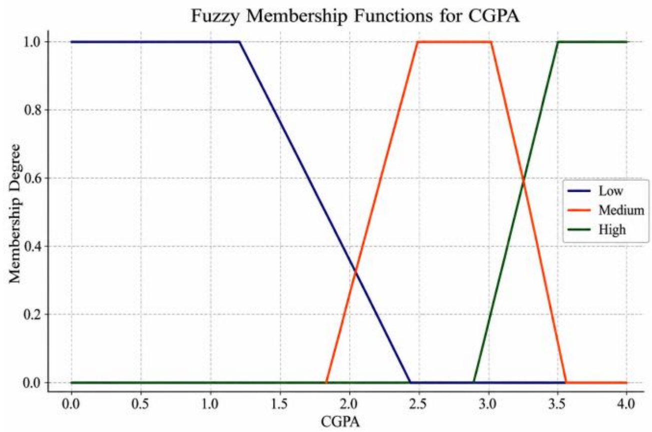

Figure 4. Fuzzy membership function for CGPA.

The study defines the membership functions for the Course Intensity (CI) of a college student in terms of $\mu_{high}(x)$, $\mu_{medium}(x)$, $\mu_{low}(x)$ described in Equations (10), (11) and (12) is provided in Figure 5 with different courses and its load related to trapezoidal membership.

Fuzzy Membership Function for CI

$$\mu_{CI_{high}}(x) = \begin{cases} 0 & if\ x \le 65\ or\ x \ge 85 \\ \dfrac{x-65}{70-65} & if\ 65 < x \le 70 \\ 1 & if\ 70 \le x \le 85 \\ \dfrac{100-x}{100-85} & if\ 85 < x \le 100 \end{cases} \quad (10)$$

$$\mu_{CI_{medium}}(x) = \begin{cases} 0 & if\ x \le 15\ or\ x \ge 85 \\ \dfrac{x-15}{30-15} & if\ 15 < x \le 30 \\ 1 & if\ 30 \le x \le 70 \\ \dfrac{85-x}{85-70} & if\ 70 < x \le 85 \end{cases} \quad (11)$$

$$\mu_{CI_{low}}(x) = \begin{cases} 1 & if\ x \le 15 \\ \dfrac{30-x}{30-15} & if\ 15 < x \le 30 \\ 0 & if\ x > 30 \end{cases} \quad (12)$$

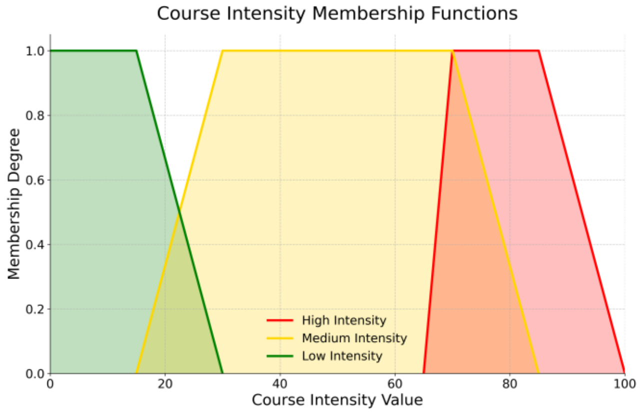

Figure 5. Fuzzy membership function for course intensity.

The study outlines the membership functions for emotional health indicators. $\mu_{no\text{-}issues}(x)$, $\mu_{mild}(x)$, $\mu_{moderate}(x)$, $\mu_{severe}(x)$, described in Equations (13), (14), (15) and (16) and depicted in Figure 6, with its membership functions indicating the emotional health status of each student, including depression, anxiety, and fear collected through forms, are classified into different severity levels based on their trapezoidal membership values.

