A Fuzzy Logic-Based Framework for Adaptive Learning Pathways

Oluyemisi Adenike Oyedemi
Department of Cybersecurity, University of Ilesa, Ilesa, Nigeria
yemisi.oyedemi@unilesa.edu.ng

***Abstract*—This paper presents a fuzzy logic-based adaptive learning framework designed to personalize educational experiences for individual learners. Using Fuzzy C-Means (FCM) clustering, the system models overlapping learner profiles based on normalized behavioral, cognitive, and performance features. Personalized learning pathways are generated by weighting cluster-specific content templates according to individual cluster memberships, allowing each learner to receive tailored instructional material. The system further adapts over time by incorporating dynamic feedback, enabling iterative updates to learner profiles and pathway assignments. Experimental validation on a synthetic dataset demonstrates the approach's effectiveness, achieving a high Fuzzy Partition Coefficient (FPC = 0.80), low Partition Entropy (PE = 0.36), a mean learner feedback score of 4.10, and a reduced Dropout Likelihood of 9%. These results suggest that the proposed model holds promise for adaptive content delivery in educational technology platforms.**

***Index Terms*—Fuzzy C-Means, Adaptive Learning Systems, Personalized Learning Pathways, Fuzzy Logic**

I. Introduction

The increasing demand for learner-centered education has driven the development of intelligent educational systems capable of delivering personalized content [1]. Traditional learning environments often struggle to accommodate the diverse needs, preferences, and progress rates of individual learners [2], [3]. Current systems often treat learner knowledge as binary (known/unknown), failing to capture partial understanding and overlapping competencies, which limits the personalization of learning pathways. Adaptive learning systems aim to address this challenge by dynamically tailoring instructional pathways based on learner data, fostering more effective and engaging educational experiences [4].

Fuzzy logic offers a compelling foundation for modeling the uncertainty and variability inherent in learner behaviors and preferences [5], [6]. Unlike hard clustering methods, fuzzy clustering, specifically Fuzzy C-Means (FCM), enables learners to exhibit partial membership across multiple clusters, thereby supporting nuanced representations of learner profiles. This flexibility is particularly useful in education, where learners often display overlapping cognitive, behavioral, and motivational characteristics.

This study proposes a fuzzy-based adaptive learning framework that integrates FCM clustering with dynamic feedback mechanisms to construct and continuously update personalized learning pathways. The system begins by preprocessing learner data, including normalization and encoding of demographic, interaction, and performance features. Learners are clustered using FCM, and each cluster is associated with a learning content template. Personalized pathways are created by aggregating content across clusters according to individual membership degrees [7]. As learners interact with the system, feedback is collected and used to update profiles, enabling the re-clustering of learners and regeneration of personalized pathways.

The framework was implemented and evaluated through simulated experiments using synthetic learner data. The results demonstrate strong clustering performance and learner satisfaction metrics, indicating the potential of the proposed approach to support adaptive content delivery in educational technology systems.

This paper makes the following key contributions:

- Development of a fuzzy logic-based adaptive learning framework using Fuzzy C-Means clustering to model overlapping learner profiles.
- Generation of personalized learning pathways through membership-weighted aggregation of cluster-specific content templates.
- Dynamic updating of learner profiles and pathways through iterative feedback-driven re-clustering.
- Experimental validation demonstrating effective clustering performance (FPC = 0.80, PE = 0.36) and positive learner feedback (mean score 4.10) with reduced dropout likelihood (9%).

II. Literature Review

The development of personalized and adaptive educational systems has gained significant attention as digital learning platforms strive to accommodate diverse learner populations [8]. Traditional clustering techniques, such as k-means, are commonly used to categorize learners based on performance metrics [9]. However, these methods assign learners to rigid, fixed groups, overlooking the overlapping, flexible, and evolving nature of learner profiles. Such limitations are critical in real-world settings, where learners often display behaviors that span multiple categories and exhibit uncertainty and ambiguity in their learning progression [10].

Fuzzy logic offers a compelling alternative by enabling partial membership across multiple clusters, thereby more accurately reflecting the complex and dynamic characteristics of learners. This fuzzy clustering approach is well-suited for modeling variations in cognitive abilities, learning preferences, and socio-cultural backgrounds, enabling the creation of adaptive learning pathways that respond to individual learners'

needs [11]. The application of fuzzy logic aligns with principles of inclusivity and Universal Design for Learning (UDL), facilitating multiple means of representation and engagement [12], [13].

