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A Fuzzy-Neural Model for Personalized Learning Recommendations Grounded in Experiential Learning Theory

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Abstract: Personalized learning is a defining characteristic of current education, with flexible and adaptable experiences that respond to individual learners' requirements and approaches to learning. Traditional implementations of educational theories—such as Kolb's Experiential Learning Theory—often follow rule-based approaches, offering predefined structures but lacking adaptability to dynamically changing learner behavior. In contrast, AI-based approaches such as artificial neural networks (ANNs) have high adaptability but lack interpretability. In this work, a new model, a fuzzy-ANN model, is developed that combines fuzzy logic with ANNs to make recommendations for activities in the learning process, overcoming current model weaknesses. In the first stage, fuzzy logic is used to map Kolb's dimensions of learning style onto continuous membership values, providing a flexible and easier-to-interpret representation of learners' preferred approaches to learning. These fuzzy weights are then processed in an ANN, enabling refinement and improvement in learning recommendations through analysis of patterns and adaptable learning. To make recommendations adapt and develop over time, a Weighted Sum Model (WSM) is used, combining learner activity trends and real-time feedback in dynamically updating proposed activity recommendations. Experimental evaluation in an educational environment shows that the model effectively generates personalized and changing experiences for learners, in harmony with learners' requirements and activity trends.

Keywords: personalized learning; fuzzy logic in education; artificial neural networks (ANNs) in education; learning style adaptation; hybrid AI for education; intelligent tutoring systems; Kolb's Experiential Learning Theory

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1. Introduction

In the era of modern technology, personalized learning software plays a significant role in enhancing educational efficiency. Traditional one-size-fits-all learning approaches often fail to meet the diverse needs of students, leading to inefficiencies in knowledge acquisition [1]. Personalized learning fosters adaptive educational experiences that align with individual preferences, cognitive abilities, and engagement patterns [2–4]. One of the most crucial aspects of personalized learning environments is selecting appropriate learning activities [5–7]. Since these activities significantly impact knowledge retention and skill development, accurately recommending them based on a learner's cognitive and behavioral preferences is of utmost importance.

Educational theories serve as the foundation for designing personalized learning environments [8]. These theories help in understanding how students interact with educational content and in structuring learning experiences to support their development. Several well-established theories—such as Vygotsky's Social Constructivism, Bloom's Taxonomy, and

Gardner's Multiple Intelligences—emphasize the importance of tailoring instructional methods to individual learners [8–10]. Among these, Kolb's Experiential Learning Theory (ELT) [11] is particularly relevant in adaptive learning systems as it categorizes learners into four distinct styles: Accommodators, Convergers, Assimilators, and Divergers. This model explains how individuals process experiences and acquire knowledge, making it a strong foundation for recommending suitable learning activities in personalized learning environments.

Artificial intelligence (AI) has played a principal role in enhancing personalized learning through dynamically altering content in relation to learner profiles. Various AI approaches—collaborative filtering, reinforcement learning, decision trees, and deep learning algorithms—have been leveraged to develop smart recommendation frameworks in educational environments [12–15]. Two such approaches, artificial neural networks (ANNs) and fuzzy logic, have proven most effective in modeling learning behavior and managing uncertainty in cognitive processes in humans [16]. Fuzzy weights enable a flexible expression of a learner's profiles by assigning a range of memberships to a range of types of learning, and ANNs can best detect trends and maximize recommendations through training with examples.

Recent studies have explored various personalization techniques in educational recommender systems, like rule-based models, decision trees, etc. [12–15]. Although these approaches may offer several benefits, they often face obstacles in adapting to complex or even evolving learner behaviors.

The integration of fuzzy logic and ANNs can show promise in educational contexts due to their complementary strengths. Fuzzy logic can manage uncertainty and represent learner preferences in a nuanced, human-understandable manner, while ANNs are capable of identifying non-linear patterns and adapting to new data over time. As such, combining these two techniques allows for better adaptability.

However, previous approaches have rarely unified these methods into a coherent framework based on learning theories like Kolb's Experiential Learning Theory. Moreover, many existing systems lack the ability to update their recommendations dynamically based on learner feedback and changing engagement patterns [12–15].

This paper proposes a hybrid fuzzy-ANN model for personalized activity recommendation in learning utilizing Kolb's Theory of Experiential Learning. This model is mainly targeted at learners, since it provides a personalized environment to them for better acquisition of the domain to be taught. First, a learner's Kolb learning style is determined through a survey for cognitive preference evaluation and then processed with fuzzy logic to obtain fuzzy weights, indicative of the extent to which a learner identifies with a Kolb learning style. The fuzzy weights serve as an input for an ANN, processing learning behavior and employing a Weighted Sum Model (WSM) for optimized recommendations. Personalized activity recommendations for a learner's dominant and secondary Kolb learning styles constitute the output. With Kolb's theory, fuzzy logic, and ANN-based learning optimization, accuracy and adaptability in activity recommendations are enhanced, and an effective and personalized environment for learning is facilitated. As a testbed for our research, this model has been incorporated into educational software for teaching the programming language C++. The novelty of this work lies in the integration of fuzzy logic and neural networks within a pedagogically grounded adaptive model offering both theoretical coherence and dynamic personalization.

2. Related Work

The use of learning style in educational software has been examined in depth in an effort to maximize individualized learning experiences. Kolb's Experiential Learning Theory (ELT) [11] has been extensively used in adaptive environments for learners to classify and build individualized educational experiences. Other frameworks, such as the Felder-Silverman Learning Style Model [17], have been used to adapt matter, pace, and collaboration style in intelligent tutoring systems. Most educational software, however, utilizes inflexible classification, putting learners in specific categories when, in reality, learning preferences can occur anywhere in a continuum. Due to its constraints, fuzzy logic has been added, providing a flexible and malleable way in which learners can be classified in terms of learning style.

Fuzzy logic has been applied in educational software for dealing with learner uncertainty in behavior and preference [18–25]. Unlike label-based categories, fuzzy logic can allow for degree-based categories, and thus, adaptive learning platforms become flexible. It has been confirmed through experiments that fuzzy logic can facilitate personalized learning through dynamically changing instruction [18] and difficulty levels [19]. Certain intelligent tutoring and recommendation frameworks apply fuzzy rules to modulate course recommendations in terms of students' gaps in knowledge, preference, and activity level. Most educational systems with fuzzy logic, nevertheless, rely on predefined rules, and thus, adaptability and scalability can become limited.

Artificial neural networks (ANNs) have also played a significant role in enriching adaptive learning experiences in educational software. ANNs have proven useful in predicting student performance, learner behavior analysis, and educational content recommendations based on past experiences [26–32]. Intelligent tutoring systems with ANN architectures can sequence content for optimized personalized planning for studies [33]. ANNs have even been adopted in computerized testing tools for evaluating the answerability of students and dynamically altering difficulty in questions [34,35]. Yet, even with ANNs' effectiveness in identifying information patterns, numerical, structured inputs are required, which cannot be directly applied to educational constructs such as learner style. By using ANNs in conjunction with fuzzy logic, this issue is resolved—fuzzy logic creates readable, flexible representations for inputs, and ANNs use their pattern-matching powers to maximize personalized guidance recommendations.

Our research stands out by unifying Kolb's Experiential Learning Theory, fuzzy logic, and artificial neural networks in a single, coherent model for personalized activity recommendation in learning. Individual aspects of learning style, fuzzy logic, and ANNs have been addressed in studies, but not in a combination that utilizes all three for enhanced accuracy and adaptability in educational software. By utilizing fuzzy weights for representing learners' level of fit for a Kolb category, our model facilitates a flexible classification over a traditional, predefined one. With the added feature of an ANN, our model gains an additional boost in activity recommendations by discovering trends and relations, in contrast to static, rule-based approaches. With a hybrid model, continuous updating of activity recommendations is assured, and therefore, the system is not only adaptable and scalable but also effective for real-life educational use cases.

