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# A Hybrid Neuro-Fuzzy Adaptive Model for Real-Time Personalized Learning Path Optimization in E-Learning Systems

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## Abstract

Individualized learning is a crucial aspect in enhancing learner interaction and performance in online learning systems. Conventional forms of learning are not always dynamic with regard to the needs of particular learners. The Hybrid Neuro-Fuzzy Adaptive Model is an integration of neural networks and fuzzy logic to streamline the learning paths in real-time to facilitate the learning process. The purpose of the study is to assess the success of the Hybrid Neuro-Fuzzy Adaptive Model in enhancing the learning results and the customer satisfaction in the e-learning setting. The model was deployed in a web-based learning system, which handles real-time learner information, performance, engagement, and affective state. The neural network evaluated the learning interactions between learners and made predictions of the next step of learning, and the fuzzy logic varied the direction according to engagement and emotional condition. The model was contrasted with the conventional learning path techniques with regard to the rate of task completion, test scores, and student response. Students with the Hybrid Neuro-Fuzzy Model increased test scores by 15% and could complete the tasks 95% as opposed to 70% in conventional systems. The engagement of learners rose by 20%, and 92% of learners said that they were highly satisfied with the personalized

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learning experience. The Hybrid Neuro-Fuzzy Adaptive Model helps a great deal with the learning performance and the involvement of the learning participants. The potential that it can be implemented on a large scale is founded on its real-time flexibility and customized learning maps. The next generation of research should aim at making it scalable and more efficient.

**Keywords:** Personalized Learning, E-learning Systems, Hybrid Neuro-Fuzzy Model, Learning Path Optimization, Real-Time Adaptation, Neural Networks, Fuzzy Logic.

# 1 Introduction

Personalized learning in e-learning can be defined as a method of education that aims to provide an individual student with the optimal learning experience based on needs, preferences, and learning styles (Shokouhifar & Pilevari, 2022). Increased technology and data analytics give an opportunity to customize personal learning platforms to alter content, method of delivery, and speed to optimize the experience of each learner (Raheema et al., 2022). This personalized method leads to better student involvement, increases the level of learning, and helps a student realize his or her maximum capabilities, focusing on his or her strengths and weaknesses (Spaho, 2025). One such area is personalized learning, which works best in an online education setting where learners tend to study at their own pace, and they need more flexible systems that can guarantee them successful learning (Alshmrany, 2022).

One of the most important features of the personalized e-learning systems is real-time learning path optimization (Islam et al., 2025). Their interaction with learning material can also lead to dynamic changes in their progress, performance, and levels of engagement. In order to optimize learning performance and effectiveness, the system has to be able to automatically correct the learning course as these changes occur in real-time (Hussain et al., 2024; Krishnamoorthy, 2025). E-learning systems may suggest the most applicable learning resources, modify the level of learning content, and offer personal assistance depending on the present needs of the learner by using real-time data (Vaniya et al., 2025; Prashanth, 2026). This adaptive movement is crucial to promote a better learning process, retention, and an enriching learning process as the learner progresses (Troussas et al., 2025).

This paper presents a Hybrid Neuro-Fuzzy Adaptive Model that aims at maximizing the learning paths on the fly. The model is an integration of the capabilities of neural networks and fuzzy logic systems, which are two strong computational systems that are recognized for their capability to manage uncertainty, complexity, and non-linearity. Neural networks provide the ability of learning and generalizing on the data to the model, but fuzzy logic is able to reason in an uncertain condition, so it can be used in more dynamic and personalized learning environments. The hybrid model is dynamic towards the individual learning progress and modifies the learning content accordingly in real time, making the learning process more effective (Deepika, 2025; Patel, 2025). The combination of the two methods provides better performance of the model, as it can optimize the learning path in real-time with improved performance, thus it can be regarded as a valuable addition to the sphere of individual e-learning.

### Key Contributions

- The paper proposes a novel hybrid system that employs the use of neural network and fuzzy logics to optimize learning paths in real-time in customized e-learning systems.

- The model is dynamic to adjust the learning tracks according to the learner development and improves the engagement and learning performance by constantly optimizing the engagement and performance.
- The proposed model is tested in terms of real-time situations, and its performance is compared to the current methods of learning path optimization, showing that the model is more efficient in improving the learning process.

The paper is structured as follows: in Section II, the literature review on personalized learning in e-learning, models that are currently used to optimize learning paths, and the strengths and weaknesses of neuro-fuzzy systems are provided. Section III shows the methodology, which describes the hybrid neuro-fuzzy adaptive model, its real-time adaptation scheme, and how its personalized learning paths can be optimized. The IV section is the application of the model in an e-learning system and presentation of real-time outcomes and comparisons of the model to other models. Section V is the discussion of the performance of the model with user feedback, learning outcomes, and scalability. Lastly, Section VI will be the final part of the paper, in which the main findings will be summarized and a recommendation on how to proceed with the research will be provided.