Several fuzzy logic-based systems have been developed to improve adaptive learning. For example, fuzzy decision-making has been applied in adaptive testing platforms to select appropriate questions or resources, enhancing personalization [14]. However, these systems often lack a comprehensive framework to design inclusive learning pathways that consider multiple learner dimensions simultaneously.

Other approaches, such as Hidden Markov Models and reinforcement learning, have been used to model learner behaviors and personalize learning paths [15], [16]. While effective in certain aspects, these methods either fail to capture overlapping learner profiles or rely on clearly defined reward signals, limiting their ability to handle ambiguous learner preferences. Fuzzy logic inherently addresses these challenges by accommodating uncertainty and partial memberships.

Rule-based recommendation systems and AI-based predictive models also contribute to personalizing education but often produce deterministic outputs that do not fully represent the nuanced or uncertain aspects of learner profiles [17], [18]. In contrast, fuzzy logic-based frameworks offer greater flexibility and inclusivity, making them well-suited to adaptive educational technology that supports diverse learners.

A. Proposed Work

The framework of the proposed system is shown in Fig. 1. It is grounded in fuzzy logic theory, enabling the system to handle uncertainty and overlapping student characteristics effectively. Fuzzy logic allows partial membership across multiple learning clusters, in contrast to traditional clustering methods that place students into rigid groups. This better reflects the varied and ever-changing nature of student learning needs and preferences. This creates a learning environment in which students receive individualized instruction tailored to their unique challenges and strengths, encouraging participation and academic achievement.

The system begins with data collection, which includes gathering a variety of learner data such as quiz attempts, quiz scores, assignment completion rates, engagement levels, learning style, and behavioral indicators. This comprehensive dataset forms the foundation for building individualized learner profiles. The collected data is processed through the Fuzzy clustering module. This module groups learners by assigning them degrees of membership in multiple clusters based on shared attributes. This approach more accurately captures the nuanced and overlapping nature of learner traits. These fuzzy clusters are then used by the Content Adaptation module to customize learning resources and pathways. Learning content is tailored to each student's needs, preferences, and performance level, creating a more inclusive learning environment. Finally, the feedback loop continuously monitors learner engagement and performance. This real-time feedback informs iterative updates to both clustering and content delivery strategies, allowing the system to evolve in tandem with the learner's progress. The integration of the framework into learning modules fosters an educational environment that promotes adaptive learning.

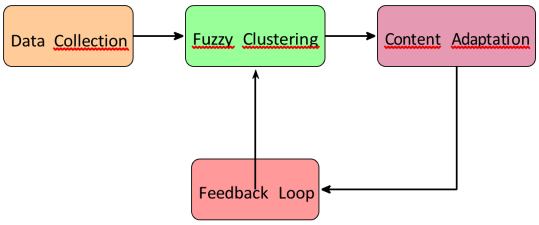


Fig. 1. Proposed Fuzzy Logic-Based Adaptive EdTech Framework for Inclusive Learning Pathways (Author's Illustration)

III. METHODOLOGY

This section outlines the methodology of the proposed fuzzy logic–based adaptive framework. It presents dataset description, data preprocessing, adaptive clustering, personalised learning pathways, and the evaluation metrics.

A. Dataset Description

The dataset used in this study was sourced from Kaggle, a reputable data repository. It consists of 10,000 records of students' interaction data collected from an online learning platform. The detailed features of the dataset presented in Table 1 include key indicators related to learner engagement, demographic attributes, and academic outcomes, making it well-suited for the analysis of adaptive learning models and personalizing educational content.

Let the dataset be denoted as $X = \{x_1, x_2, \ldots, x_N\}$, where each $x_i \in R^d$ represents a learner's profile in a d-dimensional feature space. Each vector x_i contains a combination of demographic information, behavioral patterns, performance metrics, engagement signals, and learning preferences. The diversity and richness of the dataset support the development of fuzzy learner profiles and the design of adaptive pathways.