3. Kolb's Learning Model and Fuzzy Logic Representation

Kolb's Experiential Learning Theory (ELT) describes learning as an ongoing, continuous process in which an individual learns new information through a transformation of experiences. According to theory, learners can be categorized into four types of learners, each with a specific style of processing and utilizing information:

- Accommodator ($\mu_A(t)$): Learns best through hands-on experience, experimentation, and solving problems by trial and error rather than relying on theoretical analysis.
- Converger ($\mu_C(t)$): Focuses on practical applications of knowledge, excelling in solving technical problems and drawing conclusions based on data analysis.

- Assimilator (μ_{AS}(t)): Prefers structured and logical reasoning, relying on theoretical models and abstract thinking to understand new information.
- Diverger (μ_D(t)): Thrives on observation, reflection, and creativity, excelling in brainstorming sessions and analyzing situations from multiple perspectives.

To determine an individual's learning style within this categorization, we utilize a questionnaire designed to assess personal learning preferences based on Kolb's Learning Style Inventory (LSI) (https://uwaterloo.ca/engineering-teaching-learning/sites/default/files/uploads/documents/mar2013_tdwg_resource.pdf, assessed on 10 March 2025; https://aim.stanford.edu/wp-content/uploads/2013/05/Kolb-Learning-Style-Inventory.pdf, assessed on 10 March 2025) [36]. The questionnaire consists of 20 multiple-choice questions, in which each option assigns numerical scores to each learning style dimension, providing a measurable way to evaluate a learner's tendencies. In particular, each question has 4 options, and students are asked to choose the answer that is most suitable for them. As such, the option corresponding to Accommodator, Converger, Assimilator, and Diverger gets 1, 2, 3, and 4 points, respectively. The maximum score a student can achieve on the questionnaire is 80. Thus, lower scores indicate that students are closer to the Accommodator style, while higher scores suggest that students are more aligned with the Diverger style. However, traditional methodologies sort learners into one unidimensional learning style, disregarding both continuity of preference and style overlap. In an attempt to mitigate such a flaw, fuzzy logic is used, and learning styles can then be characterized in terms of a continuous range, not discrete categories.

Each learning style is defined in terms of a fuzzy membership function, a value for how much a learner identifies with a given style. The functions are designed with piecewise linear functions, with a continuous transition between one style and another. Unlike with sharp binary categories, fuzzy membership functions allow for partial membership in a variety of styles, a reflection of real diversity in cognitive preference in real-life environments.

The fuzzy membership functions are formulated as follows:

For Accommodator (μ_A(t)),

$$\mu_A(t) = \left\{ \begin{array}{c} 0,\ if\ t \leq 20 \\ \\ 1,\ if\ 20 < t \leq 30 \\ \frac{35-t}{35-30},\ if\ 30 < t \leq 35 \\ 0,\ if\ t > 35 \end{array} \right\}$$

For Converger (μ_C(t)),

$$\mu_C(t) = \left\{ \begin{array}{c} 0,\ if\ t \leq 30 \\ \frac{t-30}{35-30},\ if\ 30 < t \leq 35 \\ 1,\ if\ 35 < t \leq 45 \\ \frac{50-t}{50-45},\ if\ 45 < t \leq 50 \\ 0,\ if\ t > 50 \end{array} \right\}$$

For Assimilator ($\mu_{AS}(t)$),

$$\mu_{AS}(t) = \left\{ \begin{array}{c} 0,\ if\ t \leq 45 \\ \frac{t-45}{50-45},\ if\ 45 < t \leq 50 \\ 1,\ if\ 50 < t \leq 60 \\ \frac{70-t}{70-60},\ if\ 60 < t \leq 70 \\ 0,\ if\ t > 70 \end{array} \right\}$$

For Diverger ($\mu_D(t)$),

$$\mu_{D}(t) = \left\{ \begin{array}{c} 0,\ if\ t \leq 60 \\ \frac{t-60}{70-60},\ if\ 60 < t \leq 70 \\ 1,\ if\ 70 < t \leq 80 \\ \\ 0,\ if\ t > 80 \end{array} \right\}$$

where t is a numerical value related to the output of the questionnaire. The membership functions are designed for Kolb's LSI distribution, and they provide a continuous transition between learning types in such a way that those who have intermediate trends remain in no group, thereby creating a balanced and real sequence.

The thresholds for both types of learning were established through a range of significant factors:

- Empirical Data in Kolb's LSI Score Scales: Kolb's Learning Style Inventory (LSI) is designed such that individual learning style scores range between 20 and 80. The fuzzy membership values have been designed with a view to fitting into such a distribution, so that real-life learner traits can best be represented through such assigned fuzzy values.
- Overlapping Learning Styles for Greater Precision: Few students fit exclusively into one single learning style. With a fuzzy model, a learner with a score of 65 in both the Diverger and Assimilator categories will have strong membership in both, offering a less discrete and truer real-life classification, not putting the learner into artificial, discrete categories.
- Gradual Transitions Instead of Abrupt Cutoffs: The transition intervals (e.g., $30 < t \leq 35$ for Accommodator, $30 < t \leq 35$ for Converger) allow for a smooth shift in learning style identification. This prevents sudden, arbitrary category assignments that might misrepresent learners with borderline scores.
- Adherence to Fuzzy Logic Best Practices: The membership functions are designed to be both interpretable and mathematically simple, making them easy to implement in educational software without sacrificing accuracy.

Once the fuzzy membership values for all four learning styles are calculated, the learner is represented as a vector of fuzzy weights, providing a more adaptive and personalized learning profile: $\mu = [\mu_A, \mu_C, \mu_{AS}, \mu_D]$, where $\mu_A + \mu_C + \mu_{AS} + \mu_D = 1$.

This vector is then processed in the ANN, in which it is analyzed in an attempt to generate individualized activity recommendations based on trends derived through previous information. By using fuzzy weights in lieu of rigid categories, the ANN can dynamically revise its predictions in such a manner that recommendations become ever more adaptable, personalized, and contextual to individual learners' cognitive profiles.

The next section will detail the structure of the ANN and its processing of fuzzy weights in a bid to maximize and simplify learning activity recommendations.

4. ANN for Learning Activity Recommendation

The ANN in the model handles processing and converting representations of fuzzy learning styles into individualized recommendations for learning activities. With the incorporation of fuzzy logic and ANN, a continuous rather than a discrete classification of learners is supported, ensuring that recommendations remain flexible and adaptable to each learner's individual preferences.

The ANN takes, as its input, the fuzzy membership values derived via Kolb's Experiential Learning Theory (ELT), and then utilizes them to fine-tune and optimize each learner's learning experience. The input vector is $\mu = [\mu_A, \mu_C, \mu_{AS}, \mu_D]$.

These values range between 0 and 1, representing the learner's degree of alignment with each learning style. Unlike traditional classification methods that assign a single, fixed learning style, fuzzy logic enables a continuous representation of learning preferences, offering a more flexible and nuanced approach.

Once the membership values enter the network, they pass through hidden layers where patterns are identified, refining the relationship between learning tendencies and recommended activities, as illustrated in Figure 1.

