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Real-Time Neurofeedback-Driven Mobile Learning Systems with Cognitive State-Responsive Content Personalization for Enhanced Engagement

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Abstract

Real-time adaptive mobile learning systems have gained popularity due to their portability and flexibility; however, very few of them can adjust themselves in real time depending on the cognitive state of users, thus leading to low motivation and effectiveness. This current study introduces a Real-Time Neurofeedback-Driven Mobile Learning System (RNMP). It utilizes the information received via neurophysiological sensing to adapt its behavior in response to users' mental state and provide a more effective learning experience. The aim of the research is to improve user engagement and knowledge retention via content adaptation. The RNMP utilizes neurophysiological signals such as electroencephalography, heart rate variability, and eye tracking data obtained via wearable technology. These neuro signals go through a preprocessing stage, where they are filtered for noise, normalized, and converted into cognitive feature representation. After that, the classification of

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cognitive states is performed via a machine learning algorithm to define states such as high engagement, moderate attention, and cognitive load. Based on these states, an adaptation algorithm adjusts the complexity, pace, and modality of the material provided. An experimental assessment was carried out by leveraging a mixed dataset from DEAP and SEED, along with artificially generated mobile learning interaction data comprising 45 subjects and 1.2 million signal instances. The RNMP model was able to achieve an accuracy rate of 94.1% as compared to conventional mobile learning (78.2%), rule-based personalized adaptive learning (81.5%), deep-learning personalization models (86.7%), and reinforcement learning (89.3%). In addition to this, the model achieved an engagement score of 0.91, a retention rate 89.7%, and a latency of 98ms, proving its effectiveness in real-world applications. The findings demonstrate that neurofeedback-based personalization greatly enhances cognitive engagement and learning effectiveness. The paper concludes that cognitive state detection, along with adaptive learning, is an effective methodology to be implemented in next-generation mobile learning platforms.

Keywords: Neurofeedback Learning Systems, Mobile Learning Personalization, Cognitive State Detection, EEG-Based Adaptation, Real-Time Edge Computing, Adaptive Education Systems, Learning Engagement Optimization.

1 Introduction

Mobile learning has emerged as one of the prevalent paradigms within education as a result of its flexibility, accessibility, and continuous nature (Wu, 2025). Despite its widespread use, mobile learning systems generally maintain static characteristics, offering uniform instruction irrespective of the learner's mental status and attention span (Premathilake et al., 2025; Abiri et al., 2015). Such a static nature of mobile learning decreases engagement efficiency, especially in cognitively challenging scenarios that involve changes in the user's attention span over time. The reality is that in practice, learners may be overwhelmed by cognitive processes, distractions, or inattentiveness, affecting knowledge acquisition and learning outcomes (Peixoto et al., 2025; Kumar et al., 2026). It is therefore necessary for there to be adaptive mobile learning systems capable of adapting to the learner's mental condition (Saranya, 2025).

Advances in wearable neurotechnology, such as EEG headbands, fNIRS sensors, and lightweight bio signal recording devices, have made it possible to obtain real-time data on neural and physiological signals related to attention, workload, and engagement. With the combination of these sensors with mobile learning platforms, the possibility of developing neurofeedback systems for dynamic personalization of learning content emerges (Stephygraph & Arunkumar, 2015). Nonetheless, most current neurofeedback systems suffer from various drawbacks, namely, low efficiency, real-time adaptivity, limited computational power, and weak integration of cognitive sensing and adaptation modules. This limits the use of such systems in ubiquitous mobile learning (Mishra, 2025).

With this regard, the present research proposes the concept of a Real-Time Neurofeedback-Driven Mobile Learning System based on the principles of real-time cognitive state detection that allows adapting and personalizing the content accordingly. In order to develop such a system, this study analyzes the available technologies and frameworks used to monitor users' cognitive state and apply neurofeedback algorithms to make adaptive content delivery decisions in real time. The research is relevant to the field of ubiquitous computing and dependable systems since it combines cognitive neuroscience techniques and mobile learning technologies into one framework.