B. Data Preprocessing

The dataset was imported using the pd.read_csv() function from the pandas library to conduct the simulation experiment to validate the effectiveness of the proposed framework. Categorical variables such as Gender, Education_Level, and Learning_Style were one-hot encoded to convert them into binary vectors suitable for machine learning algorithms. The ordinal variable Engagement_Level was mapped to numerical values (Low = 0, Medium = 0.5, High = 1), while the binary target variable Dropout_Likelihood was encoded as 0 (No) and 1 (Yes). Features including Age, Time_Spent_on_Videos, Quiz_Scores, Final_Exam_Score, Assignment_Completion_Rate, Forum_Participation, Quiz_Attempts, and Feedback_Score were normalized using Min-Max scaling to transform their values into the [0,1] range using:

$$x'_{\{i,j\}} = \frac{(x_{\{i,j\}} - \min(x_j))}{\max(x_j) - \min(x_j)} \quad (1)$$

where:

- $x_{i,j}$ is the original value of the j^{th} feature for the i^{th} sample,
- $\min(x_j)$ and $\max(x_j)$ are the minimum and maximum values of the j^{th} feature across all samples,
- $x'_{i,j}$ is the normalized value of the j^{th} feature for the i^{th} sample, scaled to the range $[0,1]$.

The dataset was split into training (80%) and testing (20%) subsets using Scikit-learn's train_test_split() function to enable unbiased model evaluation. The algorithmic representation of the data preprocessing pipeline is given in Algorithm 1.

Algorithm 1 Data Preprocessing Pipeline

Input: Raw dataset (CSV)
Output: Cleaned and preprocessed dataset

1 Import dataset using pd.read_csv()
2 Check for missing values
3 If missing values exist: Apply appropriate imputation
4 Else: Proceed without imputation
5 Apply one-hot encoding to: Gender, Education_Level, Learning_Style
6 Map Engagement_Level to numerical values: Low → 0, Medium → 0.5, High → 1
7 Encode Dropout_Likelihood: No → 0, Yes → 1
8 Normalize continuous features using Min-Max scaling
9 Split dataset into training (80%) and testing (20%) sets using train_test_split()

C. Adaptive Clustering and Personalized Learning Pathways

The preprocessed dataset was subjected to Fuzzy C-Means (FCM) clustering to capture overlapping learner profiles. This makes it possible for each learner to have varied levels of affiliation with several clusters, allowing for a more complex depiction of learner attributes. The clustering process aims to minimize the objective function using:

$$J_m = \sum_{i=1}^{N} \sum_{K=1}^{C} u_{\{ik\}}^{m} | x_i - c_k |^2 \quad (2)$$

where N is the number of learners, C the number of clusters, u_{ik} the membership degree of learner x_i in cluster k, c_k the centroid of cluster k, and m the fuzzifier. Membership degrees and centroids are updated iteratively as follows:

$$U_{ik} = \frac{1}{\sum_{j=1}^{c} (\frac{\| xi - ck \|}{\| xi - c\, j \|})^{\frac{2}{m-1}}} \;, C_k = \frac{\sum_{i=1}^{N} U_{ik}^{m} x_i}{\sum_{i=1}^{N} U_{ik}^{m}} \quad (3)$$

The iteration continues until the maximum change in membership values falls below a convergence threshold ε:

$$max \left| U_{ik}^{(t+1)} - U_{ik}^{(t)} \right| < \varepsilon \quad (4)$$

Each cluster is associated with a content template L_k, which is represented as a structured feature vector in a multidimensional content space. Specifically, each template is defined as:

$$L_k = [d_k, c_k, m_k, t_k]$$

where:

- d_k denotes the difficulty level of the learning content,
- c_k represents the content type,
- m_k represents the preferred learning modality,
- t_k denotes the estimated time required to complete the content.

This vector representation enables mathematical operations such as weighted aggregation using fuzzy membership values. Based on the resulting membership values, personalized learning pathways L_i for each learner are constructed by weighting cluster-specific learning content L_k according to cluster membership degrees:

$$L_i = \sum_{k=1}^{C} U_{ik} \, . \, L_k \quad (5)$$

The resulting personalized learning pathway L_i is therefore a weighted combination of content feature vectors, where each component reflects the learner's degree of association with the corresponding cluster. This produces a composite representation of learning content tailored to the learner's profile.