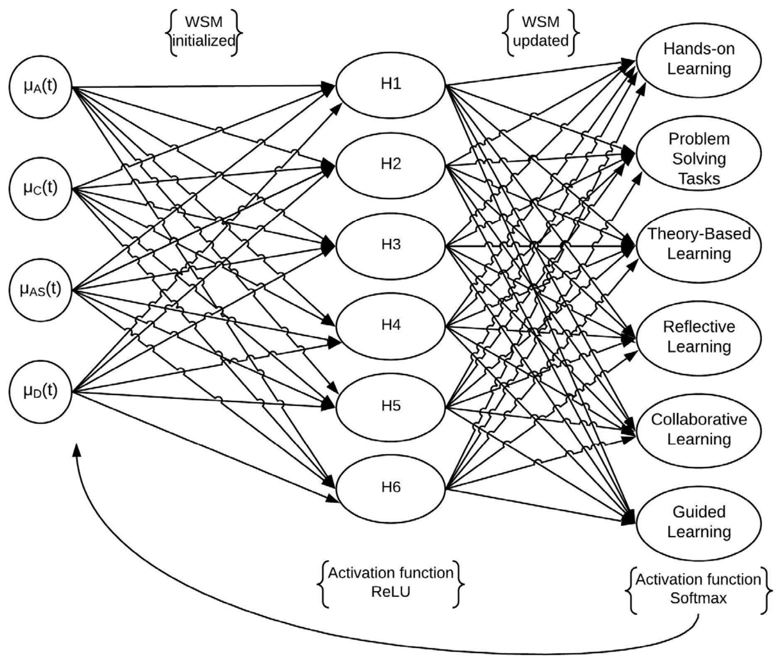

Figure 1. ANN logical architecture.

The number of hidden neurons was determined empirically through iterative experimentation, with testing configurations ranging from 4 to 20 neurons. The ANN architecture consists of one input layer, one hidden layer with 8 neurons, and one output layer that produces suitability scores for each activity type. Other hyperparameters included a batch size of 32, a learning rate of 0.001 (optimized via the Adam optimizer), and an early stopping criterion based on validation loss stagnation over 5 consecutive epochs.

Each neuron in the hidden layer carries out a weighted summation transformation, mathematically represented as

$$h_j = f\left(\sum_{i=1}^{4} w_{ij}\mu_i + b_j\right)$$

where

- h_j is the activation value of hidden neuron j;
- w_{ij} represents the weight associated with the connection between input i and neuron j;
- b_j is the bias term for neuron j;
- f(x) is the Rectified Linear Unit (ReLU) activation function, given by f(x) = max(0, x).

This transformation seeks to reveal complex, non-linear relationships between an individual learner's learning style and the types of applicable activity the person is likely to best align with their cognitive process. Here, instead of outpacing the system, the ReLU activation function is applied to enable the learning of complex patterns, while avoiding the notorious saturation phenomenon that often complicates linear approaches to activation functions. This allows the model to learn varied behaviors without being clogged by overfitting or diminishing outputs.

The input layers follow the hidden layer, where the number of neurons is found by trial and error and typically ranges between 8 and 16 neurons. This ensures that the number of iterations remains manageable and minimizes the likelihood of overfitting while also capturing significant relationships between styles and preferences in the data. Effective fine-tuning of this balance keeps the system accurate and flexible enough to offer tailored suggestions that are appropriate to an individual learner's needs.

In the output layer, the ANN produces suitability score predictions of the different types of learning activities after the hidden layer has processed the data. Every output neuron corresponds to one learning activity, ending in a score for recommendations for personalized learning pathways. The recommendations keep on evolving, thus making the system adaptive to learners' switching behaviors and engagement changes: [$y = y_1, y_2, y_3, y_4, y_5, y_6$],

where

- y_1 = Suitability for Hands-on Learning (Labs, Case Studies)
- y_2 = Suitability for Problem-Solving Tasks (Technical Projects)
- y_3 = Suitability for Theory-Based Learning (Lectures, Textbooks)
- y_4 = Suitability for Reflective Learning (Writing, Self-Study)
- y_5 = Suitability for Collaborative Learning (Group Discussions)
- y_6 = Suitability for Guided Learning (Step-by-Step Tutorials)

The Weighted Sum Model (WSM) is applied at this step to optimize the suitability scores calculated so far so that learning recommendations are further clear and customized. The WSM plays a key role in refining activity recommendations by adjusting the output layer scores of the ANN based on the historical effectiveness of activity types for learners with similar profiles. After the ANN generates raw suitability scores for each activity, the WSM multiplies these scores with activity-specific weights derived from aggregated feedback in the training dataset. These weights capture how successful each activity has been for learners with comparable fuzzy learning style vectors. The adjusted scores are then passed through a softmax layer to produce a final ranked list of personalized recommendations. This integration ensures that the final output reflects both the individual learner's preferences and the collective success of learning strategies across similar users.

This approach adds weights that give precedence to activities proven to be effective among other learners displaying similar characteristics, habits, and patterns of engagement. Using this refinement, the system is better able to not only make accurate recommendations but also relevant recommendations by ensuring that student learning activities are matched in a way that is most conducive to learner experience styles and previous interaction patterns. This flexible prioritization allows the model to adapt over time, offering each learner suggestions that best match their changing requirements and learning advancement.

From a mathematical point of view, the score of suitability for activity k is calculated as follows:

$$y_k = \sum_{j=1}^{m} v_{jk} h_j + c_k$$

where

- v_{jk} represents the weight between hidden neuron *j* and output neuron *k*;
- h_j is the activation value of the hidden layer;
- c_k is the bias term for activity k.

To normalize these scores into a probability distribution, the softmax activation function is applied:

$$\sigma(y_k) = \frac{e^{y_k}}{\sum_{j=1}^{6} e^{y_j}}$$

By making sure that larger output values are associated with better relevant learning activities, the system can produce a ranked list of recommendations per given context in terms of appropriateness and learners' requirements.

In order to create a model that can generate precise and individualized recommendations, the ANN is trained with a dataset that records past learner interactions and behaviors. This dataset consists of some important aspects:

- Fuzzy categorization of learning style representations for the learners that are in terms of Kolb's questionnaire based on the preferred learning styles of individuals.
- History of engagement with different types of learning activities, such as time spent on tasks and completion rates, to reveal patterns of behavior in learning.
- Performance metrics, such as post-activity evaluation scores and knowledge retention metrics, that indicate the extent to which learners can integrate and implement recently acquired knowledge.
- Self-reported feedback: Feedback of the effectiveness of recommended activities as assessed by the learners themselves, ratings, and satisfaction scores are sent back to fine-tune model predictions.

The goal of training the ANN is to adjust it to predict the best learning activities for every person. This is accomplished by training the network using the categorical cross-entropy loss function, which reduces prediction errors and iteratively optimizes accuracy in recommendation:

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i)$$

where

- y_i is the actual suitability score for activity i;
- $\hat{y}_i$ is the predicted suitability score generated by the ANN.

Furthermore, we optimize the model using the Adam optimizer, which automatically adjusts learning rates during the training process to guarantee efficient learning and faster convergence. Also, the model is trained with dropout regularization, which increases generalization and prevents overfitting to be able to predict better when it sees new data from the learners.

After the ANN is trained well, it is ready to be deployed for real-time learning activity recommendations. The ANN internally computes a fresh learner's feature values by feeding the learned weights of the new learner's fuzzy learning style values, outputting a list of recommended activities sorted by their degrees of suitability.

When learners interact with these suggestions, the suggestions improve over time by incorporating user feedback into real-time suggestions. Such continuous refining of the suggestions guarantees that the suggestions are aligned and adjusted to the path, proclivities, and changing needs of each learner, thereby making the learning experience more individualized and efficient.

In Appendix A, we provide an example where Kolb's Learning Style Inventory (LSI) questionnaire is completed by a student to show how a learner's journey is processed using the method put forth. In this example, we show how fuzzy weights are calculated and processed through the ANN and how they will then create custom learning activity suggestions.

5. Results

This section introduces an experimental evaluation of the fuzzy-ANN hybrid model for personalized learning activity recommendations. The analysis includes a comprehensive experimental setup, a quantitative performance assessment, a comparison with baseline models, and a qualitative case study. The objective is to evaluate the model's accuracy, adaptability, and robustness in recommending learning activities that align with students' learning styles.