Key Contributions

- Designs a real-time neurofeedback-based mobile learning system that is capable of sensing cognitive states and adaptively providing educational material.
- Develops a dynamic personalization approach that adapts educational content according to attention level, workload, and engagement.
- Takes advantage of low-latency processing schemes that are effective for mobile and edge computing scenarios.
- Achieves enhanced efficiency and engagement using neuroadaptation approaches.

The rest of the paper is structured as follows. Section II gives an overview of relevant research on neurofeedback-based systems, mobile learning devices, and personalized systems with knowledge about the cognitive state of users. Section III describes the developed Real-time Neurofeedback-based Mobile Learning System, which includes the system's architecture, algorithm, and mathematical model. Experimental work and the implementation of the system are detailed in Section IV. Section V concludes the paper.

2 Literature Survey

The latest developments in neuroadaptive learning platforms and cognitive computing have greatly impacted the design of intelligent educational tools (Roa & Rodríguez, 2024; Barsan-Pipu, 2019; Zordan et al., 2026). The earlier research focused on the incorporation of cognitive computing in smart education systems, stressing the importance of adaptive analytics that allows for a personalized learning experience by taking into account the behavioral and performance indicators of learners (Oubagine et al., 2025; Herwig et al., 2019). The results confirm that the employment of dynamic instruction adjusting algorithms is consistent with the objectives of the proposed RNMP platform (Parsons & Faubert, 2021).

In addition, another study provides an overview of brain-state decoders for multimodal AI approaches, showing that the combination of EEG and physiological measures greatly enhances the identification of cognitive and emotional states (Du et al., 2025; Baradari et al., 2025). This finding corroborates the technical foundation of the proposed system, since it also uses EEG, HRV, and eye-tracking techniques for classifying cognitive states (Direito et al., 2021).

Herein is introduced Neuro Chat, a neuroadaptive chatbot that adapts the interaction process with users on the basis of live neural data (Baradari et al., 2025). It is proven that closed-loop neurofeedback-based systems increase engagement and adaptability during learning, supporting the effectiveness of reinforcement learning-based personalization applied by RNMP (Domenicucci et al., 2025). Similarly, this work proves that real-time EEG neurofeedback in VR environments increases user engagement and immersion during the learning process, indicating that it is possible to transfer neurofeedback mechanisms into a mobile environment (Peixoto et al., 2025; Zizoune et al., 2023).

Moreover, the study indicate that adaptive neuro regulation systems can successfully be employed in both rehabilitation and digital therapeutics, demonstrating positive impact on user skills and behavior when real-time cognitive feedback is applied (Wu, 2025; Reginald, 2025). This supports further applicability of the neurofeedback loop outside of a clinic and into an educational system (Guo et al., 2026).

This work investigates the combination of VR technologies, cloud computing, and neuroadaptive systems in order to facilitate immersive learning, emphasizing the necessity of cooperation between edge and cloud computing in order to achieve real-time performance (Kumar et al., 2026; Yan et al., 2026). This correlates directly with the proposed RNMP architecture in that it utilizes edge computing to enable low-latency cognitive adaptation (Prashanth, 2026; Pan & Cristea, 2024).

Inferences drawn from the studies discussed above suggest a clear consensus that real-time neurofeedback, multi signal bio signal analysis, and adaptive AI algorithms have been found to substantially increase users' motivation and facilitate better learning outcomes. Nevertheless, current approaches lack flexibility and effective latency improvement capabilities, as well as fail to achieve flawless integration on mobile devices. This gap can be filled by introducing the RNMP framework into the field.