Learner profiles are continuously updated over time to reflect engagement and performance feedback. At each iteration $(t+1)$ a learner's profile vector x_i^{t+1} is updated by combining the previous profile $x_i^{(t)}$ and a new feedback vector P_i as follows:

$$x_i^{(t+1)} = \propto . \, x_i^t + (1 - \propto) . \, P_i \quad (6)$$

where $\alpha \in [0,1]$ controls the relative weighting of past profiles versus new feedback. This dynamic updating feeds back into the FCM clustering step, ensuring that learner clusters and personalized pathways evolve in response to ongoing learner progress.

Fig. 2 presents the process flow of the proposed framework. The system begins with the raw data module, which consists of learner information collected within the educational platform. The dataset is cleaned by the preprocessing module, which normalizes and encodes the raw inputs into a consistent format. After preprocessing, the data is fed into the FCM clustering module, which identifies groups of learners with similar characteristics. The pathway generator module constructs personalized learning paths by combining educational content tailored to each cluster. This approach enables the creation of adaptable and inclusive learning experiences that cater for learners' unique needs.

TABLE I: DESCRIPTION OF DATASET COLUMNS

Feature	**Description**
Student_ID	A unique identifier assigned to each student.
Age	The age of the student (ranging from 15 to 50 years).
Gender	The gender of the student (Male, Female, or Other).
Education_Level	The current education level of the student (High School, Undergraduate, or Postgraduate).
Course_Name	The name of the course the student is enrolled in (e.g., Machine Learning, Python Basics, Data Science, etc.).
Time_Spent_on_Videos	The total minutes spent watching educational videos.
Quiz_Attempts	The number of times a student attempts quizzes.
Quiz_Scores	The percentage score obtained in quizzes.
Forum_Participation	The number of forum discussions the student has participated in.
Assignment_Completion_Rate	The percentage of completed assignments by the student.
Engagement_Level	An ordinal measure of learner engagement (Low, Medium, High).
Final_Exam_Score	The student's final score in the course examination.
Learning_Style	Preferred learning modality (Visual, Auditory, Kinesthetic, Reading/Writing).
Feedback_Score	A numerical score indicating the student's satisfaction or perceived usefulness of the course.
Dropout_Likelihood	Indicates whether a student dropped out (Yes or No).

The tailored learning pathways are then implemented in the content delivery module, where personalized instructional materials and activities are presented to learners through the platform. As learners interact with this content, their behaviors, performance, and engagement are continuously monitored and recorded in the learner interaction logs module. These logs serve as a source of real-time feedback about learner progress and challenges. The feedback engine module analyzes interaction logs to dynamically update learners' profiles. The system adjusts the learner group and regenerates new learning pathways based on the learners' cognitive status. This enables content to be delivered to learners based on their learning progress. This process supports an adaptive educational environment for diverse learners. The algorithmic representation of the adaptive logic is given in Algorithm 2.

D. Evaluation Metrics

The clustering quality of the proposed framework was evaluated using Fuzzy Partition Coefficient (FPC) and Partition Entropy (PE), while the feedback score and dropout rate measured the learners' satisfaction and engagement. The evaluation results from these metrics validate the adaptiveness of learning pathways.

- Fuzzy Partition Coefficient (FPC): This evaluates quality of the fuzzy clusters formed during the FCM process. It is computed as:

$$FPC = \frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{C} u_{ik}^2 \quad (7)$$

where $u_{ik} \in [0,1]$ denotes the degree of membership of learner x_i in cluster c_k, N is the total number of learners, and C is the total number of clusters. Higher FPC values indicate more distinct and well-formed clusters.

- Partition Entropy (PE): This measures the uncertainty associated with cluster memberships. It is computed as:

$$PE = -\sum_{i=1}^{N} \sum_{k=1}^{C} U_{ik} \log(U_{ik}) \quad (8)$$

Lower PE values indicate greater confidence in learner cluster assignments, thereby improving personalization precision.