5.1. Experimental Setup

To evaluate its performance, an experiment was conducted in a real educational environment. The system was used in the context of an Object-Oriented Programming with C++ course for 100 undergraduate students over 15 weeks. During this period, the students interacted with the system weekly through assigned learning activities. The model generated personalized activity recommendations on a weekly basis, taking into account the learners' engagement and feedback. Each student completed Kolb's Learning Style Inventory (LSI) questionnaire, providing a baseline measurement of their preferred learning style. Unlike traditional classification methods that assign students to a single category, this model uses fuzzy membership values to represent varying degrees of preference for different learning styles. This approach facilitated a more flexible and adaptive learning experience. The selection of a 100-student sample was based on the average class size of undergraduate computer science courses at our institution, providing a realistic and representative population for testing the proposed model. The Object-Oriented Programming with C++ course was selected due to its balanced mix of theoretical instruction and practical problem-solving activities, which aligns well with the spectrum of learning styles defined in Kolb's model.

During the study, a dataset of 3000 learning activity interactions was automatically collected and exported through the course's online learning management system (LMS), where students engaged with weekly recommended materials, exercises, and quizzes tailored to Object-Oriented Programming with C++. This dataset size was determined by the number of weekly activities completed by the 100 students over the 15-week course, i.e., approximately 2 activities per student per week. This provided a sufficiently large and balanced dataset for training and validation. Moreover, all interactions were exclusively related to the Object-Oriented Programming with C++ course, ensuring that they reflected learner behavior and engagement within this context. In particular, each interaction included key elements such as Kolb's LSI scores transformed into fuzzy membership values, assigned learning activity types categorized into six instructional methods (Hands-on Learning, Problem Solving, Theory-Based Learning, Reflective Learning, Collaborative Learning, and Guided Learning), engagement metrics (time spent on activities, completion rates, and frequency of interaction), and performance indicators (assessment scores and knowledge retention rates). Additionally, learner feedback was gathered using a 5-point Likert scale, where students rated the usefulness of each recommended activity.

To validate the accuracy of the recommendations, a team of five educational experts reviewed the dataset and established ground truth validation labels. These experts manually evaluated a subset of the recommendations to ensure that they aligned with pedagogical best practices. The final validation dataset contained 600 test cases, where experts determined the ideal learning activities based on instructional guidelines. Each expert independently assessed a portion of the dataset, around 120 cases, and for quality assurance, a subset of the cases, namely 20% of the test cases, was reviewed by multiple experts. This allowed for the identification and resolution of any discrepancies through group discussion, ensuring consistency and agreement in the final labels. These expert-assigned labels were then used to compare with the model's predictions and compute performance metrics. While the course's LMS facilitated the automated collection of interaction data, generating the ground truth validation labels was resource-intensive. The expert review process lasted approximately three weeks and was both effortful and time-consuming.

The dataset was split into 80% training data and 20% validation data, ensuring that the model was trained on diverse learning patterns while being evaluated on new, unseen learners. The fuzzy-ANN model was implemented as a feedforward neural network with one input layer, one hidden layer, and one output layer. The input layer received four fuzzy membership values corresponding to the Accommodator, Converger, Assimilator, and Diverger learning styles. The hidden layer consisted of eight neurons, each applying a weighted sum transformation, followed by a ReLU activation function. The output layer contained six neurons, representing different learning activity types, with suitability scores computed using the WSM and softmax normalization.

To optimize performance, the model was trained using the Adam optimization algorithm, with an initial learning rate of 0.001 and a decay factor of 0.9, to stabilize learning. The categorical cross-entropy loss function was applied to minimize prediction errors. Training was conducted for more than 50 epochs, incorporating dropout regularization (with a probability of 0.2) to prevent overfitting, along with early stopping based on validation performance. The categorical cross-entropy loss function was used to evaluate how closely the model's predicted learning activity probabilities aligned with expert-labeled ground truth. Loss convergence was carefully monitored over multiple epochs to maintain model stability and prevent overfitting. The model achieved validation loss stabilization at 0.36, indicating that it was effectively generalized to new learners without relying on memorization, ensuring adaptability to unseen data.

Learners rated the effectiveness of the suggested learning activities using a 5-point Likert scale. If an activity was assigned a score of 4 or 5, it was rewarded in the model to give it a higher likelihood of reappearing in future recommendations. On the other hand, if an activity was rated 1 or 2, the learning style weightings were altered in order to better fit future predictions of model activity. As the learning preferences kept changing, the system dynamically catered to the change with the help of real-time feedback. Such a wok-based continuous refinement improved recommendation quality through a process that ensured that the predicted type of learning activity, at any given time, was relevant, personalized, and matched the evolving needs of each learner.

This innovative adaptive learning framework that implements artificial neural networks (ANNs), learner feedback, and fuzzy logic was demonstrated to be a scalable and successful personalized education solution. Through its blended structured learning representations with AI-enabled adaptability, the model delivers an average level of personalization that can evolve according to the real-time engagement patterns and learning progress of each learner.

5.2. Baseline Models for Comparison

In order to test the performance of the fuzzy-ANN hybrid model, its performance was tested against three baseline models employing other approaches for recommending learning activities. The difference between recommended items resulted in an improved proportion of the average number of recommended items.

Baseline 1 model used a fixed rule-based structure, wherein a single predominant learning style was assigned to learners, with recommendations being made according to a preset mapping. This approach provided a set structure, but was inflexible, and therefore recommendations failed to change with the student or adapt to feedback. In this approach, once a learner was placed into a category, that determined the suggested activities, even though their learning styles could change.

The second baseline model (Baseline 2) removed this restriction by introducing fuzzy membership values, thus being more flexible than the rule-based model. It did not learn from past interactions or improve its suggestions based on new engagement data because it did not use machine learning. Although this provided a consistent classification of each person's preferences towards learning, it did not learn from user feedback in real time, which limited its ability to adapt to a user's changing needs.

The last baseline model (Baseline 3) did not use fuzzy logic transformations at all and modeled Kolb scores directly as input. This model depended exclusively on the neural network's pattern and relationship recognition, enabling more versatility in how it catered to diverse learners. It operated using these as vague concepts, and thus the decision-making process was much less transparent because there were no rigidly defined, falsifiable hypotheses behind it. As a result, its recommendations at times were inconsistent and did not reflect learners' actual preferences. In Baseline 3, hyperparameters were selected empirically without a formal grid search, and although we tested architectures with two hidden layers, a single hidden layer performed more reliably, given the dataset size.

The fuzzy-ANN hybrid model, unlike the baseline approaches, integrates structured learning style representation (facilitated by fuzzy logic) and the flexible learning ability of ANNs. Through this integration, the system is able to remain interpretable each moment it identifies a relationship between a contingent state and a precondition or postcondition while simultaneously refining recommendations based on the actions and responses of a learner. The model proposes the use of fuzzy logic to directly capture subtle differences in learning styles and the ability of ANNs to recognize patterns to effectively adapt to student learning, providing a personalized learning experience that is continuously updated.

As a result, the technique outperforms traditional static recommendation methods, since it is more flexible, accurate, and able to respond to each learner's needs.

5.3. Performance Evaluation Metrics

5.3.1. Accuracy of Learning Activity Recommendations

How accurate a learning recommendation is will largely determine whether a model fits students' learning needs and the expert validation model. By being more accurate, students gain personalized learning activities designed around their cognitive involvement, thereby improving both their study experience and their general academic performance. It is calculated as follows:

$$Accuracy = \frac{Correct\ Predictions}{Total\ Test\ Cases} \times 100\%$$

The fuzzy-ANN hybrid model showed strong performance, with a success rate of 88.4%, higher than any of the baseline models (Table 1). This represents a 26.1% increase in the rule-based approach. It is an opportunity for personalized course recommendations that are more closely aligned with individual ways of learning and the patterns of engagement in the E-learning system.