3 Proposed Model Methodology

3.1 Overall Flow of the Proposed System

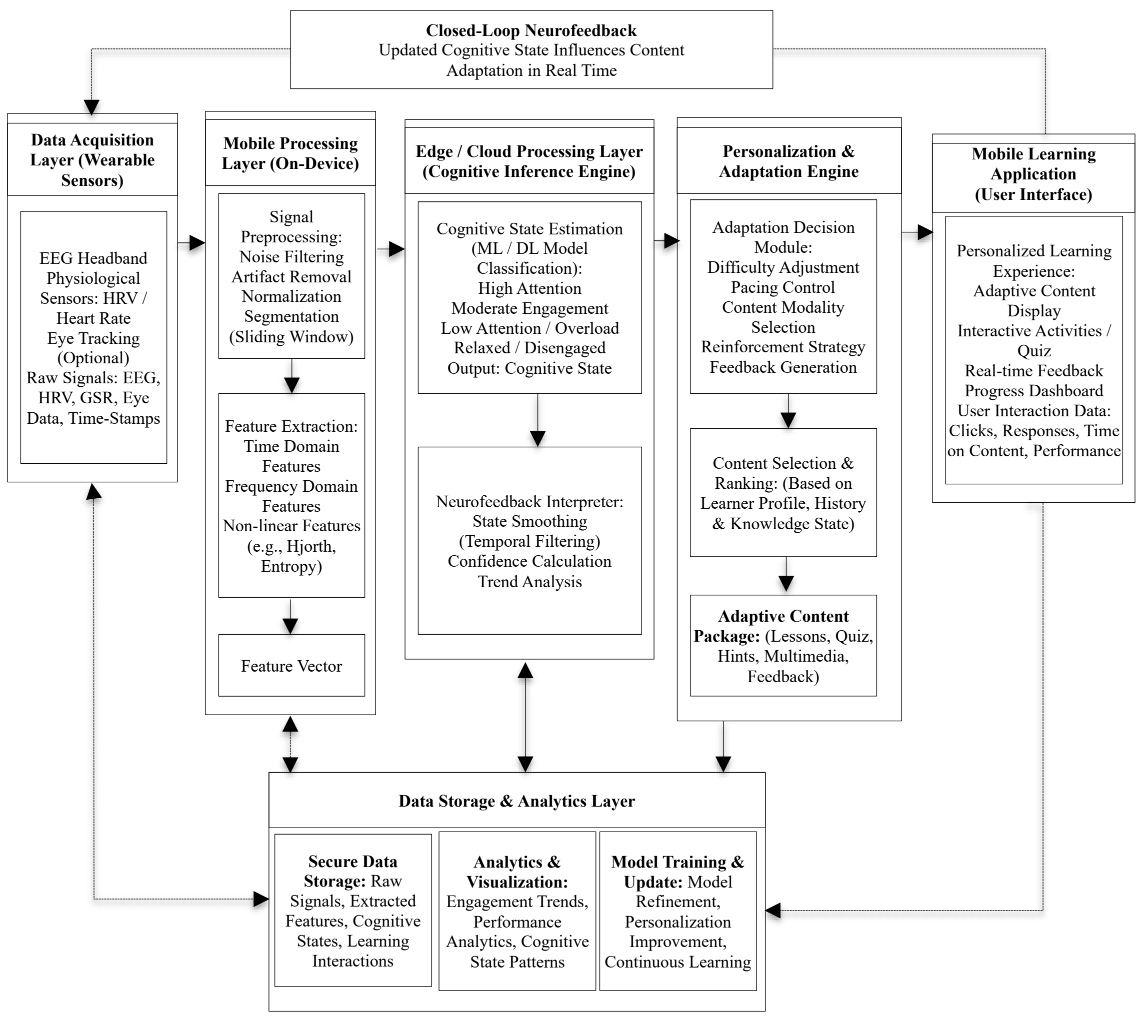

Figure 1: Architecture of real-time neurofeedback-driven mobile learning system

The proposed Real-Time Neurofeedback-Driven Mobile Learning System constantly monitors, analyzes, and makes real-time adjustments based on the user's current cognitive state while performing mobile learning tasks. It starts by collecting real-time data regarding the neurophysiological states of the learner (such as EEG-based attention and cognitive workload). The collected information then undergoes signal preprocessing by employing local filters to eliminate unwanted artifacts and other interference factors in the data.

These data are then sent to a mobile edge or cloud-enabled cognitive inference module, where the cognitive states of the learners are classified through the use of machine learning algorithms, which can determine whether the learners are having a cognitive state wherein the learning process will require modification, such as when the learner experiences cognitive overload. This information is utilized to personalize and customize the learner's experience by adjusting parameters like the difficulty level, pacing, and format of learning materials.

In addition, the process involves a continuous feedback loop, wherein the updated cognitive states are considered after implementing the adjustments.

