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PAPER

AI-Driven Personalized Learning in Mobile Applications Using Edge Computing and Federated Learning

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ABSTRACT

Artificial intelligence (AI)-assisted educational systems have opened up new possibilities for personalized learning in higher education, but they also raise significant issues with platform fragmentation and data protection. As cloud computing continues to develop, security, privacy, and compliance concerns must continue to receive attention. However, issues with latency, network dependency, and data privacy are frequently brought up by conventional cloud-based personalization techniques. Due to the sensitive nature of student data and the varied infrastructure present in academic institutions, traditional centralized training approaches become impractical. Therefore, this study explores the integration of AI, edge computing, and federated learning (FL) to develop an efficient and privacy-preserving personalized learning framework for mobile applications. The suggested system analyses learner behavior, preferences, and performance in real time using on-device AI models that are deployed via edge computing. FL ensures improved privacy and security by facilitating cooperative model training across several devices without sending private user information to centralized servers. The system lowers communication overhead, speeds up reaction times, and keeps recommendations customized for each learner by fusing distributed learning methods with local data processing. When compared to traditional cloud-centric approaches, experimental research shows that the suggested framework increases system efficiency, learning engagement, and recommendation accuracy. The study emphasizes the promise of FL and edge-based AI as a scalable solution for future intelligent mobile learning environments.

KEYWORDS

artificial intelligence (AI), edge computing, federated learning (FL), personalized learning

1 INTRODUCTION

Learning is most successful when it takes place through personalized experiences that enhance students' abilities [1], knowledge, perspectives, and comprehension. Personalized learning has become a popular method in recent decades for delivering

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more meaningful education based on each student's unique needs. Cloud computing is drastically changing our digital infrastructures by offering previously unheard-of flexibility, scalability, and cost-effectiveness, but it also presents enormous security risks that need to be addressed. In terms of handling data breaches, insider threats, unsecured application programming interfaces (APIs), and sharing of physical and virtual resources, the rapid expansion of cloud services has fundamentally altered conventional security paradigms. Because cloud computing environments are dynamic and decentralized by nature, they are vulnerable to increasing attacks on sensitive data [2], necessitating the use of methods to protect data availability, confidentiality, and integrity.

Cloud computing has advanced quickly to offer both individuals and corporations a strong, adaptable, and scalable processing and storage resource. Nowadays, privacy, secrecy, and security against cyber threats are more important than ever because the majority of data is stored on distant servers [3]. Some of the basic security strategies rely on centralized data control, which means that a large amount of data is gathered and processed in one place, generating bottlenecks, additional threats, and privacy issues.

According to recent studies, insider threats, ransomware, and advanced persistent attacks continue to pose a danger to cloud infrastructure security [4]. These risks are exacerbated by the fact that cloud security is split between the customer and the provider, which results in insufficient defences. Furthermore, because cloud computing systems are distributed and very scalable, typical security measures are ineffective, leaving the system vulnerable to threats, including configuration errors [5], illegal user access, and data loss. In order to ensure the security of cloud data, these security concerns necessitate new solutions that use contemporary technologies.

Artificial intelligence (AI) and federated learning (FL) provide an effective way to deal with new security risks. Since no data is given to a third party, FL, a type of distributed learning, stops data from being routed to a central server. This is because FL makes it possible for various devices to train models without transferring raw data, which is a major problem in cloud computing. In addition to lowering the possibility of data leakage [6], FL also lowers resource consumption in situations where data security is crucial. FL lowers resource utilization in situations where data protection is crucial, in addition to the possibility of data leakage. As a result, FL shows promise for resolving these problems by training machine learning models across dispersed devices or servers without exchanging raw data with a central repository. Since only model updates are shared and sensitive data never leaves a local device, this decentralized model promotes data privacy. Threat detection, predictive analytics, and real-time reaction capabilities are all enhanced when AI is incorporated into cloud security frameworks. Large volumes of data can be analyzed in real-time by AI, which can spot trends and abnormalities that could indicate cyberthreats that conventional methodology could have missed [7]. Additionally, AI-driven automation reduces the time it takes to address security issues, such as ransomware or insider threats, in order to minimize the harm they might cause. Additionally, using AI for cybersecurity makes it possible to employ predictive models that can anticipate and prevent future threats, strengthening cloud environments' overall security posture [8].

However, there are still many obstacles to overcome before FL and AI can be used practically in cloud security [9]. FL reduces privacy concerns by 25% during AI model training while protecting sensitive patient data, according to a study conducted in the healthcare industry. Additionally, FL can be used for real-time anomaly identification in IoT networks, a crucial component of the contemporary cloud environment. By enabling safe, cooperative model training [10], FL has proven essential in detecting and resolving threats. However, significant operational and technical difficulties, such as data heterogeneity, transmission overhead, and susceptibility to hostile attacks, outweigh these advantages.