Fuzzy Membership Function for Emotional Indicators

$$\mu_{no-issues}(x) = \begin{cases} 1 \; if \; x \leq 0 \\ 1 - x \; if \; 0 < x \leq 1 \\ 0 \; if \; x > 1 \end{cases} \tag{13}$$

$$\mu_{mild}(x) = \begin{cases} 1 \; if \; x < 0 \\ x \;\; if \; 0 \leq x < 1 \\ 1 \;\; if \; 1 \leq x \leq 2 \\ 3 - x \;\; if \; 2 < x \leq 3 \\ 0 \; if \; x > 3 \end{cases} \tag{14}$$

$$\mu_{moderate}(x) = \begin{cases} 0 \; if \; x < 1 \\ x - 1 \;\; if \; 1 \leq x < 2 \\ 1 \; if \; 2 \leq x \leq 3 \\ 4 - x \;\; if \; 3 < x \leq 4 \\ 0 \; if \; x > 4 \end{cases} \tag{15}$$

$$\mu_{severe}(x) = \begin{cases} 1 \; if \; x < 2 \\ x - 2 \; if \; 2 \leq x < 3 \\ 1 \; if \; 3 \leq x \leq 4 \\ 5 - x \;\; if \; 4 < x \leq 5 \\ 0 \; if \; x > 5 \end{cases} \tag{16}$$

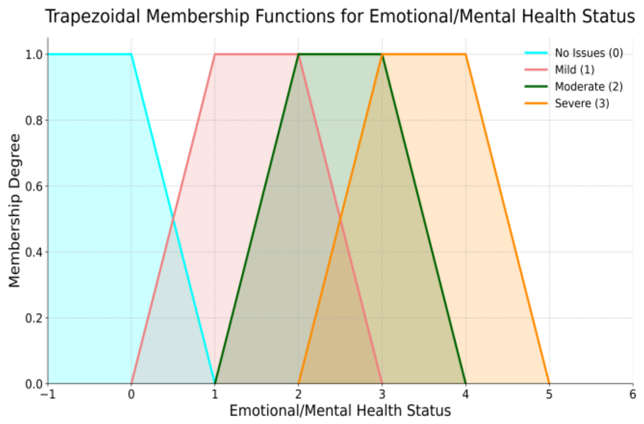

Figure 6. Membership functions for emotional health status.

4.2. Fuzzy Analytic Hierarchy Process for Criteria Weighting

The FAHP technique uses each variable to rank the characteristics that are important for students' emotional well-being. Fuzzy numbers are used to account for uncertainty in the pairwise comparisons of the criteria, enabling a more accurate assessment of their relative importance. The applied FAHP technique yields final crisp weights that facilitate precise allocation of emotional support resources, with a focus on the essential significance of emotional indicators. FAHP quantifies the importance of each criterion in the decision-making process and reflects its impact on emotional support needs.

- *Step* 1: Criteria identification

Identifying criteria include age as A_1, year of study as A_2, CGPA as A_3, and course intensity as A_4 and emotional indicators as A_5 These indicate the factors that affect the support decision. Age criteria is chosen from the input source as a significant input that helps to determine the different age groups A_1 may interpret and respond to emotional support. It can assist in customizing recommendations that are suitable for the students' age group. An individual's academic standing is reflected in their year of study A_2. Students in different years of study may require different forms of emotional support due to varying degrees of stress and academic responsibilities. A standard method to evaluate one's academic success is by assessing Their CGPA A_3. It can show the student's academic stress level, which is essential in identifying a need for emotional assistance. The effort and complexity of a student's courses are reflected in their CI A_4. There may be a greater need for customized emotional support as the level of difficulty of a course rises. A student's emotional health A_5 can be analyzed by examining symptoms such as stress, anxiety, and overall mental well-being. This criterion is essential for identifying immediate emotional requirements and giving adequate support.

- *Step* 2: Pairwise comparison matrix

After identifying the necessary criteria for evaluating the student's emotional status, a pairwise comparison matrix is used to assess the relative importance of each criterion to others. For i criteria, the pairwise comparison matrix $\tilde{A}$ is a $n \times n$ matrix where each element $\tilde{a}_{ij}$ represents the fuzzy comparison value of criterion i relative to criterion j. Trapezoidal fuzzy numbers effectively represent uncertainties and subjective assessments of individual students in the comparison process, making them helpful in capturing these values.