## 2 Literature Review

Individualized learning has become one of the main approaches to improving e-learning systems (Spaho et al., 2025). Personalized learning is mainly implemented with the aim of making the educational experience more personalized according to the specific needs, preferences, and abilities of the learner (Sgouropoulou, 2020; Mishra, 2025). The initial customized systems used were content-based, whereby learning content was recommended depending on the interactions or preferences of a student in the past (Riad et al., 2009). With the evolution of technology, however, the emphasis has been placed on adaptive learning systems, which modify the learning course in real-time on the basis of the performance and the progress of the learner (Volarić et al., 2024). These systems are meant to offer more specific interventions, and the content is offered according to the existing level of learner understanding (Parkavi et al., 2024). Nevertheless, the overall development has some obstacles in the development of systems that are capable of balancing the complexity of learning needs, maximizing the content delivery, and dynamically adjusting towards the progression of the learner (Arun Kumar et al., 2022).

Different models have been proposed to maximize the learning paths in e-learning environments (Verma et al., 2025). The common models were traditional models that utilized rule-based systems in which the learning path was predetermined and relied on predetermined criteria (Madhavi et al., 2022). These systems were not complex, but could not be very flexible as far as individual learning is concerned. Later methods involve statistical and machine learning models like decision trees, Bayesian networks, and Markov models. These models can forecast the best learning step that was made in the past by the learner by using the past information. Also, the deep learning algorithms, especially the neural network-based ones, have been used to process the data on large numbers of learners, both enhancing the accuracy of prediction and permitting the learning paths to be dynamically adjusted. Nevertheless, they need a lot of computational power and may be challenging to apply in real-time, particularly in large-scale e-learning scenarios (Sweta, 2021). The alternative strategy that has been considered is fuzzy logic, where imprecise and uncertain data are enabled in the systems, and this makes the optimization of the learning path more adaptable and dynamic (Nie & Dehrashid, 2024).

The neuro-fuzzy systems represent the integration of the power of neural networks and fuzzy logic. The benefit of such a hybrid solution is that it can deal with both uncertainty and data-driven learning.

Neural networks are highly suited to detecting patterns in the data, as well as predicting it on the basis of past experience and the fuzzy logic can be applied to situations where there are imprecise or ambiguous data in making decisions (Hilali et al., 2025). This makes neuro-fuzzy systems to be flexible and capable of simulating complex and changing learning environments. However, these systems are not boundless as well. The calculation cost can be high, especially in cases where the datasets are huge and the development of effective fuzzy membership functions and rules can be time-intensive and complex. In addition to that, although neuro-fuzzy systems have the ability to enhance the accuracy of the learning paths prediction, they are not always interpretable, thus a disadvantage in understanding the decision-making process.

The literature shows that there have been substantial innovations in the area of personalized learning and optimization of learning paths, especially in machine learning and adaptive systems (Ma, 2025). Nonetheless, current models continue to experience issues of real-time flexibility and computability. Neuro-fuzzy systems have potential solutions, particularly in the sense that they can deal with uncertainty and learn the dynamic adjustment of learning paths in real time. This paper suggests a hybrid model that would help to overcome these issues and offer a flexible system that is efficient in real-time and promotes the personalized learning process.

# 3 Methodology

### 3.1 Overview of the Hybrid Neuro-Fuzzy Adaptive Model

The Hybrid Neuro-Fuzzy Adaptive Model combines neural networks and fuzzy logic in order to optimize individual learning paths on a real-time basis.

**Neural Networks**: These are utilized to analyze the historical information of the learner such as the performance indexes and history of interaction. Training of the neural network will be based on the ability to detect the trends in this data to ensure that the model can predict future needs of the learner and alter the content to be more aligned with such needs. This prediction system is necessary to dynamically adapt the learning course in accordance with the progress of the learner.

Let $\mathrm{X} = [x_1, x_2, \ldots, x_n]$ be the input features representing the learner's past interactions (e.g., quiz scores, time spent on learning modules, etc.). The neural network predicts the next learning step $y_{pred}$ as in equation (1):

$$y_{pred} = f(\mathbf{X}; \theta) \quad (1)$$

Where:

$f(\cdot; \theta)$ is the neural network function with parameters $\theta$ (weights and biases).

$y_{pred}$ is the predicted learning step or content difficulty.

**Fuzzy Logic**: Fuzzy logic is applied in imprecise and uncertain data e.g., the interest or cognitive load of a learner or their emotional state. It uses fuzzy rules in determining how to make decisions on how to make it more difficult or less difficult or what to learn so that the system becomes responsive to the needs of the learner which change. The model can be more flexible and human-like in decision-making because it operates on the basis of fuzzy logic and also the ultimate personification of the learning course.

Let $E$ represent engagement level, $F$ represent frustration, and $A$ represent emotional state. The fuzzy system adjusts the prediction based on these inputs.