In this study, we explore the integration of artificial intelligence (AI), edge computing, and federated learning to develop an efficient and privacy-preserving personalized learning framework for mobile applications. The suggested system analyses learner behavior, preferences, and performance in real time using on-device AI models that are deployed via edge computing. FL ensures improved privacy and security by facilitating cooperative model training across several devices without sending private user information to centralized servers. The system lowers communication overhead, speeds up reaction times, and keeps recommendations customized for each learner by fusing distributed learning methods with local data processing.

2 RELATED WORKS

The work in [11] focuses on developing and implementing AI-powered individualized learning routes. The use of data analytics and machine learning algorithms has changed students' educational experiences in recent years. These procedures help tailor instruction to the needs of the students. Numerous applications, including AI-powered learning management systems like IBM's Watson Education, have been studied. Additionally, adaptive learning websites like Duolingo have been mentioned as examples of AI-based learning platforms. The study also illustrates the difficulties and opportunities of AI-oriented individualized education. Additionally, the study suggests using networked learning, the EDUBOT program, and AI-based characters to enhance teaching through adaptive systems.

The architecture introduced in [12] enables privacy-preserving AI model training across decentralized higher education platforms. To address data security and model heterogeneity, our system facilitates adaptive aggregation, differential privacy, and knowledge distillation. The suggested solution greatly reduces privacy leakage and communication overhead while achieving accuracy comparable to centralized baselines, according to experimental results on multi-campus datasets. This study fosters cross-institutional collaboration and cooperation without jeopardizing the privacy of individual data by offering a scalable and safe foundation for AI-driven educational analytics.

Ecosystem used FL, a well-known distributed machine learning technique [13]. We draw attention to the potential advantages that FL can provide to institutions, classrooms, and students. Additionally, we pinpoint a number of logistical, ethical, and technical issues that prevent FL from being implemented sustainably in the education sector. Lastly, we address a number of unexplored research avenues that centre on complex facets of FL deployment in educational settings. In order to ensure that FL deployment is technologically sound, advantageous, and equitable for all parties concerned, these directions seek to investigate and address the challenges of implementing FL in a variety of educational settings.

The difficulties of safeguarding private student data from online threats, illegal access, and data breaches has been discussed in [14]. To protect educational data, it looks at best practices and cutting-edge technology, including encryption, access control, and federated learning. The legislative environment controlling data privacy in EdTech and the necessity of adhering to standards like GDPR and FERPA are also discussed in the paper. This study demonstrates the revolutionary effects of cloud computing on AI-driven tailored learning and the necessity of strong data security frameworks through case studies and practical implementations. Cloud-powered EdTech solutions can open up new opportunities for customized education while upholding data integrity and trust by finding a balance between innovation and security.

A blockchain-enabled distributed edge cluster for PFL (BPFL) that integrates the advantages of edge computing with blockchain is presented in [15]. By storing transactions on immutable distributed ledger networks, blockchain technology can improve client selection and clustering while also enhancing client privacy and security. In order to bring computational processing closer to customers, the edge computing system provides dependable storage and computation locally within the edge infrastructure. Consequently, PFL's low-latency connectivity and real-time services are enhanced. Nevertheless, more effort is needed to create a representative dataset for the analysis of similar attack types and responses for a reliable BPFL technique.

3 METHODOLOGY

In this work, we suggest integrating AI, edge computing, and FL to create an effective and privacy-preserving personalized learning framework for mobile applications in order to address the privacy and interoperability issues in AI-assisted education. Our model enables educational institutions to jointly train a shared global model without moving private student data between platforms, as shown in Figure 1.

3.1 Data collection

Data about user interactions is gathered directly on the mobile device. To protect privacy and do away with the need for centralized data collecting, all data is stored locally.

3.2 Local model initialization

Every participating university acts as a federated client [16]. Every client keeps local records of student interactions, learning behaviour traits, and context-specific teaching cues. A local AI model created to assist with tasks like emotional sentiment analysis, dropout prediction, and personalized feedback is refined using these data. We use a modular neural architecture that combines classification/regression heads with feature extractors. Each client uses stochastic gradient descent (SGD) to minimize a standard loss function $\mathcal{L}_{local}$ using local training.

$$\mathcal{L}_{local}^{(i)} = E_{(x,y)\sim D_i}[t(f_\theta^{(i)}(x), y)] \quad (1)$$

In Eq. (1), $f_\theta^{(i)}$ and D_i are the local model parameters and the local dataset of the client i.