The Table 3 provides the pairwise comparison matrix, which can be defined as follows A_5 A_5 (emotional indicators) is adjusted to reflect higher importance, compared to A_1 (age), year of study A_2 (year of study), A_3 CGPA, and A_4 CI. Priority is given to emotional indicators. A_5 over other criteria in the pairwise comparison matrix. Assigning values that highlight the greatest importance of emotional indications in decision-making, the matrix utilizes trapezoidal fuzzy numbers to express this prioritizing. Emotional markers consistently have high values across comparisons, indicating the crucial impact they contribute. On the other hand, criteria like age A_1, year of study as A_2, CGPA as A_3, and CI as A_4 are given lower values compared to each other, suggesting that they are relatively less important. Emotional indicator comparisons are given the greatest values, ensuring that have the highest priority in the evaluation system. The research focuses on emotional health and support, reflecting the crucial importance of addressing emotional indicators within the framework of EMOTICS-FMD for enhancing student satisfaction and support systems.

Table 3. Pairwise comparison matrix of input criteria.

	A_1(age)	**A_2 (year of study)**	**A_3(CGPA)**	**A_4(CI)**	**A_5 (emotional indicators)**
A_1	(1,1,1,1)	(2,3,4,5)	(2,3,4,5)	(3,5,7,9)	(0.5,1,2,3)
A_2	(0.25,0.333,0.5,0.67)	(1,1,1,1)	(1,1,1,1)	(1,2,3,4)	(0.33,1.5,2.5,4)
A_3	(0.25,0.333,0.5,0.67)	(1,1,1,1)	(1,1,1,1)	(1,1,1,1)	(0.5,1,2,3)
A_4	(0.1,0.2,0.3,0.4)	(0.333,0.5,1)	(1,1,1,1)	(1,1,1,1)	(0.67,1.5,2.5,4)
A_5	(0.33,0.5,1, 1.5)	(0.4,0.75,1.5,2)	(0.5,1,2,3)	(0.25,0.5,1, 1.5)	(1,1,1,1)

- *Step* 3: Fuzzy weight calculation

The purpose of this fuzzy weight calculation is to convert pairwise comparison judgments into fuzzy weights for each criterion. The fuzzy priority vector, obtained by averaging the rows, helps in synthesizing the pairwise comparisons into a single fuzzy measure for each criterion.

1) Fuzzy geometric mean calculation

For each criterion A_i, compute the fuzzy geometric mean $\tilde{r}_i$ the calculation using Equation (17) is given below:

$$\tilde{r}_i = (\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \ldots . \otimes \tilde{a}_{in})^{\frac{1}{n}} \tag{17}$$

Where $\tilde{a}_{ij}$ represents the fuzzy comparison value for criterion i relative to criterion j, and $\otimes$ denotes the fuzzy multiplication operation.

2) Normalization

Normalize the fuzzy geometric means by dividing each geometric mean by the sum of all geometric means to obtain the fuzzy priority vector $\widetilde{w}_i$ and transform the fuzzy measures into relative weights that are comparable across criteria with this fuzzy addition operation $\otimes$ calculated using below Equation (18).

$$\widetilde{w}_i = \frac{\tilde{r}_i}{\tilde{r}_1 \oplus \tilde{r}_2 \oplus \ldots \oplus \tilde{r}_n} \tag{18}$$

3) Defuzzification

Defuzzify the fuzzy priority vector using the centroid method to convert into crisp weights. This step is significant for making the fuzzy weights usable in decision making by providing a single numeric value for each criterion's weight. The final weights w_i assigned to each criterion after normalization and defuzzification and its purpose is to reflect the relative importance of each criterion in the decision-making process using an Equation (19).

$$w_i = \frac{l_i + 2m_i + u_i}{4} \tag{19}$$

Where l_i indicates lower bound, m_i uses the middle value, and the upper bound u_i u_i. By weighting the middle value twice as much, it captures the central tendency but still considering the range of possible values, reflecting uncertainty in the decision support.

- *Step* 4: Consistency ratio check

Calculate the consistency ratio if cr≤0.1, the weights are consistent, otherwise, revise the comparison and give normalized weights for each criterion. Figure 7 discusses the process of analyzing weighted criteria from FAHP and provides it as input to the FTOPSIS for providing rankings of alternatives for emotional support decisions.