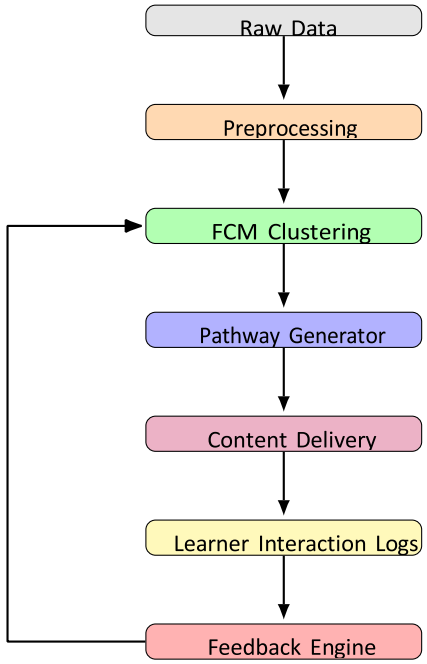


Fig. 2. Process Flow of the Adaptive Learning System (Author's Illustration)

Algorithm 2 Fuzzy-Based Adaptive Learning Algorithm

- Normalize and encode all learner features in the dataset.
- Initialize fuzzy membership matrix u_{ik} randomly.
- Repeat until convergence $max\left|U_{ik}^{(t+1)} - U_{ik}^{(t)}\right| < \varepsilon$:

∗ Compute cluster centroids $C_k = \frac{\sum_{i=1}^{N} U_{ik}^{m} x_i}{\sum_{i=1}^{N} U_{ik}^{m}}$

∗ Update membership degrees

$$U_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|xi-ck\|}{\|xi-cj\|}\right)^{\frac{2}{m-1}}}$$

- Construct personalized learning pathways

$$L_i = \sum_{k=1}^{C} U_{ik} . L_k$$

- During each learning iteration:
  - ∗ Monitor learner performance and engagement to generate feedback vector P_i.
  - ∗ Update learner profile using weighted feedback:

$$^{(t+1)}x_{i.} = \alpha \cdot x_i^{(t)} + (1-\alpha) \cdot P_i$$

  - ∗ Recompute cluster centroids and membership degrees using updated x_i^{t+1}
  - ∗ Regenerate personalized learning pathways l_i based on updated memberships.

- Feedback Score Mean and Variance: These reflect overall satisfaction among learners, indicating how well the personalized content and delivery met their expectations. It is computed as:

$$\mu_F = \frac{1}{N}\sum_{i=1}^{N} F_i,\ \sigma_F^2 = \frac{1}{N}\sum_{i=1}^{N}(F_i - \mu_F)^2 \qquad (9)$$

where $F_i \in [1,5]$ denotes the learner feedback score corresponding to a Likert scale with the following qualitative ratings: Very Poor (1), Poor (2), Neutral (3), Helpful (4), and Very Helpful (5).

- Dropout Likelihood (DL): Indicates the proportion of learners who disengaged from the course. A lower rate suggests the adaptive system supports learner retention through personalized content delivery. It can be computed as:

$$DR = \frac{|\int_d|}{|\int|} \times 100\% \qquad (10)$$

where $|\int_d|$ is the number of learners who disengage (i.e., incomplete pathways, low activity threshold), offering a retention signal sensitive to personalization quality.

E. Simulation Design

The feedback score and the dropout behaviour were simulated to evaluate the adaptive performance of the proposed framework. Feedback scores were computed as the degree of alignment between each learner's feature vector and their personalized learning pathway. Learners with higher cluster membership coherence, i.e., stronger association with dominant clusters, were assigned higher feedback scores, while learners with more uncertain or distributed memberships received lower scores. Dropout likelihood was simulated using a rule-based approach incorporating key learner attributes,
including engagement level, assignment completion rate, and content alignment. Learners exhibiting low engagement, low completion rates, and weak alignment with recommended learning pathways were assigned a higher probability.

Each learner is modeled as an agent whose feedback P_i and dropout likelihood are dynamically determined based on their current profile and learning experience. The feedback score of each learner is computed as a weighted aggregation of their membership degrees across clusters:

$$P_i = \sum_{k=1}^{C} U_{ik} . S_k \qquad (11)$$

where U_{ik} is the membership degree of learner i to cluster k and S_k is a simulated satisfaction score associated with the cluster's content.

Each learner's probability of disengagement is calculated as a function of engagement level, assignment completion rate, and alignment with the recommended learning pathway.

Learners with low engagement, low completion rates, or poor content alignment are assigned a higher probability of dropping out.

The learner profile vector is updated iteratively using:

$$S_i^{(t+1)} = \alpha . x_i^t + (1 - \alpha) \cdot P_i \qquad (12)$$

where $\alpha \in [0,1]$ balances the influence of prior profile and new feedback. Updated profiles feed back into the FCM clustering to regenerate personalized learning pathways.