3.3 Gradient sharing for privacy-preserving

Each client sends encrypted model changes (gradients or weights) to the server for aggregation after local convergence. We use secure aggregation methods and differential privacy noise to safeguard data privacy. The transmitted update $\Delta\theta^{(i)}$ is disturbed for every client i.

$$\Delta\tilde{\theta} = \Delta\theta^{(i)} + N(0,\ \sigma^2 I) \tag{2}$$

In the equation, N stands for Gaussian noise calibrated in accordance with a global privacy budget ε, guaranteeing privacy at the user level [17].

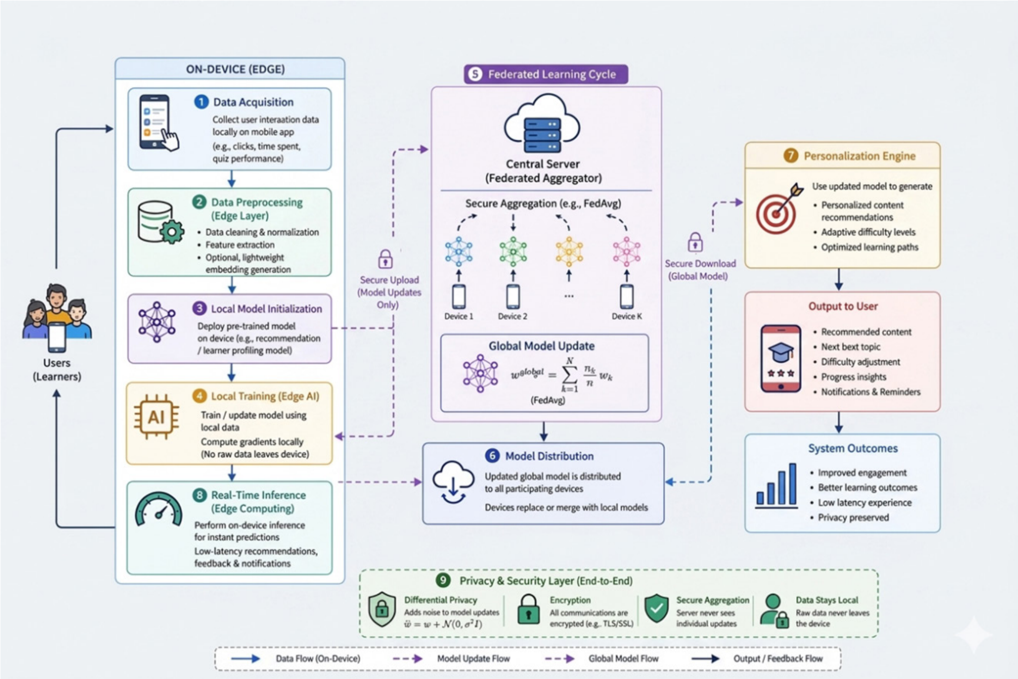

Fig. 1. Working process of the proposed model

3.4 Federated aggregation

Using the common FedAvg algorithm, the central aggregator—which is installed on cloud or university-owned infrastructure—performs weighted averaging over the encrypted updates.

$$\theta^{(t+1)} = \sum_{i=1}^{N} \frac{n_i}{n} \cdot \Delta\tilde{\theta} \tag{3}$$

Here, $n = \Sigma_i n_i$ is the total training data across clients, and n_i is the number of training samples on client i. We present an adaptive aggregation approach that dynamically re-weights client contributions based on previous alignment and local validation loss in order to reduce divergence brought on by diverse data distributions. This enhances model stability and convergence across universities with various data modalities and academic systems [18].

3.5 Global model aggregation

Every participating client receives a broadcast of the combined global model. Each client either does fine-tuning to maintain domain-specific performance or replaces its local parameters after receiving the revised model. In the event of instability or abnormality, clients have the option to cache global checkpoints for rollback.

3.6 Model distribution

Every device that takes part receives the updated global model. To improve its local performance, every device incorporates the global model. We include a knowledge distillation module to guarantee semantic congruence among clients due to the diversity of educational tasks (e.g., language vs. STEM courses) and hardware platforms (cloud vs. edge devices). In particular, each local model is a pupil, and the global model is a teacher. Kullback-Leibler divergence is used to train the learner to match the teacher's predictions:

$$\mathcal{L}_{KD}^{(i)} = KL\left(f_{\theta_g}(x) \,||\, f_{\theta^{(i)}}(x)\right) \tag{4}$$

This enables clients to keep local job specialization while gaining access to globally acquired information. We also employ modality-specific attention to align feature spaces during distillation in multimodal environments (e.g., video, text, and sensor). Several universities share encrypted updates for aggregation, train models locally, and serve as clients. A global model for knowledge alignment is returned by the server.