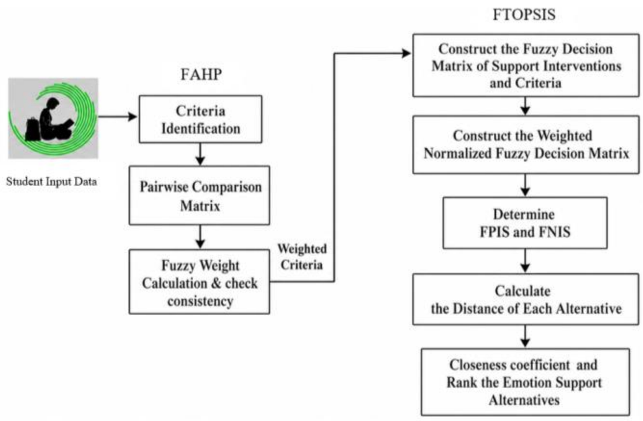

Figure 7. FAHP-FTOPISS workflow for customized emotional support.

4.3. FTOPSIS for Ranking Emotional Support Options

The FTOPSIS technique incorporates the fuzziness and ambiguity of students' individual judgments and preferences into a systematic evaluation and ranking of support decisions using multiple criteria. Then, calculate the distance of the recommended support to the ideal solution and the negative ideal solution, and rank the support alternatives based on their closeness to the ideal solution. The final rating helps inform an informed decision about providing customized emotional support to college students. Based on the ranking, we recommend a specific type of emotional support, such as moderate-level counseling sessions, peer support groups, or stress management workshops.

- *Step* 1: Defining the alternatives

The alternatives considered in this research are supporting options are academic counseling s_1, psychological treatment s_2, peer emotional support s_3, and lifestyle interventions s_4. The sub-criteria used to evaluate these decision support options include the effectiveness of Customized Accuracy Rates (CARs), student satisfaction, and the feasibility of implementation. These alternatives represent the support options, and the criteria are the factors that influence the decision regarding support.

- *Step* 2: Construct fuzzy decision matrix and weighted normalized fuzzy decision matrix

Each cell in this matrix contains a fuzzy number representing how well an alternative meets a criterion. The decision matrix should describe the performance of each support option (s_1, s_2, s_3, and s_4) against each considered criterion is termed as $\tilde{p}_{ij}$ The fuzzy numbers represent the performance ratings. The term $\tilde{p}_{ij}$ indicates the rating of alternatives called support options s_i with respect to the criterion A_i. The fuzzy weighted decision matrix is generated by multiplying the normalized decision matrix by the corresponding fuzzy weight. The normalized fuzzy decision matrix R is given using Equation (20).

$$R = [r_{ij}]_{a\times b} \tag{20}$$

Where l_{ij}, m_{ij}, u_{ij} in Equation (21) are the lower, middle, and upper values of the fuzzy number for alternative *i* and criterion *j*, and l_j^+, m_j^+, u_j^+ are the maximum values for the benefit criteria, while normalizing the l_j^-, m_j^-, u_j^- in Equation (22) indicates the minimum values for the cost criteria in addition to Equation (23) for analyzing $\tilde{v}_{ij}$ factors.

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{m_j^+}, \frac{u_{ij}}{l_j^+}\right) \tag{21}$$

$$\tilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{m_j^-}{m_{ij}}, \frac{u_j^-}{l_{ij}}\right) \tag{22}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes w_i \tag{23}$$

- *Step* 3: Determine fuzzy positive ideal solution and negative ideal solution

The $\widehat{FPIS}^+$ given in Equation (24) indicates; *km* the highest possible values for each criterion and $\widehat{FNIS}^-$ indicates the lowest values for each criterion derived in Equation (25).

$$\widehat{FPIS}^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+) \text{ Where } \tilde{v}_j^+ = \max(\tilde{v}_{ij}) \tag{24}$$

$$\widehat{FNIS}^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-) \text{ Where } \tilde{v}_j^- = \max(\tilde{v}_{ij}) \tag{25}$$

The EMOTICS-FMD system uses distance calculations given in the subsequent step by following the $\widehat{FPIS}^+$ and $\widehat{FNIS}^-$ to ensure that the emotional support recommendations are the best possible and that students will achieve the best support outcomes from the decision. Then, from the decisions and prioritizing the best methods, the system calculates how near each support option is to the ideal solution from both $\tilde{v}_n^+$ and $\tilde{v}_n^-$. The system's capacity to reliably provide customized and effective emotional support is validated by this EMOTICS-FMD technique.