This environment setup ensures that the simulated agents exhibit realistic feedback and dropout behavior, enabling a controlled evaluation of the adaptiveness and effectiveness of the fuzzy-based personalized learning framework.

F. Implementation

The proposed fuzzy-based adaptive learning model was implemented in Python using the preprocessed dataset (Table 1) and the scikit-fuzzy library, which facilitated fuzzy clustering, membership computation, and evaluation. Other Python libraries, such as pandas and numpy, were employed for data preprocessing, while matplotlib and seaborn were used for visualization and presentation of results. The profiles of learners and their interactions were simulated in Python to experimentally validate the performance of the proposed framework.

Learners were represented as vectors in a feature space, forming the data matrix $\boldsymbol{X} \in \mathbb{R}^{N \times d}$, where N is the number of learners and d is the number of selected features. FCM clustering was applied to group learners with overlapping memberships, enabling nuanced learner segmentation. The parameters, including the number of clusters C, fuzzifier m, and convergence threshold ε, were determined through empirical tuning to optimize model performance. The number of clusters C was varied from 2 to 10, with $m = 2$ and $\varepsilon = 10^{-5}$. Personalized learning pathways for each learner were generated by combining cluster-specific content templates weighted by the learner's membership degrees using:

$$L_i = \sum_{k=1}^{C} U_{ik} \cdot L_k \qquad (13)$$

where U_{ik} represents the membership degree of learner i to cluster k, and L_k is the content template associated with cluster k. Following profile updates, FCM clustering was reapplied to capture learner evolution over time, allowing dynamic adaptation of learning paths.

IV. Results and Discussion

This section presents the evaluation results of the proposed fuzzy-based adaptive learning model. The fuzzy clustering process was performed using Fuzzy C-Means (FCM), and its effectiveness was evaluated using the Fuzzy Partition Coefficient (FPC) and Partition Entropy (PE). As shown in Table II and visualized in Fig. 3, the configuration with $C = 5$ yielded the most optimal clustering quality, with the highest FPC value of 0.80 and the lowest PE value of 0.36. This indicates a balance between distinct clusters and moderate overlap, a desirable characteristic in fuzzy systems that aim to model nuanced learner profiles.

The feedback scores and Dropout Likelihood presented are derived from the simulation environment. These results are based on the assumption that each learner is modeled as an agent whose feedback and engagement behavior depend on the alignment between their profile and the personalized learning pathway, as well as their engagement level and assignment completion rate.

TABLE II
FPC and PE Scores Across Different Numbers of Clusters

Number of Clusters (C)	FPC	PE
2	0.60	0.52
3	0.68	0.45
4	0.75	0.40
5	0.80	0.36
6	0.76	0.39
7	0.72	0.41
8	0.70	0.43
9	0.68	0.46
10	0.65	0.48

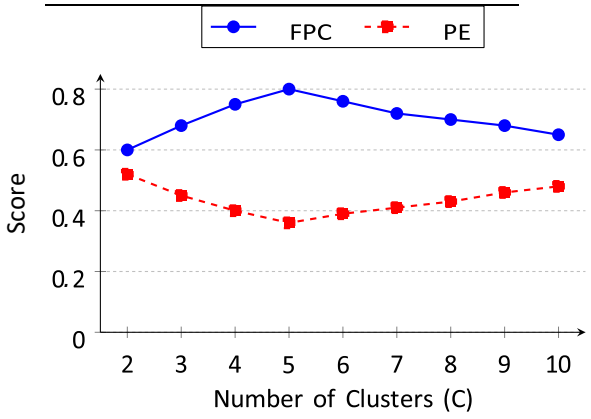


Fig. 3. FPC and PE Scores Across Varying Cluster Numbers

Fig. 4 illustrates the visual interpretation of the clustering output using the fuzzy membership matrix heatmap. Each row corresponds to a learner, and each column to a cluster. Color intensity reflects the strength of membership. The visualization confirms that many learners are strongly affiliated with a specific cluster, while others exhibit partial memberships, validating the system's ability to accommodate overlapping learning characteristics. The feedback score distribution from learners is presented in Table III and illustrated visually in Fig. 5. Over 75% of learners rated the system 4 or 5, yielding a mean feedback score of 4.10. This high rating reflects general satisfaction and supports the conclusion that the system delivers a relevant and engaging learning experience. The simulation results recorded a

low Dropout Likelihood of 9%, suggesting that the personalized pathways helped sustain engagement.