Table 1. Accuracy results.

Model	Accuracy (%)
Baseline 1 (Rule-based)	62.3
Baseline 2 (Fuzzy Only)	75.1
Baseline 3 (ANN Only)	81.5
Fuzzy-ANN Hybrid (Proposed)	88.4

In fact, a closer look at this 26.1% improvement shows that the fuzzy-ANN hybrid model includes structured learning style representation (achieved through fuzzy logic) as well as flexibility (enabled by artificial neural networks). Unlike traditional rule-based models, which offer static suggestions, the hybrid approach refines its recommendations according to learners' feedback and engagement patterns. As a result, teaching can change shape with time: learning activities become flexible over a period of time and change along with the student's preferences and behaviors.

This flexibility is additionally realized in that the model uses fuzzy membership values to accommodate many different learning styles simultaneously; it does not stick learners in one single predefined category according to traditional baseline models. The system can thus make more personalized and responsive recommendations and accommodate each learner's particular educational needs in a manner not attainable by traditional models.

5.3.2. Precision, Recall, and F1-Score

These evaluation metrics measure the accuracy and comprehensiveness of the recommender system available and are used to assess the quality of the recommendations generated by the model (Table 2). This means that recommendations are very much tailored to your needs, and the accuracy rate is significantly high. Meanwhile, high recall will ensure that the system is identifying and accounting for a wide range of relevant learning, exposing the learner to a broad and appropriate range of learning opportunities that are in the best interests of their learning journey and engagement.

Table 2. Evaluation metrics.

Model	Precision (100%)	Recall (%)	F1-Score (%)
Baseline 1 (Rule-based)	67.1	64	65.4
Baseline 2 (Fuzzy Only)	78.6	75.2	76.9
Baseline 3 (ANN Only)	82.4	83.2	82.8
Fuzzy-ANN Hybrid (Proposed)	85.2	87.8	86.8

As shown in Table 2, the proposed fuzzy-ANN hybrid model achieved the highest performance across all evaluation metrics, with a precision of 85.2%, recall of 87.8%, and an F1-score of 86.8%. This clearly outperformed the baseline models, where the best-performing alternative (Baseline 3) reached an F1-score of 82.8%, while Baseline 2 and Baseline 1 scored 76.9% and 65.4%, respectively. The consistent improvement in performance—particularly the 4-point gain in F1-score over the strongest baseline—demonstrates the effectiveness of integrating fuzzy logic with neural networks. Although no formal statistical tests were conducted, the magnitude and consistency of the improvements indicate the robustness of the hybrid model.

5.4. Qualitative Case Study

This case study aims to evaluate how the individual capabilities of fuzzy logic and neural networks perform separately, and how their combination in a hybrid model can improve the accuracy and personalization of the recommendations. This case study aims to evaluate the suggestions produced from the predicted model and comparing them against the suggestions collected from the Fuzzy Logic Only (Baseline 2) and ANN Only (Baseline 3) models (Table 3). The aim is to demonstrate that an ANN-based model integrated with fuzzy logic can make more accurate, context-aware, and user-oriented recommendations.

Table 3. Case study results.

Learner	Kolb's Learning Style Scores (Raw)	Fuzzy Membership Values (For Fuzzy-ANN and Baseline 2)	ANN Hidden Layer Outputs	Final Recommendation (Fuzzy-ANN)	Recommendation (Baseline 2—Fuzzy Only)	Recommendation (Baseline 3—ANN Only)
L1	Accommodator: 85, Converger: 55, Assimilator: 15, Diverger: 30	(0.9, 0.6, 0.0, 0.0)	(0.88, 0.72)	Hands-on Learning, Case Studies	Hands-on Learning	Hands-on Learning, Problem-Solving
L2	Accommodator: 25, Converger: 80, Assimilator: 85, Diverger: 40	(0.0, 0.85, 0.9, 0.0)	(0.30, 0.87)	Theory-Based Learning, Guided Learning	Theory-Based Learning	Theory-Based Learning, Reflective Learning
L3	Accommodator: 50, Converger: 35, Assimilator: 90, Diverger: 70	(0.0, 0.0, 0.95, 0.75)	(0.92, 0.78)	Reflective Learning, Collaborative Learning	Reflective Learning	Theory-Based Learning

The constraint of fuzzy weight prevents each learner from showing more than two predominant learning styles. Fuzzy logic differs from conventional classification methods, where only one learning style can be assigned; fuzzy logic allows a continuous representation of learning style. But two clear dominant models per learner are retained in the fuzzy membership values for model interpretability and as a guard against overgeneralization. To avoid overgeneralization, the model restricts its recommendations to the learner's primary cognitive styles, ensuring that the suggestions remain personalized and educationally meaningful.

The transformed activation values are derived from the two most important fuzzy memberships of the learner's inputs to give the hidden layer outputs. The final recommendation scores depend on these values, so adaptive learning is possible. In contrast, static rule-based approaches do not change their learning style classifications, while the ANN component updates these activations as learners engage in activities. This dynamic adjustment mechanism ensures that learners consistently receive personalized suggestions tailored to their unique and changing learning behaviors.

The Weighted Sum Model (WSM), based on previous learner interactions, assigns importance weights for recommendations given to each learning activity. If a specific activity has been successful in the past for a specific learner type, its weight goes up—logically making it more likely that the activity will be recommended. Through a dynamic weighting mechanism, recommendations are strongly influenced by recorded actual learning habits, while knowledge-based learning style preferences are still a key factor, providing the system with a near to full real-world adaptive nature with fully personalized learning understanding.

The fuzzy-ANN model following a combination of learning algorithms, provides a precise representation of structured learning style representation (via fuzzy logic) while permitting real-time adaptive recommendations (via ANN learning), leading to a more generalizable, and likely valid, learning style recommendation set. What Works: The model reviews engagement history and adjusts recommendations, which means learning paths are more nuanced and real-time.

Recommendations are stagnant in Baseline 2 (Fuzzy Only), as the model only recommends activities based on the fuzzy membership values assigned at the start. Baseline 2 cannot be improved over time, since it does not learn from previous interactions. For instance, L3 receives recommendations for all Reflective Learning but none for Collaborative Learning, despite possible value from most.

Baseline 3 (ANN Only) does not fit every learning activity to the preferred learning style due to the absence of a fuzzy logic structure, which causes some misalignment between learning activities and preferred learning styles. However, ANN does not encode the relations among learning styles and activity types explicitly; therefore, it sometimes misclassifies learners. So, for instance, L3 gets a Theory-Based Learning recommendation that does not align well with what they are very highly inclined towards—Reflective and Collaborative Learning.

The findings show that the fuzzy-ANN hybrid model, which is both structured and adaptable, is more effective in providing personalized, explainable, and adaptive learning recommendations.

5.5. Discussion

The results from this study demonstrate that the fuzzy-ANN hybrid model is better than traditional rule-based approaches and independent AI-driven systems in delivering customized learning activity recommendations via examples. Integrating fuzzy logic to construct a formalized representation of learning styles with artificial neural networks (ANNs) for adaptive education, the system continually refines its recommendations by observing patterns in student engagement. This discussion explores the implications of these findings and how they relate to prior research in other fields, as well as possible future directions of inquiry. Various previous research works have illustrated the superiority of combining fuzzy logic with personalized education. As shown in [37], when it comes to classifying learning styles in a precise and multifaceted manner that traditional rule-based approaches cannot match, fuzzy logic models possess greater flexibility and accuracy than traditional rule-based ones. While the above approach has an adaptive mechanism, one limitation is its inability to adjust its model according to changes in the learning behaviors of students over time. This limitation was also present in our study when the Fuzzy Logic Only baseline model achieved a moderate accuracy rate of 75.1%. Although fuzzy classification provides a well-structured basis, it does not have the means to dynamically update recommendations based on real-time learning engagement. Likewise, artificial neural networks (ANNs) are widely used in personalizing teaching and learning, especially in intelligent tutoring systems (ITS). As shown in [32], ANN-based models are most effective at meeting learners' needs when they change over time. Still, a major predicament with these models is their low understandability—they suffer from inconsistency in recommendation patterns. In our study, the ANN-only baseline model had an accuracy rate of 81.5%, exceeding both rule-based and fuzzy logic models. However, although it had a higher accuracy than them, it was not always consistent with established theories of learning styles, sometimes giving recommendations that had no educational consistency.