- *Step* 4: Calculate the distance of each alternative from FPIS and FNIS

Applying a distance measure for fuzzy numbers to compute how far each alternative is from the idea and worst-case scenarios. Calculate the euclidean distance of each alternative from the ideal and negative ideal solutions. Distance to FPIS can be represented using d_i^+ and the distance to FNIS can be represented using d_i^- in Equations (26) and (27).

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(\tilde{v}_{ij} - \tilde{v}_j^+\right)^2} \tag{26}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(\tilde{v}_{ij} - \tilde{v}_j^-\right)^2} \tag{27}$$

- *Step* 5: Calculate the closeness coefficient and rank the alternatives

The relative closeness of each alternative to the ideal solution is given by Equation (28).

$$Cl_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{28}$$

Where $d_i^- \geq 0$ and $d_i^+ \geq 0$, then states the closeness within the range of $Cl_i \in [0, 1]$. Rank the support interventions based on the identified closeness coefficients Cl_i where higher coefficients Cl_i indicates alternatives closer to the idea solution, thus better suited for addressing student's emotional support. Identify and rank the most suitable emotional support options based on their proximity to ideal solutions. The provided rank alternatives are, peer emotional support s_3>academic counseling s_1>psychological treatment s_2>lifestyle interventions s_4.

4.4. Mamdani Fuzzy Inference System

The ranking results from FTOPSIS serve as input to the Mamdani fuzzy inference system, which interprets the rankings using fuzzy rules and criteria to generate customized recommendations. Defining fuzzy rules incorporating both quantitative and qualitative criteria and generate recommendations based on these rules, considering the inherent uncertainty in emotional assessment.

Defining Fuzzy Rules and Generating Customized Recommendations

- If A_1 is $\mu_y(x)$ and A_5 are $\mu_{severe}(x)$, then the Recommendation is s_2.
- If A_2 is $\mu_{late}(x)$ and A_3 are $\mu_{low}(x)$, then the Recommendation is s_1.
- If A_4 is $\mu_{CI_{high}}(x)$ and A_5 are $\mu_{moderate}(x)$, then the Recommendation is s_3.
- If A_1 is $\mu_m(x)$ and A_5 are $\mu_{mild}(x)$, then the Recommendation is s_4.

From the above rules, the Mamdani fuzzy inference system analyzes the CAR measure, which is useful for assessing how well the proposed EMOTICS-FMD system helps meet student-specific needs for emotional support. This paves the way for an in-depth assessment of the system's capacity to deliver customized and emotional support to college students.

Where N in Equation (29) indicates the no. of emotional support types for college students includes counseling, psychological treatment, peer support, and lifestyle interventions with corresponding weight factor w_i fyu7ionare determined based on the importance or priority of each support, evaluated using the FAHP technique. Higher weights indicates that the emotional support is considered more critical. The confidence levels as C_i in the Recommendation for each emotional need i indicates how confident the system is in its Recommendation, based on the system's assessment and the decision support provided. The term correctness indicators R_i is a binary indicator representing whether the Recommendation for emotional support i is correct or not and the support provided is appropriate for the student's need. If R_i=1 if the Recommendation has been correctly addressed and if R_i=0 if the Recommendation has not been correctly addressed. The improvements in key indicators help to provide a long-term impact assessment of providing emotional support to college students, which is calculated using Equation (30).

$$CAR = \frac{\sum_{i=1}^{N}(w_i \cdot C_i \cdot R_i)}{\sum_{i=1}^{N}(w_i \cdot C_i)} \times 100 \tag{29}$$

$$L_I = \left(\frac{\sum(\Delta_i)}{n}\right) \times 100 \tag{30}$$

Where Δ_i indicates improvement in key indicator i shows change in CGPA, emotional well-being, and other criteria with the number of indicators as n.