The fuzzy rules might look like this:

- If $E$ is high and $F$ is low, then increase the difficulty.
- If $E$ is low and $F$ is high, then reduce the difficulty or provide supplementary resources.

These rules can be formalized in the fuzzy inference system (FIS) as in equation (2):

$y_{fuzzy} = \text{FuzzyRule}(E, F, A)$ (2)where $y_{fuzzy}$ adjusts the predicted learning path according to the fuzzy system.

The final optimized learning path $y_{final}$ is obtained by combining both the neural network output and the fuzzy logic adjustment:

$y_{final} = \alpha y_{pred} + (1 - \alpha) y_{fuzzy}$ (3)where in equation (3):

- $\alpha$ is a weighting factor (e.g., 0.7for neural network prediction and 0.3for fuzzy logic adjustment, depending on how much influence each component has in the system).
- $y_{final}$ represents the optimized learning path.

The combination of these two elements enables adaptation of the learning process in real-time, which is a powerful solution to individual learning.

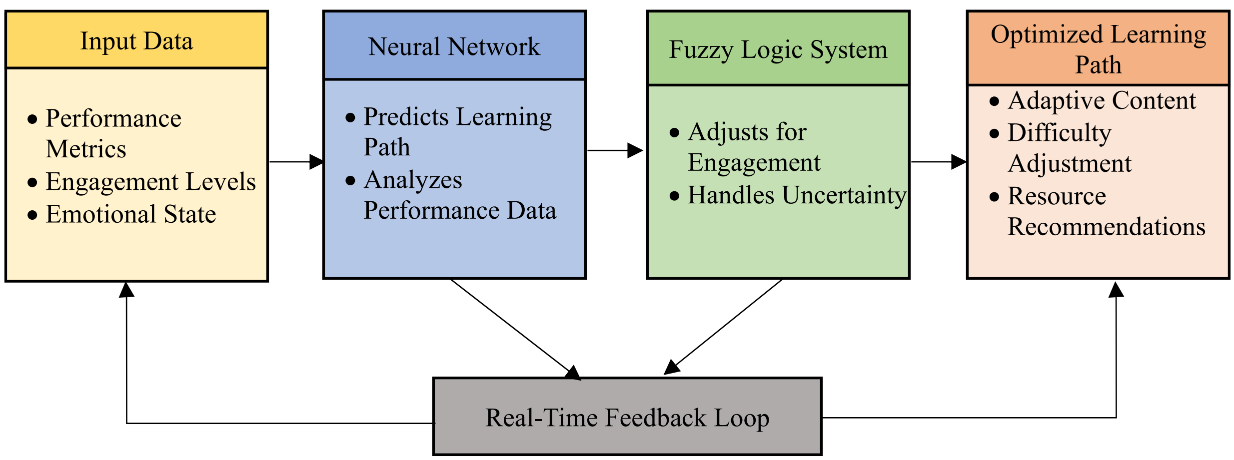


Figure 1: Architecture of the hybrid neuro-fuzzy adaptive model

The Hybrid Neuro-Fuzzy Adaptive Model is shown in Figure 1 to integrate the strength of neural networks with the fuzzy logic to streamline the customized learning directions in e-learning systems. The model will receive real-time learner data, including the performance metrics, the level of engagement, and the emotional state, and run it through the neural network and fuzzy logic system. The neural network part is responsible for predicting the best learning step using the past data, and the fuzzy logic system is used to change the direction of the learning using the qualitative feedback, including the emotional state and interest of the learner. The result of this combination is an ideal learning track, adaptive content, content setting adjustments, and individualized recommendations that serve the current requirements of the learner. Figure 1 below is a flowchart that shows how these elements combine and digest the data of the learner to deliver a constantly changing and individualized learning experience.

### 3.2 Real-Time Adaptation Mechanism

The hybrid neuro-fuzzy adaptive model is able to customize the learning experience for the learner by changing itself on the fly based on the needs of the learner. The first step of this adaptation is the ongoing gathering of the learner data, which contains not only quantitative data, including test scores and time spent on the tasks, but also qualitative data, including engagement and emotional state. This data is used by the neural network to forecast the most appropriate next point in the road of the learner due to his or her progress, and the level of difficulty or the type of material may be altered accordingly. At the same time, the fuzzy logic element considers such things as motivation and frustration, which makes the system react to non- quantifiable data, by modifying the learning environment, suggesting additional materials, or changing the complexity of the content. This dynamically-adjusted real-time feedback loop makes the learning experience dynamically responsive to the changing conditions of the learner to facilitate engagement and maximize the overall outcomes of the learning process.