On the other hand, the fuzzy-ANN hybrid model achieved better results, with an accuracy rate of 88.4%. This confirms the earliest conclusion from our research paper: when AI-driven adaptability is combined with structured learning style representation, learning personalization gradually improves. More performance data further illustrate this point: The hybrid model's F1-score rose to 86.8%, compared with 82.8% for an ANN-only model and 76.9% for fuzzy logic alone. The statistics prove what the authors of [38–40] reported in their paper. AI-driven personalization works most effectively when supported by structured domain representations, which increase both accuracy and interpretability at once.

The performance differences highlight the strengths and weaknesses of each approach. The fuzzy-only model was limited by its static rule-based nature, while the ANN-only model offered better adaptability but lacked pedagogical grounding. The hybrid model effectively combined structure and flexibility, adapting to evolving learner profiles while preserving interpretability. This balance proved especially beneficial for learners with mixed or changing styles, supporting more robust personalization.

Our research results offer at least three important implications for adaptive learning technologies. First, the results suggest that structured theoretical frameworks such as Kolb's Experiential Learning Theory can help rule-based methods join forces with AI-driven models in order to improve recommendation accuracy. It also allows AI to fine-tune predictions dynamically on the basis of previous learner responses. Unlike models that are based solely on historical learning data and so may be very sophisticated technically but lacking in educational substance, the fuzzy-ANN hybrid model effectively balances structure and adaptability. These findings also show that fuzzy logic increases interpretability, while AI improves adaptability, making this combination especially effective.

A third key result of the research is the importance of real-time feedback in personalizing learning. Models lacking integrated feedback mechanisms (such as fuzzy-only or ANN-only baselines) tended to provide standardized and inconsistent turnouts. In contrast, the fuzzy-ANN hybrid model continually evolved based on learner interactions, ensuring that accuracy of recommendation increased over time while continuing to match students' changing needs.

While the proposed model shows promising results in personalized learning activity recommendations, there are several limitations. One limitation lies in the reliance on predefined learning style vectors (based on Kolb's theory), which may not fully capture the dynamic nature of learners' cognitive and emotional states. Additionally, the ANN requires a sufficient volume of high-quality interaction data to generalize effectively, which might not be available in a smaller number of learners.

In terms of practical implementation, the model can be integrated into learning management systems (LMSs) or intelligent tutoring systems, provided that learner interaction data are continuously collected. Its hybrid nature makes it adaptable to evolving learner behavior, although real-world deployment would require regular monitoring, and possibly additional interpretability layers for instructors.

Similar approaches combining fuzzy logic and neural networks have been successfully applied in adaptive educational systems [41,42], confirming the viability of hybrid models in real educational environments. Our results align with these studies, further validating the potential of such systems to improve learner engagement and instructional personalization.

Recent studies have also highlighted the effectiveness of hybrid and explainable AI models in personalization tasks [43–46]. Fuzzy-ANN systems have shown enhanced adaptability [43], and AI-driven pattern prediction improves personalization [44], while explainable and ensemble models increase transparency and accuracy [45,46]. These findings further support the direction and design of the proposed model.

Finally, it must be noted that although the experiment was conducted within a specific course and discipline, the proposed model is not domain-dependent. Its architecture can be easily adapted to other educational settings where learner preferences and activity types can be defined. For example, in humanities or social sciences courses, learning activities such as debate, essay writing, or group discussions could replace programming-oriented activities, while still benefiting from the model's adaptive and personalized recommendations.

6. Conclusions

This paper introduces a fuzzy-ANN hybrid model that intends to improve the accuracy of study activity recommendations by adding elements of Kolb's Experiential Learning Theory into fuzzy logic and artificial neural networks (ANN). Experimental testing clearly shows that the model enjoys better performance in terms of accuracy, adaptability, and consistency with established educational theories than both traditional rule-based methods and AI-driven systems acting alone. As opposed to strict classifying systems, which tend to pigeon-hole, this model acknowledges that learning preferences may change. It attaches fuzzy membership values to its learners so they may be variously aligned with multiple learning styles. This supple nature enhances the accuracy of certain recommendations; integration with ANNs ensures that suggestions for learning activities will change continuously in response to how much attention a student is paying. Consequently, the system evolves dynamically, providing recommendations that remain both relevant and personal on every possible level for each individual.

To further test this model's feasibility, a real-world experimental study was conducted, with results proving that accuracy reached 88.4%—26.1% higher than traditional rule-based classification and 6.9% more accurate than the ANN alone. In addition, the fuzzy-ANN model had precision recall and F1-score higher than any other model—indicating just how effective it is at delivering individually tailored learning experiences. A qualitative case study repeated these observations, showing how the model adjusts learning activities to accommodate different individual students with widely varying learning styles.

Beyond the immediate results, the research contributes to the broader field of AI-driven education by illustrating how hybrid intelligent systems can support adaptive and learner-centered pedagogies. The model's architecture offers a promising foundation for integration into intelligent tutoring systems and learning platforms.

Despite its strengths, the model has some limitations. This study was conducted with a sample of 100 students over a 15-week period, making it necessary for future research to extend evaluations across various academic disciplines and learning environments to assess scalability and long-term effectiveness.

One major challenge is the cold start issue, where a student without any learning history may receive less accurate recommendations. Incorporating more behavior data and demographics could improve the model's predictive accuracy and also make personalized learning pathways even better.

Looking ahead, the integration of reinforcement learning could allow for dynamic adjustment of recommendation strategies based on live user feedback about how to learn. Furthermore, by expanding the model to encompass multimodal study activity analytics such as eye movement tracking or speech recognition, it may provide even more direct insights into how students engage and the burden on their minds, leading to a yet more precise level of personalization that adapts in real time rather than reacting after each lesson. Another good future direction should include adding more functionality to determine how the model can recommend collaborative learning suggestions. This would allow it to present instructional methods in groups based on the various styles of its participants. Finally, future research could explore enhancements, such as incorporating reinforcement learning for real-time adaptation based on continuous learner feedback. Additionally, testing the model across various disciplines and educational contexts would provide further evidence of its generalizability and practical value.

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Appendix A

A student, Alex, completes the questionnaire. Based on Alex's responses, his score was 67/80. This score needs to be converted into fuzzy membership values to allow for continuous classification instead of rigid, predefined categories. Using fuzzy membership function equations, we compute the fuzzy weights for each learning style, ensuring a more adaptive and accurate representation of Alex's learning preferences. Using the previously defined fuzzy membership equations, we calculate the fuzzy weights as follows:

For Accommodator (μ_A), with t = 67: $\mu_A = 0$.

For Converger (μ_C), with t = 67: $\mu_C = 0$.

For Assimilator (μ_{AS}), with t = 67: $\mu_{AS} = \frac{70-67}{70-60} = \frac{3}{10} = 0.30$.

For Diverger (μ_D), with t = 67: $\mu_D = \frac{67-60}{70-60} = \frac{7}{10} = 0.70$.

Thus, the computed fuzzy membership vector for Alex is $\mu = [\mu_A, \mu_C, \mu_{AS}, \mu_D] = [0, 0, 0.30, 0.70]$. These values reveal that Alex demonstrates a strong tendency toward the Diverger style, while also showing a moderate inclination toward Assimilator.