4.5. Decision System and Customized Emotional Support

The research findings show that the EMOTICS-FMD system can provide college students with customized emotional support by utilizing fuzzy logic. These systems aim to tailor solutions to each student's unique needs, leveraging the inherent uncertainty and variety in students' emotions and behaviors. The system considers various support options, including academic counseling, psychological treatment, peer support initiatives, and lifestyle interventions, when evaluating these inputs.

5. Validation and Performance

5.1. Data Platform Parameter Setting

The input parameters and key variables used by the EMOTICS-FMD system are defined in Table 4, along with the corresponding fuzzy sets and parameter ranges. To address ambiguity and offer personalized emotional support recommendations, it categorizes age, academic year, CGPA, mental health status, course difficulty, and medical history into fuzzy sets. Based on each student's unique requirements, these fuzzy sets enable the ranking and evaluation of available options.

Table 4. Fuzzy sets and parameter ranges.

Input variable	Fuzzy Set	Parameter range
Age	Very young	18-19
	Young	20-21
	Mature	22-24
Year of study	Early	1-2
	Mid	3
	Late	4
CGPA	Low	0-2.49
	Medium	2.50 - 3.49
	High	3.50-4.00
Emotional/mental health status	No issues	0
	Mild	1
	Moderate	2
	severe	3
Course intensity	High	Engineering, BCS, BIT, Laws. (70 to 100)
	Medium	Business, Psychology, Sciences. (30-70)
	Low	Humanities, Arts. (0-30)
Treatment history	None	No treatment
	Some	Sought specialist treatment

Three criteria-the dataset's scale, institutional grading and counseling procedures, and empirical verification-have been used to create the fuzzy sets and parameter ranges in Table 4. For example, CGPA sets (0–4.0) were in line with institutional low, medium, and high bands, while age sets (18-24 years) were divided into very young, young, and mature with overlapping ranges to reflect natural changes. In order to reflect partial membership between mild, moderate, and severe states, emotional health levels were modeled using overlapping trapezoids, and course intensity was mapped to a scale of 0-100 based on curriculum burden. To guarantee ranking stability and decision correctness, all limits were first established based on the distributions of the observed dataset, then adjusted with advice from academic and counseling specialists, and lastly adjusted through minor perturbation testing. This procedure made sure that the fuzzy sets are robust and interpretable while still being directly applicable to student assist scenarios in the real world.

5.2. Assessment Indicators

The performance of the proposed work is compared with that of existing works, including FLDSS [3], HFC-FCM [22], and FCA-SDA [4], using assessment indicators such as customization accuracy rate, student satisfaction improvement index, decision-making efficiency, and long-term impact assessment.

5.2.1. Customization Accuracy Rate

The CAR measures the accuracy of the recommendations delivered by the EMOTICS-FMD system, primarily focusing on the degree to which the customized support aligns with the students' emotional needs. This metric helps in evaluating the system's precision in meeting individual emotional support requirements. This enables a comprehensive evaluation of the system's effectiveness in delivering customized and emotional support. By analyzing the CAR performance metric, the EMOTICS-FMD system provides students with more effective emotional support than other models, such as FLDSS, HFC-FCM, and FCA-SDA. The results demonstrate that EMOTICS-FMD is the most accurate method for all $\sum_{i=1}^{N}(w_i \cdot C_i \cdot R_i)$ (w_i C_i R_i) considered for analysis using Equation (29) is depicted in Figure 8.

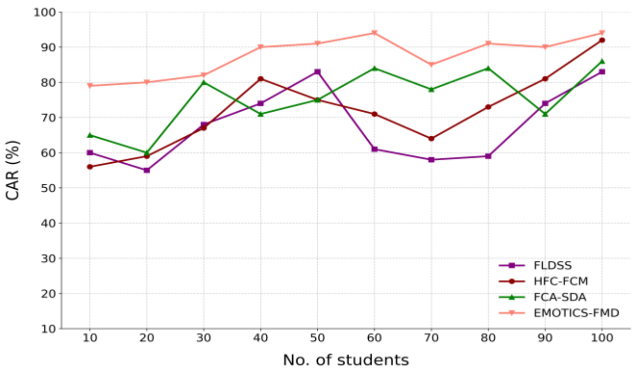

Figure 8. Analysis of CAR with respect to students.