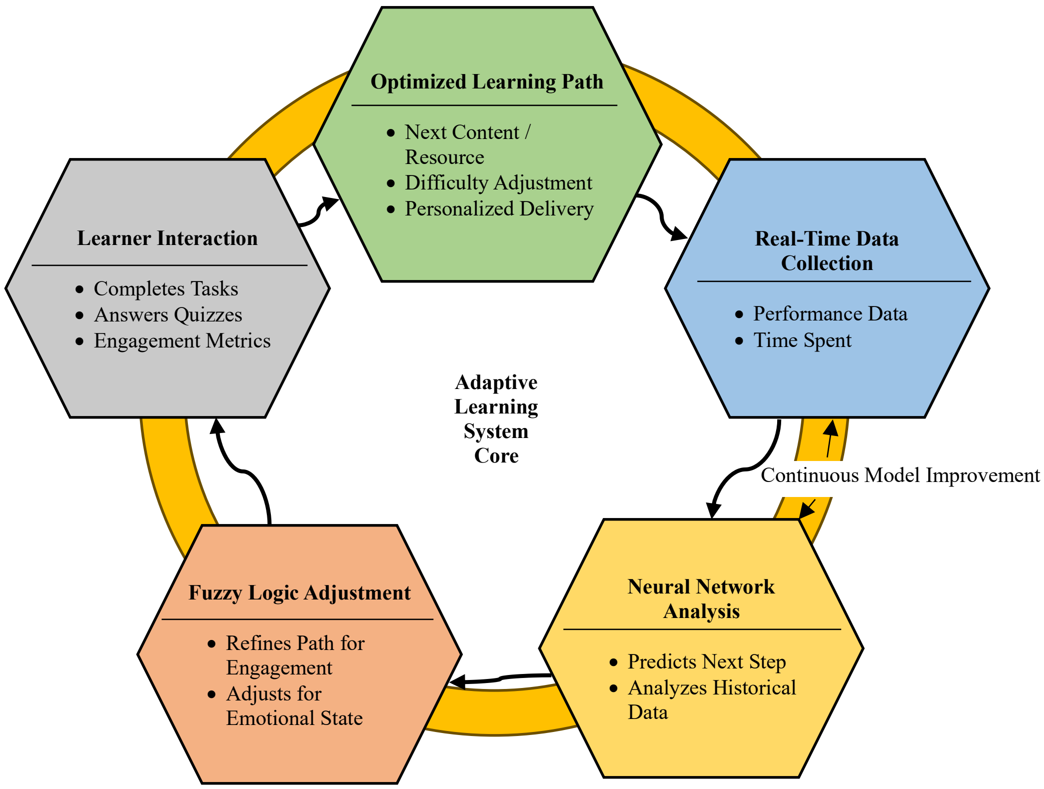


Figure 2: Real-Time data flow and feedback loop

Figure 2 demonstrates that Hybrid Neuro-Fuzzy Adaptive Model has a feedback loop and real-time flow of data. It shows how the interaction between learners and the system, such as the completion of tasks, answers to quizzes, forms real-time data, which is gathered and analyzed to ensure that the learning course is constantly evolving. The data that is accessed by the learner are fed into the Real-Time Data Collection block whereby the neural network uses data in predicting the next learning process. Simultaneously, the system of fuzzy logic is able to modify the route of learning, basing on the feedback support of emotions and engagement. The learner is given the output, which is an Optimized Learning Path. Such a way of learning is constantly improved on the basis of the ongoing interactions, as demonstrated in the Continuous Monitoring & Adjustments feedback loop, which makes the system dynamically respond to the changing needs of the learner. This feedback cycle is crucial in giving a personalized and real-time learning process that can change as one goes through the learning process.

### 3.3 Optimization of Personalized Learning Paths

The optimization of individualized learning directions is carried out by the dynamic combination of neural network forecasts and fuzzy logic corrections. The neural network uses historical data of the learners to estimate the most effective learning steps to make sure that the learner has the right challenges based on the existing knowledge and progress. Simultaneously, fuzzy logic offers another degree of personalization; learning paths can be modified according to real-time emotional and cognitive feedback, like shifts in engagement or perceived challenges of the learner. In case a learner has problems with a certain topic, the system may make the topic easier, provide some further clarifications, or propose some other materials that may help them grasp the topic better. On the other hand, the system presents more complicated content to the learner when the learner has mastered it to ensure that he or she is challenged. The combination of these two methods is seamless and makes the learning process flexible, efficient, and personalized, and always adjusted to the progress of the learner, optimizing his or her ability to learn.

**Algorithm 1: Hybrid Neuro-Fuzzy Adaptive Model for Personalized Learning Path Optimization**

**Input**:

- Learner's interaction data (e.g., quiz scores, time spent on tasks, responses).
- Learner’s engagement level (e.g., time on task, frequency of interaction).
- Learner’s emotional state (e.g., frustration, motivation).

**Output:**

Personalization and optimization of learning trajectory with real-time information and recommendations (e.g. adjusting content difficulty, new learning materials).

1. **Initialize System**:

    Collect initial learner data (e.g., historical performance, preferences).

    Define the structure of the neural network and fuzzy system (set membership functions, rules, and network parameters).