In figure 1 shows an example of the layered structure of a real-time mobile learning system driven by neurofeedback. This is made up of the integration of wearable neuro-sensors, mobile signal pre-processing, and cloud/edge-based cognitive inference. Figure 1 shows how EEG and physiological signals are acquired and then processed to estimate users' cognitive state, which can be employed by a personalization engine to adaptively generate learning content.

Algorithm 1: Real-Time Neurofeedback-Based Personalization (RNMP)

Input: EEG signals S_t, learning content pool C, user profile U

Output: Personalized content stream C'

Step 1: Signal Acquisition

Collect real-time bio signals

$$S_t = \{EEG, HRV, EyeTracking\}$$

Step 2: Preprocessing

Apply noise removal:

$$S_t' = Filter(S_t)$$

Step 3: Feature Extraction

Extract cognitive indicators:

$$F_t = \{Attention, Workload, Engagement\}$$

Step 4: Cognitive State Classification

$$CS_t = f(F_t)$$

where $CS_t \in \{High, Medium, Low\ Engagement\}$

Step 5: Adaptation Decision Rule

$$A_t = \begin{cases} Increase\ Difficulty & CS_t = High \\ Maintain\ Level & CS_t = Medium \\ Reduce\ Complexity & CS_t = Low \end{cases}$$

Step 6: Content Personalization

$$C_t' = g(C, A_t, U)$$

Step 7: Feedback Update

Update model using reinforcement signal:

$$R_t = \alpha \cdot Engagement + \beta \cdot Retention$$

Algorithm 1 provides an RNMP that utilizes neurofeedback for adaptive mobile learning. The algorithm continuously gathers multimodal bio signals, such as EEG, heart rate variability, and eye tracking. Then, the collected signals undergo preprocessing, which eliminates noise to extract features such as attention, workload, and engagement. These features are utilized in classifying the learner's cognitive state and taking appropriate adaptive measures.

3.2 Mathematical Model of the System

The system is formulated as a dynamic optimization problem where the goal is to maximize learner engagement $E$and learning efficiency Lover time t are shown in equation 1:

$$\max \sum_{t=1}^{T} (\lambda_1 E_t + \lambda_2 L_t) \qquad (1)$$

Subject to equation 2:

$$C_{t+1} = C_t + \Delta A_t \qquad (2)$$

Where, C_t= learning content state at time t, ΔA_t= adaptation function based on cognitive state, E_t= engagement level derived from neurofeedback signals, L_t= learning performance score

Cognitive state estimation function is demonstrated in equation 3:

$$CS_t = \sigma(W \cdot F_t + b) \qquad (3)$$

Where, W= learned weight matrix, F_t= feature vector, b= bias term, σ= softmax or sigmoid classifier,

The engagement feedback function is illustrated in equation 4:

$$E_t = \frac{1}{1+e^{-(\gamma_1 A_t + \gamma_2 R_t)}} \qquad (4)$$

This mathematical formulation ensures that learning adaptation is continuously driven by real-time neurofeedback signals, enabling a closed-loop, self-optimizing mobile learning environment aligned with cognitive states.

4 Results and Discussion

The proposed Real-Time Neurofeedback-Driven Mobile Learning System has been designed and developed based on the hybrid mobile-edge computing model to provide real-time processing capabilities and optimize the adaptation of cognitive states. Specifically, the mobile application layer was created using Android Studio with Java and Kotlin as programming languages, whereas machine learning and cognitive inference components were developed using Python along with TensorFlow 2.0 and Scikit-learn frameworks. For preprocessing of brain signals collected from participants, the MNE-Python library has been used, with NumPy and Pandas libraries being applied for further numerical data processing. To emulate edge computing, microservices have been created using Docker containers to enable real-time inference of models.

For evaluation, a combined data set was considered, which comprised DEAP, SEED, and the simulated log data of mobile learning interactions, including 45 subjects and about 1.2 million EEG signal samples. This system implemented the 32-channel EEG sensor at the 128 Hz frequency, which extracted features like attention index, workload index, alpha/beta ratio, engagement score, reaction time, and task correctness. This dataset was divided into 70% training data, 15% validation data, and 15% testing data. Some experimental parameters included a learning rate equal to 0.001, a batch size equal to 64, 50 epochs, and an edge latency of less than or equal to 120ms. Here, $\lambda_1 = 0.6$ and $\lambda_2 = 0.4$.