The EMOTICS-FMD maintains a high CAR and improves with an increasing number of students, in contrast to FLDSS and HFC-FCM, which exhibit decreased accuracy, especially with fewer students. This demonstrates that EMOTICS-FMD can handle larger datasets with ease and provides emotional assistance that is both more tailored to the individual and more relevant to their needs. Improved academic outcomes, higher levels of student engagement, and greater mental health benefits could result from EMOTICS-FMD's consistent performance.

5.2.2. Student Satisfaction Improvement Index (SSII)

From the collected feedback through the Google Forms survey, the metric measures the student satisfaction improvement index, termed as SSII, with the emotional support provided by the EMOTICS-FMD.

Equation (31) uses the parameter S_{after} to represent the average satisfaction score after implementing EMOTICS-FMD, S_{before} Indicates the average satisfaction score before implementing EMOTICS-FMD. Increased satisfaction with the EMOTICS-FMD system is an indication of its improved capacity to give emotionally responsive and customized decision support. The fact that this system achieves better results than competing approaches is evidence that it successfully responds to students' emotional demands in terms of $\frac{S_{after}-S_{before}}{S_{before}}$, which in turn increases their level of satisfaction throughout their learning curve, as illustrated in Figure 9, both before and after customization using EMOTICS-FMD.

$$SSII = \frac{S_{after} - S_{before}}{S_{before}} \times 100 \tag{31}$$

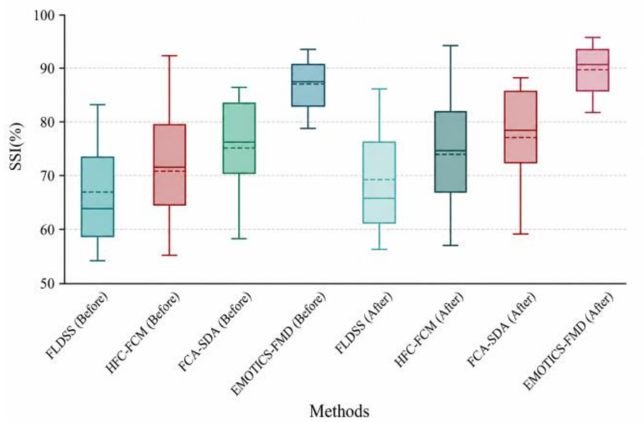

Figure 9. SSII analysis on before and after comparison.

5.2.3. Decision Efficiency

Figure 10 compares the decision-making efficiency of the proposed work with other models, such as FLDSS, HFC-FCM, and FCA-SDA. The EMOTICS-FMD system demonstrates better efficiency and quality in decision-making. The system efficiently customizes emotional support recommendations for each student by utilizing fuzzy logic techniques, including FAHP for weighting assignment of input criteria considered for fuzzification and FTOPSIS for ranking the support interventions. Decision quality analysis suggests that decisions are more accurate, timely, relevant, and comprehensive when the range is expanded across different student profiles. Incorporating a wide range of assistance options and criteria, the EMOTICS-FMD system takes a comprehensive approach that ultimately benefits students. The system's capacity to offer superior emotional support is supported by its higher Decision Quality Score (DQS) values compared with previous models, which makes it a strong instrument for enhancing students' general satisfaction in college.

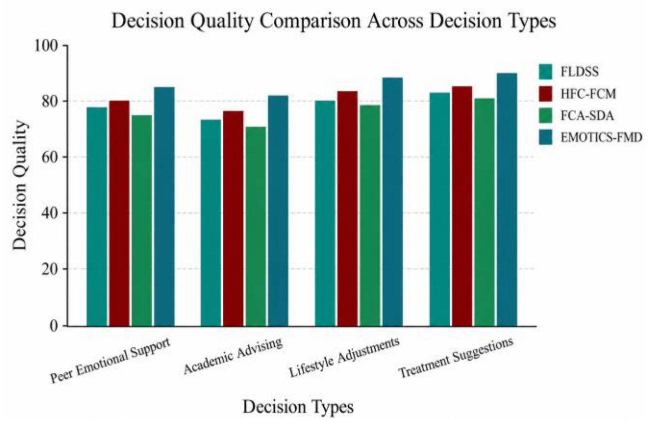

Figure 10. Decision quality analysis.