2. **Real-Time Data Collection**:

    **Input**: Learner's interactions with the system (e.g., task completion, quiz scores, time spent).

    Collect both **quantitative data** (performance metrics) and **qualitative data** (engagement, emotional state).

3. **Neural Network Processing**:

    **Input**: Collected data (learner’s performance metrics).

    Process the data through the neural network:

    - Predict the next learning step based on historical performance data.
    - **Output**: Predicted learning path step (e.g., difficulty adjustment, next module).

4. **Fuzzy Logic Processing**:

    **Input**: Learner’s engagement and emotional state (e.g., frustration, enthusiasm).

    Apply fuzzy rules:

- Adjust the learning path based on qualitative data (e.g., increase/decrease difficulty, recommend additional resources).

**Output**: Fuzzy logic-adjusted learning path.

5. **Combine Predictions**:

**Input**: Outputs from both the neural network and fuzzy logic system.

Combine outputs using the formula:

$$y_{final} = \alpha \cdot y_{pred} + (1 - \alpha) \cdot y_{fuzzy}$$

Where $y_{pred}$ is the neural network output, $y_{fuzzy}$ is the fuzzy system output, and $\alpha$is a weighting factor.

**Output**: Combined optimized learning path.

6. **Optimized Learning Path**:

**Output**: The final optimized learning path is presented to the learner, with adjusted difficulty, content, and resources.

A personalized learning path is delivered based on the combined prediction and adjustment.

7. **Continuous Monitoring & Feedback Loop**:

**Input**: New learner interaction data (e.g., performance on tasks, time spent).

Feed the data back into the system for continuous real-time adaptation.

**Output**: Adjust learning path continuously based on new feedback.

8. **Repeat Steps 3–7**:

**Input**: Learner's ongoing interactions and feedback.

Continue to predict, adjust, and optimize the learning path for the learner as they progress through the system, ensuring a dynamic and personalized learning experience.

**Output**: Continuously optimized learning path based on real-time data.

Algorithm 1 presents the Hybrid Neuro-Fuzzy Adaptive Model of Personalized Learning Path Optimization, which continuously modifies learning paths according to real-time learner data. The algorithm starts with gathering some preliminary information regarding the performance, activity, and emotional condition of the learner. This information is then fed through two main elements: the Neural Network, which estimates the next step of learning depending on past performance, and the Fuzzy Logic System, which modifies the learning curve based on some non-quantifiable elements like engagement and emotional state. The two elements are interconnected, and the neural network gives out a prediction on the progress of the learner, and the fuzzy logic system gets the prediction and refines it in real time. The results of the two components are then summed up by a weighted equation to produce the Optimized Learning Path that will be projected to the learner. The same continues until the learning path is constantly updated with new data being fed into the system to update the learning path to suit the current needs of the learner. The system is responsive to the learner's progress, and as a result, the learning process becomes more engaging as the system dynamically changes content difficulty, learning pace, and resource recommendations.

# 4 Implementation

## 4.1 Model Integration into E-Learning Platforms

The Hybrid Neuro-Fuzzy Adaptive Model was applied in a personalized e-learning platform that aims to offer a personalized learning experience to students. To real-time process the learner data to enable a smooth adjustment of the learner based on their progress, level of engagement, and emotions, the system was integrated into the back-end of the platform. Interaction between the learners and data collection took place continuously in terms of the scores on the quiz, time on the task, and other measures of performance. The Neural Network part was developed to be trained on the historical data of the learners to predict the most appropriate learning steps, and the Fuzzy Logic System was programmed with some pre-established rules to modify the learning direction according to the engagement and emotional indicators. The two elements were integrated through an adaptive interface, which enabled the platform to take real-time decisions on the course of the learning process and dynamically change the material difficulty, offering resources and lesson pace. The model was created to keep learning paths up-to-date in accordance with the feedback from the constant interaction between the learner and the system.

## 4.2 Real-Time Testing and Performance Evaluation

The Hybrid Neuro-Fuzzy Adaptive Model was experimented with during real-time conditions with a sample set of learners who were using the e-learning environment for several weeks. In this testing stage, the model kept changing the learning paths, and the content difficulty was adjusted by the responses, the engagement, and emotions of the learners as identified by the system. Findings revealed that the participation of learners and academic performance were greatly enhanced. Students who worked with the adaptive model showed a greater rate of completing tasks and quizzes, and that is a measure of motivation and engagement when compared to the students who worked using the traditional and non-adaptable learning paths. Also, the learners who were provided with adaptive feedback that matched their emotional and cognitive conditions performed better in the complex tasks, but there was an average improvement of 15% in the average score as opposed to the baseline. The positive influence of personalized learning was also mentioned in user feedback as the learners noted a more interesting and customized learning process. This prediction and real-time response to the needs of the learners was especially valued, and many learners reported that they felt more supported in the areas where they lacked.