The computed fuzzy weights now serve as input for the artificial neural network (ANN): x = [0, 0, 0.30, 0.70].

The hidden layer neurons process the input values using a weighted sum transformation:

$$h_j = f\left(\sum_{i=1}^{4} w_{ij}x_i + b_j\right)$$

where:

- h_j is the activation value of hidden neuron j;
- w_{ij} represents the weight associated with the connection between input i and neuron j;
- b_j is the bias term for neuron j;
- f(x) is the Rectified Linear Unit (ReLU) activation function: f(x) = max(0, x).

For this example, we assume 8 hidden neurons with randomly initialized weights.

To illustrate the process, we present the calculations for a single hidden neuron:

$h_1 = f((0.5{\cdot}0) + (0.3{\cdot}0) + (0.2{\cdot}0.30) + (0.4{\cdot}0.70) + 0.1) = f(0 + 0 + 0.06 + 0.28 + 0.1)$ $= f(0.44) \Rightarrow h_1 = 0.44$ (since ReLU preserves positive values).

Each of the 8 hidden neurons follows the same computational process, generating feature-transformed values that help refine the learner's profile.

Once the data have been processed through the hidden layer, the final suitability scores for each learning activity are calculated using the WSM:

$$y_k = \sum_{j=1}^{m} v_{jk} h_j + c_k$$

where

- v_{jk} are the weights between the hidden layer neurons and the output neurons;
- h_j are the hidden layer activations;
- c_k are the bias values in the output layer.

Let us assume that the computed scores before softmax are y = [1.2, 0.8, 4.5, 3.9, 4.2, 1.0], where:

- y_1 = 1.2 (Hands-on Learning)
- y_2 = 0.8 (Problem-Solving Tasks)
- y_3 = 4.5 (Theory-Based Learning)
- y_4 = 3.9 (Reflective Learning)
- y_5 = 4.2 (Collaborative Learning)
- y_6 = 1.0 (Guided Learning)

To convert the scores into probabilities, we apply softmax activation:

$$\sigma(y_k) = \frac{e^{y_k}}{\sum_{j=1}^{6} e^{y_j}}$$

Computing the normalized values,

$$\hat{y} = [0.03, 0.02, 0.36, 0.26, 0.30, 0.03]$$

The top three recommended learning activities for Alex are as follows:

- Theory-Based Learning (36%) $\rightarrow$ Structured lectures, textbooks.
- Collaborative Learning (30%) $\rightarrow$ Group discussions, teamwork.
- Reflective Learning (26%) $\rightarrow$ Writing assignments, self-paced study.

This recommendation is consistent with Alex's fuzzy learning style profile, as he benefits most from structured, theory-driven instruction, collaborative learning with peers, and reflective exercises that allow deeper analysis.

References

1. Yang, S.; Tian, H.; Sun, L.; Yu, X. From One-Size-Fits-All Teaching to Adaptive Learning: The Crisis and Solution of Education in The Era of AI. *J. Phys. Conf. Ser.* **2019**, *1237*, 042039. [CrossRef]
2. Troussas, C.; Krouska, A.; Sgouropoulou, C. Dynamic Detection of Learning Modalities Using Fuzzy Logic in Students' Interaction Activities. In *Intelligent Tutoring Systems. ITS 2020*; Kumar, V., Troussas, C., Eds.; Lecture Notes in Computer Science; Springer: Cham, Switzerland, 2020; Volume 12149, p. 24. [CrossRef]
3. Xia, Y.; Shin, S.-Y.; Shin, K.-S. Designing Personalized Learning Paths for Foreign Language Acquisition Using Big Data: Theoretical and Empirical Analysis. *Appl. Sci.* **2024**, *14*, 9506. [CrossRef]
4. Annuš, N.; Kmet', T. Learn with M.E.—Let Us Boost Personalized Learning in K-12 Math Education! *Educ. Sci.* **2024**, *14*, 773. [CrossRef]
5. Troussas, C.; Krouska, A. Path-Based Recommender System for Learning Activities Using Knowledge Graphs. *Information* **2023**, *14*, 9. [CrossRef]
6. Niu, Y.; Lin, R.; Xue, H. Research on Learning Resource Recommendation Based on Knowledge Graph and Collaborative Filtering. *Appl. Sci.* **2023**, *13*, 10933. [CrossRef]
7. Villegas-Ch, W.; Sánchez-Viteri, S.; Román-Cañizares, M. Academic Activities Recommendation System for Sustainable Education in the Age of COVID-19. *Informatics* **2021**, *8*, 29. [CrossRef]