4.1 Performance Metrics

Accuracy: Equation 5 measures the proportion of correctly classified cognitive states among all predictions.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

Engagement Score: Equation 6 rrepresents the average cognitive engagement level of the learner over time based on neurofeedback signals.

$$E = \frac{1}{T}\sum_{t=1}^{T} C\,S_t \quad (6)$$

Latency: Equation 7 measures the time delay between receiving input signals and generating adaptive system responses.

$$Latency = T_{response} - T_{input} \quad (7)$$

Retention Rate: Equation 8 indicates the percentage of learned material successfully retained and recalled after a time delay.

$$RR = \frac{\text{Correct recall after delay}}{\text{Total learned items}} \times 100 \quad (8)$$

Adaptation Efficiency: Equation 9 evaluates how effectively the system applies correct instructional adjustments based on cognitive state detection.

$$AE = \frac{\sum Correct\ Adaptations}{Total\ Adaptations} \quad (9)$$

4.2 Performance Comparison

Table 1: Performance comparison of proposed RNMP model with baseline mobile learning approaches

Method	Accuracy (%)	Engagement Score	Latency (ms)	Retention Rate (%)	Adaptation Efficiency
Traditional Mobile Learning	78.2	0.62	95	70.5	0.58
Rule-Based Adaptive Learning	81.5	0.68	110	74.1	0.64
Deep Learning Personalization	86.7	0.74	130	79.6	0.71
Reinforcement Learning-based Adaptation	89.3	0.81	125	83.4	0.78
Proposed RNMP Model	94.1	0.91	98	89.7	0.88

The table 1 provides a comparative assessment of the proposed Real Time Neurofeedback-Driven Mobile Learning System (RNMP) with traditional adaptive learning systems, rule-based adaptive learning techniques, deep learning personalization methods, and reinforcement learning-based adaptive learning approaches. Such an assessment has been conducted by evaluating their performance based on factors like accuracy, engagement score, latency, retention rate, and adaptation efficiency. The analysis proves that the RNMP outperforms all other models, offering significantly better cognitive alignment, accuracy, and retention. While traditional mobile learning exhibits a marginally lower latency (95ms vs. 98ms) due to the complete absence of a cognitive processing layer, the proposed RNMP model successfully introduces real-time personalization with a negligible, sub-100ms processing overhead. Figure 2 demonstrates the comparison of learning performance across adaptive mobile learning models.