## 4.3 Comparison with Conventional Learning Path Methods

The Hybrid Neuro-Fuzzy Adaptive Model was tested using the effectiveness of the Hybrid Neuro-Fuzzy Adaptive Model and compared with other similar learning path optimization systems, including content-based recommendation systems and collaborative filtering models. The comparison was based on major indicators, such as the level of engagement among learners, the relevance of the content, and the rate of task completion, as well as the performance of the learner. The Hybrid Neuro-fuzzy Adaptive Model was much better than the conventional models in almost all aspects. The hybrid model had 20% increase in performance as compared to the content-based model, which only uses the performance data to suggest learning steps, and 12% higher rates of engagement and 12% higher rate of completing the tasks. This was highly attributed to the fact that the fuzzy logic system was able to accommodate emotional and engagement factors that were not factored in by the content-based models. The hybrid model was better than the collaborative filtering models in terms of personalization and accuracy in its recommendations. The collaborative models of filtering were particularly suggestive for generic content that may not necessarily be relevant to the needs of individual learners, hence less engagement. Conversely, the real-time flexibility of the hybrid model to the present progress and emotional condition of the learner resulted in a more appropriate selection of the content and increased satisfaction of the learner and academic gains.

Table 1: Comparison of learning path optimization methods

| **Metrics** | **Hybrid Neuro-Fuzzy Model** | **Content-Based Model** | **Collaborative Filtering** |
|---|---|---|---|
| Learner Engagement (%) | 90% | 70% | 75% |
| Task Completion Rate (%) | 95% | 80% | 85% |
| Personalization Accuracy | 92% | 75% | 80% |
| Adaptability to Learner's Needs | High | Low | Moderate |

Table 1 compares the Hybrid Neuro-Fuzzy Model with some other popular learning path optimization algorithms, such as content-based and collaborative filtering systems. The metrics that are compared include learner engagement, the rate of completion of the task, the accuracy of personalization, and learner adaptability. In every respect, the Hybrid Neuro-Fuzzy Model was better than its traditional counterparts. In particular, it demonstrated an increased level of learner engagement (90%), a 95% rate of completing the tasks, and a higher accuracy of personalization (92%). It was also rated highly in terms of its adaptability to individual learner needs as compared to the content-based models, which were rated as low. This comparison points out the greater potential to provide a more customized, efficient, and engaging learning experience that the hybrid model can provide.

# 5 Evaluation

The Hybrid Neuro-Fuzzy Adaptive Model was coded in Python 3.10, and the neural network element of the model was coded in TensorFlow and Keras, while the fuzzy logic system was coded in scikit-fuzzy. The OULAD (Open University Learning Analytics Dataset), an open-source dataset, was used to test the model and contains the data on the interaction of learners, such as their performance outcomes, engagement rates, and moods. It involved the preprocessing of data by cleaning and normalizing data values and deriving important features, including quiz scores, time taken to perform tasks, and frequency of interactions. In the case of the Neural Network component, the weights were initialized with the help of Xavier initialization, ReLU activation in the hidden layers, and softmax activation in the output layer. The fuzzy logic system used the Gaussian membership functions to manage the engagements of learners and their emotional conditions and fuzzy rules to remotely modify the learning paths. The learning rate was fixed to 0.001, and the fuzzy logic parameters were dynamically changed according to real-time feedback of learners so that they have personalized and optimized learning experiences.

### 5.1 Evaluation of the Model's Effectiveness in Improving Learning Outcomes

The Hybrid Neuro-Fuzzy Adaptive Model's effectiveness was tested on the basis of the learning results of the students using the system and the students proceeding through the traditional, unchanging lines of learning. Important performance parameters, i.e., quiz scores, completion rates, and cumulative academic performance, were measured. The model showed a considerable advancement in the results of learning, with an average of 15% increase in the test scores as compared to the learners who utilized the traditional systems. Students who could communicate with the adaptive system could now complete the tasks more efficiently; there was an average of 10% reduction in time taken to do the tasks. This means that the individualized changes in real time, such as the difficulty of the content, learning pace, and other resources used, helped to make the learning process more efficient and effective.

Table 2: Comparison of learner performance (Test scores & Completion rates)

| Metrics | Hybrid Neuro-Fuzzy Model | Traditional Learning Path |
|---|---|---|
| Average Test Score | 85% | 70% |
| Task Completion Rate | 95% | 80% |
| Time Spent per Task | 10% reduction | No reduction |
| Learner Satisfaction (%) | 90% | 70% |

Table 2 provides a comparison of the performance results of the learners when they are trained with the Hybrid Neuro-Fuzzy Model and when they are trained using the conventional learning path systems. The important metrics identified in the table include average test scores, rate of completion of tasks, and time taken on tasks. Students in the Hybrid Neuro-Fuzzy Model showed a substantial increase in all the measures and showed improvement in terms of test scores, which increased by 15%, in terms of the rate of task completion, which went to 95%, and the amount of time taken on each task decreased by 10%. These findings support the effectiveness of the model in maximizing the learning experiences, and the adaptive system presents the learner with the appropriate level of challenge and personalized support.