8. Hammad, R.; Khan, Z.; Safieddine, F.; Ahmed, A. A review of learning theories and models underpinning technology-enhanced learning artefacts. *World J. Sci. Technol. Sustain. Dev.* **2020**, *17*, 341–354. [CrossRef]
9. Rajan, M.H.; Herbert, C.; Polly, P. A synthetic review of learning theories, elements and virtual environment simulation types to improve learning within higher education. *Think. Skills Creat.* **2025**, *56*, 101732. [CrossRef]
10. Marougkas, A.; Troussas, C.; Krouska, A.; Sgouropoulou, C. Virtual Reality in Education: A Review of Learning Theories, Approaches and Methodologies for the Last Decade. *Electronics* **2023**, *12*, 2832. [CrossRef]
11. Kolb, D.A. *Experiential Learning: Experience as the Source of Learning and Development*; Prentice-Hall: Hoboken, NJ, USA, 1984; ISBN 0132952610.
12. Kulkarni, P.V.; Rai, S.; Sachdeo, R.; Kale, R. Deep Learning-based Educational User Profile and User Rating Recommendation System for E-Learning. *J. Inf. Syst. Telecommun.* **2023**, *11*, 185–195. [CrossRef]
13. Troussas, C.; Krouska, A.; Virvou, M. Multi-Algorithmic Techniques and a Hybrid Model for Increasing the Efficiency of Recommender Systems. In Proceedings of the 2018 IEEE 30th International Conference on Tools with Artificial Intelligence (ICTAI), Volos, Greece, 5–7 November 2018; pp. 184–188. [CrossRef]
14. Huynh-Cam, T.-T.; Chen, L.-S.; Le, H. Using Decision Trees and Random Forest Algorithms to Predict and Determine Factors Contributing to First-Year University Students' Learning Performance. *Algorithms* **2021**, *14*, 318. [CrossRef]
15. Tang, Y.; Wang, W. A Literature Review of Personalized Learning Algorithm. *Open J. Soc. Sci.* **2018**, *6*, 119–127. [CrossRef]
16. Lima-Junior, F.R. Advances in Fuzzy Logic and Artificial Neural Networks. *Mathematics* **2024**, *12*, 3949. [CrossRef]
17. Felder, R.M.; Silverman, L.K. Learning and teaching styles in engineering education. *Eng. Educ.* **1988**, *78*, 674–681.
18. Jan, N.U.; Naqvi, S.; Ali, Q. Using Fuzzy Logic for Monitoring Students Academic Performance in Higher Education. *Eng. Proc.* **2023**, *46*, 21. [CrossRef]
19. Damastuti, F.A.; Firmansyah, K.; Arif, Y.M.; Dutono, T.; Barakbah, A.; Hariadi, M. Dynamic Level of Difficulties Using Q-Learning and Fuzzy Logic. *IEEE Access* **2024**, *12*, 137775–137789. [CrossRef]
20. Ivanova, M.S. Fuzzy Set Theory and Fuzzy Logic for Activities Automation in Engineering Education. In Proceedings of the 2019 IEEE XXVIII International Scientific Conference Electronics (ET), Sozopol, Bulgaria, 12–14 September 2019; pp. 1–4. [CrossRef]
21. Anifah, L.; Sulistiyo, E.; Zuhrie, M.S.; Achmad, F.; Nugroho, Y.S.; Schulte, S. Decision Support System of Student Learning Outcomes Assessment on Digital Electronic Subject using Fuzzy Logic. In Proceedings of the 2021 Fourth International Conference on Vocational Education and Electrical Engineering (ICVEE), Surabaya, Indonesia, 2–3 October 2021; pp. 1–6. [CrossRef]
22. Zhang, Y. Application and Analysis of Fuzzy Hierarchical Model in Education and Teaching Quality Assessment. In Proceedings of the 2024 IEEE International Conference on Information Technology, Electronics and Intelligent Communication Systems (ICITEICS), Bangalore, India, 28–29 June 2024; pp. 1–4. [CrossRef]
23. Gupta, M.; Kumar, R.; Arora, A.; Kaur, J. Fuzzy logic-based Student Placement Evaluation and Analysis. In Proceedings of the 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), Greater Noida, India, 16–17 December 2022; pp. 1503–1507. [CrossRef]
24. Dhokare, M.; Teje, S.; Jambukar, S.; Wangikar, V. Evaluation of Academic Performance of Students Using Fuzzy Logic. In Proceedings of the 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA), Coimbatore, India, 8–9 October 2021; pp. 1–5. [CrossRef]
25. Barbosa, R.; Pelzl, M.; Cordero, R.; Caramalac, M.; Suemitsu, W. Didactic FPGA-in-the-Loop Scalar Fuzzy Control Setup for Motor Drive Education. In Proceedings of the 2023 IEEE 8th Southern Power Electronics Conference and 17th Brazilian Power Electronics Conference (SPEC/COBEP), Florianopolis, Brazil, 26–29 November 2023; pp. 1–5. [CrossRef]
26. Baashar, Y.; Alkawsi, G.; Mustafa, A.; Alkahtani, A.A.; Alsariera, Y.A.; Ali, A.Q.; Hashim, W.; Tiong, S.K. Toward Predicting Student's Academic Performance Using Artificial Neural Networks (ANNs). *Appl. Sci.* **2022**, *12*, 1289. [CrossRef]
27. Rodríguez-Hernández, C.F.; Musso, M.; Kyndt, E.; Cascallar, E. Artificial neural networks in academic performance prediction: Systematic implementation and predictor evaluation. *Comput. Educ. Artif. Intell.* **2021**, *2*, 100018. [CrossRef]
28. Valencia-Arias, A.; Uribe-Gómez, J.A.; Flores-Siapo, E.; Palacios-Moya, L.; Gallegos, A.; Martínez Rojas, E. Application of Artificial Neural Networks to Predict the Use of Mobile Learning by University Students. *Hum. Behav. Emerg. Technol.* **2024**, *9*, 1518987. [CrossRef]
29. Kord, A.; Aboelfetouh, A.; Shohieb, S.M. Academic course planning recommendation and students' performance prediction multi-modal based on educational data mining techniques. *J. Comput. High Educ.* **2025**. [CrossRef]
30. Khan, I.; Ahmad, A.R.; Jabeur, N.; Mahdi, M.N. An artificial intelligence approach to monitor student performance and devise preventive measures. *Smart Learn. Environ.* **2021**, *8*, 17. [CrossRef]
31. Gambo, Y.; Shakir, M.Z. An Artificial Neural Network (ANN)-Based Learning Agent for Classifying Learning Styles in Self-Regulated Smart Learning Environment. *Int. J. Emerg. Technol. Learn. (iJET)* **2021**, *16*, 185–199. [CrossRef]
32. Borhani, K.; Wong, R.T.K. An artificial neural network for exploring the relationship between learning activities and students' performance. *Decis. Anal. J.* **2023**, *9*, 100332. [CrossRef]

33. Gligorea, I.; Cioca, M.; Oancea, R.; Gorski, A.-T.; Gorski, H.; Tudorache, P. Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review. *Educ. Sci.* **2023**, *13*, 1216. [CrossRef]
34. Rastrollo-Guerrero, J.L.; Gómez-Pulido, J.A.; Durán-Domínguez, A. Analyzing and Predicting Students' Performance by Means of Machine Learning: A Review. *Appl. Sci.* **2020**, *10*, 1042. [CrossRef]
35. Alnasyan, B.; Basheri, M.; Alassafi, M. The power of Deep Learning techniques for predicting student performance in Virtual Learning Environments: A systematic literature review. *Comput. Educ. Artif. Intell.* **2024**, *6*, 100231. [CrossRef]
36. Kolb, A.Y.; Kolb, D.A. *The Kolb Learning Style Inventory-Version 4.0: A Comprehensive Guide to the Theory, Psychometrics, Research on Validity and Educational Applications*; Experience Based Learning Systems, Inc.: Kaunakakai, HI, USA, 2013; pp. 1–234.
37. Shahidan, W.N.W.; Ishak, N.R.; Muhamad, S.N.N. Learning Styles Preferences Using Fuzzy Logic System. *J. Comput. Res. Innov.* **2021**, *6*, 55–67. [CrossRef]
38. Kamalov, F.; Santandreu Calonge, D.; Gurrib, I. New Era of Artificial Intelligence in Education: Towards a Sustainable Multifaceted Revolution. *Sustainability* **2023**, *15*, 12451. [CrossRef]
39. Alzaid, M.; Fkih, F. A Fuzzy Model for Analyzing Students' Feedback About e-Learning. In Proceedings of the Future Technologies Conference (FTC) 2023; Arai, K., Ed.; Lecture Notes in Networks and Systems. Springer: Cham, Switzerland, 2023; Volume 815, p. 19. [CrossRef]
40. Bani Saad, M.; Jackowska-Strumillo, L.; Bieniecki, W. Hybrid ANN-Based and Text Similarity Method for Automatic Short-Answer Grading in Polish. *Appl. Sci.* **2025**, *15*, 1605. [CrossRef]
41. Zhao, L.; Sun, Y.; Tian, T. Fuzzy Neural Network Model for Intelligent Course Development in Music and Dance Education. *Int. J. Comput. Intell. Syst.* **2024**, *17*, 140. [CrossRef]
42. Kalaycı Alas, D.; Tezer, M. Artificial Neural Network and Adaptive Neuro Fuzzy Inference System Hybridized Models in the Sustainable Integration of Language and Mathematics Skills: The Case of Singapore and Hong Kong. *Sustainability* **2024**, *16*, 7806. [CrossRef]
43. Hoshino, Y.; Rathnayake, N.; Linh Dang, T.; Rathnayake, U. Cascaded-ANFIS and Its Successful Real-World Applications. In *Fuzzy Logic Controllers and Applications*; IntechOpen: London, UK, 2024. [CrossRef]
44. Kumar, S.; Agarwal, M.; Deshpande, V.; Cooper, J.R.; Khosravi, K.; Rathnayake, N.; Hoshino, Y.; Kantamaneni, K.; Rathnayake, U. AI-driven predictions of geophysical river flows with vegetation. *Sci. Rep.* **2024**, *14*, 16368. [CrossRef] [PubMed]
45. Makumbura, R.K.; Mampitiya, L.; Rathnayake, N.; Meddage, D.P.P.; Henna, S.; Dang, T.L.; Hoshino, Y.; Rathnayake, U. Advancing water quality assessment and prediction using machine learning models, coupled with explainable artificial intelligence (XAI) techniques like Shapley additive explanations (SHAP) for interpreting the black-box nature. *Results Eng.* **2024**, *23*, 102831. [CrossRef]
46. Alsulamy, S.; Kumar, V.; Kisi, O.; Kedam, N.; Rathnayake, N. Enhancing Water Level Prediction Using Ensemble Machine Learning Models: A Comparative Analysis. *Water Resour. Manag.* **2025**, 1–20. [CrossRef]