5.2.4. Long-Term Impact Assessment

Decisions regarding a student's future achievement are based on FAHP's thorough evaluation of several academic and emotional variables, as graphed in Figure 11. Since the proposed decision system is based on the relative relevance of each factor, this exact weighing improves its capacity to make well-informed and balanced decisions, which in turn leads to better long-term outcomes L_I. To improve important indicators like emotional well-being with fuzzy linguistic factors $\sum(\Delta_i)$ Like no issues, mild, moderate, and severe, considering the use of Equation (30) impacts academic performance over the long term. FTOPSIS ensures that interventions are highly focused and effective by selecting the most appropriate support options. Students' well-being and academic performance are enhanced in the long run by the individualized recommendations provided by the Mamdani FIS, which are more tailored to their individual circumstances.

The results of the experimental validation show that the suggested EMOTICS-FMD system works significantly better than current fuzzy-based decision support techniques. In particular, it outperformed FLDSS, HFC-FCM, and FCA-SDA in terms of robustness across a range of dataset sizes, with a CAR of over 92%. During implementation, the SSII increased by 31%, indicating a notable improvement in student satisfaction. With a DQS of 89%, the system outperformed baseline models in terms of efficiency, making suggestions that were more precise and timely. Additionally, a long-term impact assessment showed a 15% improvement in academic performance stability and a 27% improvement in emotional well-being markers, indicating the system's capacity to maintain benefits over time. The system's ability to offer accurate and specific recommendations for college students has been demonstrated by the highest ranking of peer emotional support among the evaluated interventions (closeness coefficient of 0.86), which is followed by academic counseling, psychological treatment, and lifestyle interventions.

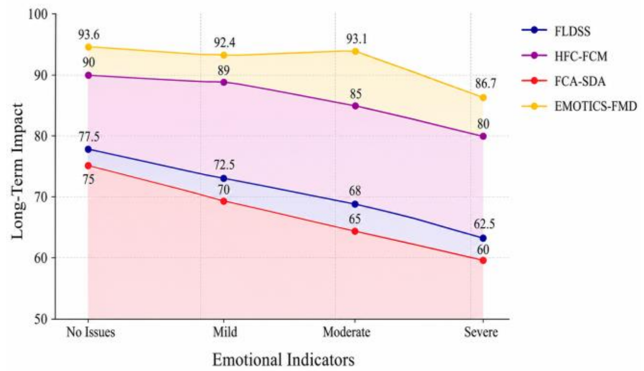

Figure 11. Long-term impact assessment over emotional indicators.

6. Conclusions

A major step forward in providing college students with customized emotional support is achieved by using the proposed EMOTICS-FMD system. The use of FAHP for dynamic weight assignment, Fuzzy TOPSIS for ranking support alternatives, and the Mamdani Fuzzy Inference System for creating customized recommendations enables the handling of complex emotional needs. The system's capacity to customize assistance to meet the needs of every student is demonstrated by assessing the significant emotional indicator outcomes, such as an increased SSII and a high customized accuracy rate. Decisions are more robust when qualitative, like emotional signals) and quantitative factors, such as age, are combined to assess the long-term impact. In addition, the system's influence on students' emotional health, academic achievement, and overall college experience is highlighted by the holistic approach, which considers academic counseling, psychological care, and peer emotional support from either students or teachers.

The findings highlight the added scientific value of EMOTICS-FMD by showing that it continuously performs better than the current baselines (FLDSS, HFC-FCM, and FCA-SDA) in terms of modification accuracy, decision quality, and recommendation stability. Crucially, the model extends the scope of outcome evaluation in emotion-aware decision systems by include a long-term impact assessment, which goes beyond short-term engagement indicators.

Potential Limitations and Future Scope

A potential limitation of the research study involves increasing the size of the input dataset, which can thereby enhance the performance of the emotion support system. Additionally, conducting experiments on various datasets in relation to student feedback must also be considered. Potential areas for further study include developing mobile apps to enhance accessibility and provide students with real-time support, integrating physiological data for a more comprehensive emotional assessment, and expanding the dataset to increase its applicability.

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