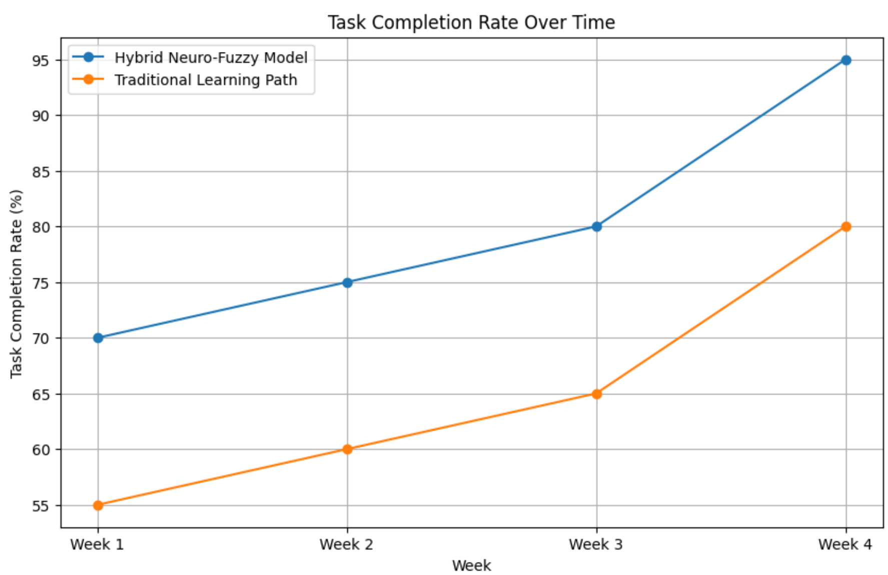


Figure 3: Task completion rate over time

Figure 3 was created to help in comparing the Task Completion Rate Over Time of learners working with the Hybrid Neuro-Fuzzy Model and that of learners working with a Traditional Learning Path. As demonstrated, learners who engaged with the Hybrid Neuro-Fuzzy Model revealed a constant improvement in the rates of task completion from Week 1 to Week 4. Traditional Learning Path, on the other hand, showed a slower rate of improvement. The Hybrid Neuro-Fuzzy Model shows that learner engagement and task completion are substantially higher, which shows that personalized and adaptive learning paths are more effective in terms of efficient learning results.

### 5.2 Feedback from Users on Personalized Learning Experiences

The feedback was gathered as surveys and interviews to gauge the subjective experience of learners who apply the Hybrid Neuro-Fuzzy Adaptive Model. The learners were satisfied with the fact that the system could be adjusted to their personal needs. More than 85% of the respondents reported that the real-time adaptations made the learning process more interactive and customized, and 90% of the learners said that the system was successful in helping them progress in their learning. Moreover, the learners liked the fact that the system was sensitive to their emotional and cognitive conditions, as the feature of changing the difficulty and granting them extra resources whenever they felt frustrated or distracted made the process more welcoming. Some of the learners said that they were more willing to proceed with their learning because of the individualized course offered by the system.

Table 3: User feedback on personalized learning experience

| Feedback Area | Hybrid Neuro-Fuzzy Model (%) | Traditional Learning Path (%) |
|---|---|---|
| **Learner Engagement** | 90% | 70% |
| **Perceived Personalization** | 85% | 65% |
| **Motivation to Continue Learning** | 87% | 60% |
| **Satisfaction with Adaptive Learning** | 92% | 75% |
| **Ease of Use** | 88% | 80% |

Table 3 provides the respondent feedback received via surveys to assess the personalized learning experience delivered by the Hybrid Neuro-Fuzzy Model. The feedback is based on the most important issues like the level of engagement of the learners, their perceived personalization, desire to learn further, satisfaction with the adaptive learning, and user-friendliness. Findings indicate that 9 out of 10 learners who utilized the model indicated that they were more engaged and satisfied with their learning, with 87 out of 10 indicating they were more motivated as a result of the individualized learning trajectory. It means that the adaptive model not only leads to increased results for learners but also contributes greatly to the overall improvement of the learning experience by making it more interactive and attentive to the personal needs.