To contextualize the effectiveness of the proposed fuzzy-based adaptive learning model, its performance was compared with two baseline methods: K-Means-based personalization

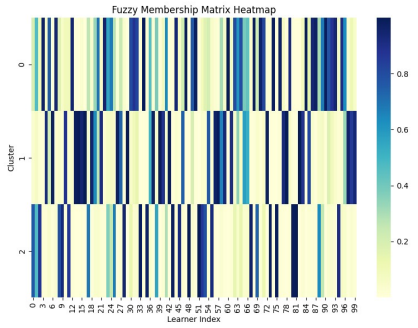


Fig. 4. Fuzzy Membership Matrix Heatmap

TABLE III
FEEDBACK SCORE FREQUENCY DISTRIBUTION

Feedback Score	Frequency
1 (Very Poor)	80
2	128
3	272
4	560
5 (Very Helpful)	960

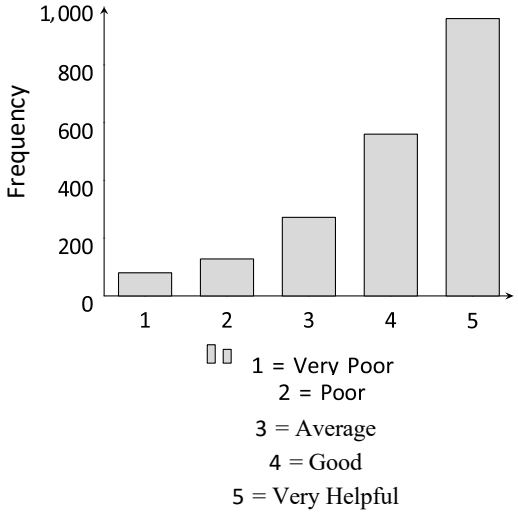


Fig. 5. Feedback Score Frequency Distribution

and Rule-Based Path Allocation. The comparison focused on mean feedback scores, Dropout Likelihood, and clustering metrics.

As shown in Table V, the proposed model achieved the highest mean feedback score of 4.10, indicating superior learner satisfaction. Additionally, it recorded the lowest Dropout Likelihood (9%), highlighting better engagement and retention. Unlike the baselines, the fuzzy model captures overlapping learner characteristics, enabling more nuanced personalization.

TABLE IV
BASELINE COMPARISION

Method	Mean Feedback Score	Dropout Likelihood (%)
Fuzzy C-Means (Proposed)	4.10	9.00
K-Means	3.65	14.00
Rule-Based	3.20	20.00

These results demonstrate the adaptability of the fuzzy-based framework compared with conventional clustering and static rule-based systems. The superior performance of Fuzzy C-Means (FCM) over K-Means stems from its soft clustering mechanism, which allows learners to belong to multiple clusters with varying degrees of membership. This flexibility enables the generation of personalized learning pathways that better match the nuanced attributes of each learner, rather than forcing them into a single rigid category. As a result, learners receive content that aligns more closely with their profile, leading to higher simulated feedback scores. In contrast, K-Means assigns each learner to a single cluster, which can reduce content relevance for learners with mixed characteristics and lower their perceived satisfaction.

V. CONCLUSION AND FUTURE WORKS

The evaluation results of the proposed fuzzy-based adaptive learning framework demonstrated its effectiveness in supporting personalized learning experiences. Empirical evaluation confirms its effectiveness, with an optimal clustering FPC of 0.80, a PE of 0.36, a mean feedback score of 4.10, and a reduced Dropout Likelihood of 9%. These outcomes demonstrate the model's ability to enhance inclusive learning pathways for diverse student populations. The integration of this model into adaptive systems will enable educators to dynamically adjust content delivery in line with learners' cognitive status, thereby enhancing teaching effectiveness.

The scope of this work is to build the framework and evaluate it experimentally. Future work will explore deployment and benchmarking with existing intelligent tutoring systems. This would provide a platform to measure the system stability under incomplete or noisy learner data.

REFERENCES

[1] C. M. Reigeluth, S. Aslan, Z. Chen, P. Dutta, Y. Huh, D. Lee, and W. R. Watson, "Personalized integrated educational system: Technology functions for the learner-centered paradigm of education," *J. Educ. Comput. Res.*, vol. 53, no. 3, pp. 459–496, 2015, doi: 10.1177/0735633115603998.