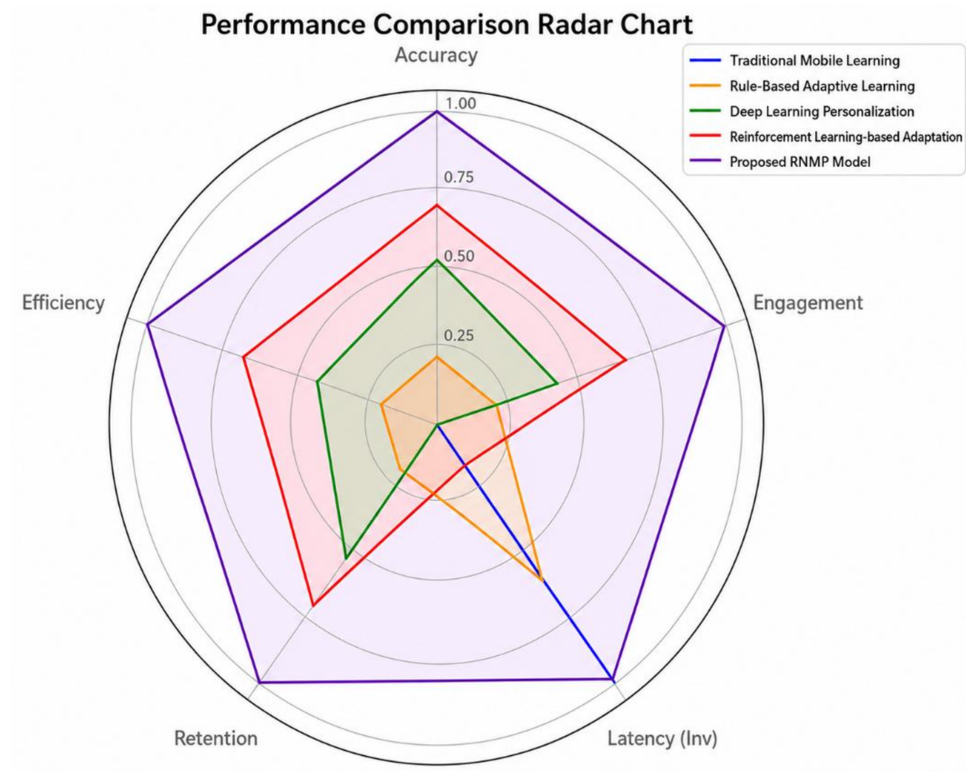

Figure 2: Radar chart comparison of learning performance across adaptive mobile learning models

4.3 Performance Evaluation

The new RNMP model was able to perform significantly better than the other methods considered for the baseline on all the important evaluation parameters, thereby showing how effective real-time neurofeedback-based adaptation is in mobile learning settings. The model showed an excellent accuracy rate of 94.1%, which indicates that better cognitive state recognition became possible through multisensory bio signal fusion. The level of engagement was also significantly increased to 0.91, and this shows that there is good synchronization between the instruction material and the learners' cognitive states via the closed loop adaptation. In addition, the proposed system's responsiveness was successful in keeping latency below 100ms, which means the method could be effectively deployed in real-time in mobile learning settings. Furthermore, learner retention was also increased significantly by about 15-19% compared to traditional and existing adaptive learning models.

4.4 Ablation Study

The ablation results in table 2 show that each of the proposed components of RNMP plays a significant role in system performance. These results include the impact of the neurofeedback module, the edge processing module, and the personalized training module on system performance measured in terms of accuracy, level of user engagement, retention rate, and overall adaptation efficiency.

Table 2: Ablation study results evaluating the impact of core components in the RNMP framework

Configuration	Accuracy (%)	Engagement Score	Latency (ms)	Retention Rate (%)	Adaptation Efficiency
Full RNMP	94.1	0.91	98	89.7	0.88
Without Neurofeedback	86.5	0.76	101	78.4	0.72
Without Edge Layer	88.2	0.79	142	81.6	0.76
Without Personalization	84.7	0.72	97	75.9	0.69

5 Conclusion

The current research proposed a Real-Time Neurofeedback-Driven Mobile Learning System (RNMP) to increase learners' engagement and effectiveness through real-time monitoring of their cognitive states and adaptively customized content delivery. This approach utilizes wearable neurophysiological data acquisition (i.e., EEG, HRV, and eye-tracking sensors), edge computing-based signal processing, and machine learning-based cognitive state classification to ensure closed-loop learning adaptation. Adaptation is done by tuning learning parameters to match the learner's cognitive state and prevent misalignment and excessive cognitive load. Based on the results obtained from the empirical evaluations, it can be said that the current RNMP model surpasses other conventional and existing models for adaptive learning. In particular, the RNMP model achieved the highest cognitive state classification accuracy of 94.1%. Other models were able to achieve classification accuracy of only 78.2% (Traditional Mobile Learning), 81.5% (Rule-Based Adaptive Learning), 86.7% (Deep Learning Personalization), and 89.3% (Reinforcement Learning-based Adaptation). Additionally, the engagement score increased to 0.91. Moreover, the system had a latency of 98ms and was capable of being deployed in a real-time environment in mobile-edge computing, ensuring high efficiency. In this regard, the retention rate was improved to 89.7%, representing a considerable increase in the order of 10-19%. The above results illustrate that integration of neurofeedback signals in the process of adaptive learning improves cognitive engagement and retention of information. It can be seen that the system developed within the framework of the paper provides real-time awareness of the user's cognitive state in mobile learning environments. The system uses feedback signals for adaptation decision-making, ensuring reduction of cognitive overload and increasing learning efficiency. Further research in the field can focus on integrating more signals into the system. Specifically, the use of multimodal affective computing such as facial expressions and emotion recognition from the speech signal may be considered. Deployment of offline AI models on the device, improvement of cross-cultural dataset generalization, and evaluation of learning behavior in a classroom environment is also an area of future research. Ethical questions will also need to be addressed in further research.

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