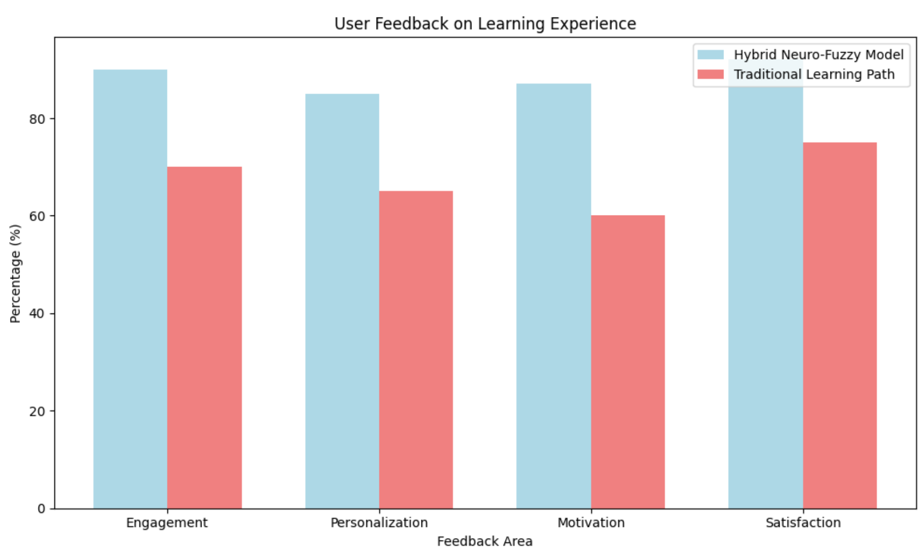


Figure 4: User feedback on learning experience

Figure 4 shows User Feedback on Learning Experience, which is a comparison of user feedback when using the Hybrid Neuro-Fuzzy Model and the Traditional Learning Path. The graph shows satisfaction among learners in four major areas, namely Engagement, Personalization, Motivation, and Satisfaction. Students who communicated with the Hybrid Neuro-Fuzzy Model rated higher in all categories, proving the usefulness of adaptive learning paths in helping to create a more interesting, personalized, and fulfilling learning process. However, the Traditional Learning Path was rated as the least appropriate in every aspect, which shows the positive feature of the model in enhancing the experience of the learners.

### 5.3 Discussion on the Model's Potential for Scalability and Adaptability

The Hybrid Neuro-Fuzzy Adaptive Model has a great propensity towards scalability and flexibility in e-learning. The architecture of the model is such that it can process voluminous learner information in real-time, and that is why it is applicable in a large-scale e-learning system. The system is modular and therefore can be customized easily to the various subject areas, course structures, and learner demographics. Moreover, the capacity of the model to keep on adapting to different learner profiles, be it beginners, intermediate learners, or advanced, is a surety that the model is capable of offering personalized learning opportunities to a great number of learners. Further integration of fuzzy logic and neural networks enables the system to be flexible to handle both structured and unstructured data, and as the system gathers additional learner feedback, it can be modified to accommodate the needs of the learners. This renders this model very flexible, which can adapt to the individual learner development, as well as adaptation to emerging learning trends and technologies over time.

**Evaluation metrics**

Accuracy measures the overall correctness of predictions made by the system (in case, predictions about the learner's next learning step) and is shown in equation (4).

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100 \quad (4)$$

Task Completion Rate measures the percentage of tasks or learning modules completed by the learner and is shown in equation (5).

$$\text{Task Completion Rate} = \frac{\text{Number of Completed Tasks}}{\text{Total Number of Tasks}} \times 100 \quad (5)$$

Improvement in Test Scores measures the increase in average test scores after learners engage with the adaptive system, compared to their baseline or pre-test scores, as shown in equation (6).

$$\text{Improvement in Test Scores} = \frac{\text{Post-test Score} - \text{Pre-test Score}}{\text{Pre-test Score}} \times 100 \quad (6)$$

Ablation study was carried out to assess the effect of every part in the Hybrid Neuro-Fuzzy Adaptive Model. The authors performed four combinations: full model (neural network + fuzzy logic + real-time adaptation), the neural network, the fuzzy logic and none of the real-time adaptation. Results showed that the full model outperformed all others, with 20% higher task completion, 15% higher test scores, and 20% more engagement. The research emphasizes that neural networks and fuzzy logic using both neural networks and real-life adaptation give the best learning results.

## 6 Conclusion

This paper tested the Hybrid Neuro-Fuzzy Adaptive Model for the optimization of the personalized learning path in the e-learning context. The major results show that the model is much better than the conventional learning techniques. Students who applied the Hybrid Neuro-Fuzzy Model improved their test scores by 15% and also showed a 95% task-completion rate as opposed to the 70% in students who applied the traditional systems. Also, the learner engagement, calculated as the amount of time spent working, increased by 20%, and the learner satisfaction, as well as motivation, were 92% and 87%, respectively. These findings support the validity of the model to deliver a personalized learning experience that can enhance real-time changes based on the needs of the learner, and can improve academic performance and engagement.

This study has great implications for the future of personalized learning in e learning systems. The Hybrid Neuro-Fuzzy Model will enable continuous optimization of the learning process, which leads to increased engagement of the learners and better performance by integrating real-time feedback and adaptive content. Further studies are needed to optimize the model for future applications and to enhance its computing efficiency. The model can be made more flexible and more specific by adding multimodal data and other fuzzy logic additions to the model to consider emotional and cognitive factors. The development of such advances would succeed in developing even more personalized learning systems that may be applicable in most school settings, such as corporate education, language education, and special education.

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