[2] A. N. Nizami, M. R. Mirza, M. Yousaf, and M. Usman, "The role of artificial intelligence in shaping personalized education and studentcentered learning in Pakistan," *The Critical Review of Social Sciences Studies*, vol. 3, no. 3, pp. 2989–3003, 2025.

[3] A. Asrifan, K. N. A. Tayibu, M. Muhayyang, S. S. Ingilan, and A. Mahfud, "Traditional learners vs. non-traditional learners: Bridging the educational divide," in *Mitigating Learner Disadvantages in Teaching and Learning*, IGI Global Scientific Publishing, pp. 59–90, 2025.

[4] H. E. Sari, B. Tumanggor, and D. Efron, "Improving educational outcomes through adaptive learning systems using AI," *Int. Trans. Artif. Intell.*, vol. 3, no. 1, pp. 21–31, 2024.

[5] S. Papadimitriou and M. Virvou, "Fuzzy logic and applications in education and games: Theory, practical implementations and a literature review," in *Artificial Intelligence—Based Games as Novel Holistic Educational Environments to Teach 21st Century Skills*, pp. 95–127, 2025.

[6] P. K. Bansal and M. Ahmed, "Fuzzy logic-based analysis of student behavior patterns in educational environments," *AIP Conference Proceedings*, vol. 3224, no. 1, p. 020047, Feb. 2025.

[7] A. Shepitsen, J. Gemmell, B. Mobasher, and R. Burke, "Personalized recommendation in social tagging systems using hierarchical clustering," in *Proceedings of the 2008 ACM Conference on Recommender Systems*, pp. 259–266, 2008.

[8] E. R. Griff and S. F. Matter, "Evaluation of an adaptive online learning system," *British Journal of Educational Technology*, vol. 44, no. 1, pp. 170–176, 2013.

[9] S. M. Miraftabzadeh, C. G. Colombo, M. Longo, and F. Foiadelli, "Kmeans and alternative clustering methods in modern power systems," *IEEE Access*, vol. 11, pp. 119596–119633, 2023.

[10] Y. Park and I.-H. Jo, "Factors that affect the success of learning analytics dashboards," *Educational Technology Research and Development*, vol. 67, no. 6, pp. 1547–1571, 2019.

[11] F. N. Memon and S. N. Memon, "Digital divide and equity in education: Bridging gaps to ensure inclusive learning," *Impact of Digitalization on Education and Social Sustainability*, pp. 107–130, IGI Global, 2025.

[12] S. I. Mohammad, N. Yogeesh, N. Raja, P. William, M. S. Ramesha, and A. Vasudevan, "Integrating AI and fuzzy systems to enhance education equity," *Applied Mathematics*, vol. 19, no. 2, pp. 403–422, 2025.

[13] W. Klosgen and J. M. Zytkow, "The knowledge discovery process," in¨ *Handbook of Data Mining and Knowledge Discovery*, pp. 10–21, 2002.

[14] A. A. Khan and O. Naseer, "Fuzzy logic based multi user adaptive test system," *arXiv preprint arXiv:1401.6348*, 2014.

[15] A. Gupta, D. Garg, and P. Kumar, "Mining sequential learning trajectories with hidden Markov models for early prediction of at-risk students in e-learning environments," *IEEE Transactions on Learning Technologies*, vol. 15, no. 6, pp. 783–797, 2022.

[16] S. Amin, M. I. Uddin, A. A. Alarood, W. K. Mashwani, A. Alzahrani, and A. O. Alzahrani, "Smart E-learning framework for personalized adaptive learning and sequential path recommendations using reinforcement learning," *IEEE Access*, vol. 11, pp. 89769–89790, 2023.

[17] A. O. Elfaki, K. M. Alhawiti, Y. M. AlMurtadha, O. A. Abdalla, and A. A. Elshiekh, "Rule-based recommendation for supporting student learning-pathway selection," *Recent Advances in Electrical Engineering and Educational Technologies*, pp. 155–160, 2014.

[18] P. Gupta, T. Kulkarni, and B. Toksha, "AI-based predictive models for adaptive learning systems," in *Artificial Intelligence in Higher Education*, pp. 113–136, CRC Press, 2022.