4 EXPERIMENTAL RESULTS

In this study, we use PyTorch and the FL framework to build the suggested model, which supports safe aggregation, client dropout recovery, and differential privacy. With adaptive learning rates, each client trains for 10 to 30 local epochs. The server complies with GDPR and FERPA regulations for educational data because it operates on a secure virtual node with SSL-encrypted communication channels. Using student interaction datasets gathered from three anonymized university platforms, we carried out comprehensive experiments to assess the efficacy of the suggested federated learning framework in real-world educational contexts. Quiz records, learning resource access patterns, assignment submissions, and emotion-tagged feedback are all included in these datasets. To replicate simulated federated situations, each institution's dataset was processed and kept locally.

We used a cross-campus data split in which each client that corresponded to an institution provided a non-IID subset that was influenced by its teaching practices and course structure. The aim was to use sequential learning behaviours to forecast student engagement drop-off, which was framed as a binary classification problem.

4.1 Accuracy of recommendation

The test accuracy progression of the proposed approach in comparison to the centralized baseline is displayed in Figure 2. The proposed approach narrows the performance gap despite stringent privacy and decentralized data constraints, achieving 82.7% accuracy by round 20, whereas the centralized model hits 93% accuracy early.

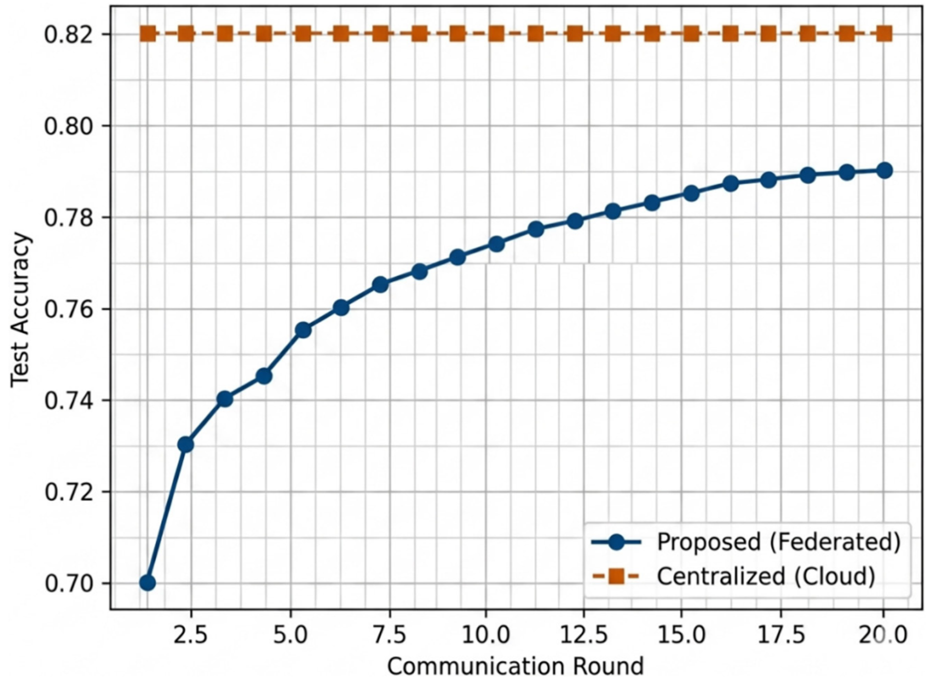

Fig. 2. Accuracy of recommendation

Despite platform and privacy limitations, the federated paradigm gradually gets closer to the centralized baseline. The naive FL baseline, on the other hand, converges much more slowly and has a lower end accuracy of 82.1% after 20 rounds. Its lack of measures to reduce transmission noise and data heterogeneity is the main cause of this lag. The algorithm has trouble generalizing across campuses with non-IID data without knowledge distillation or privacy calibration, especially in early rounds. The difference in performance between the improved approach and naïve FL shows how important privacy-aware training and semantic alignment are in federated academic settings.

4.2 Precision-recall analysis

We evaluated the PR performance of the centralized and federated models on a common test set in order to evaluate the accuracy of the categorization. As seen in Figure 3, the proposed model exhibits great predictive stability by maintaining high precision even at high recall. Despite decentralized learning, the proposed framework exhibits remarkable performance. In contrast, the precision of the basic FL model decreases more sharply with increasing recall levels. This implies that when applied to unseen data, it tends to overfit client-specific patterns and fails to maintain predictive balance.

Unstable decision limits result from the lack of global information transfer, particularly for minority behavior classes. The usefulness of our system in preserving generalizable categorization under privacy limitations is further supported by this contrast.

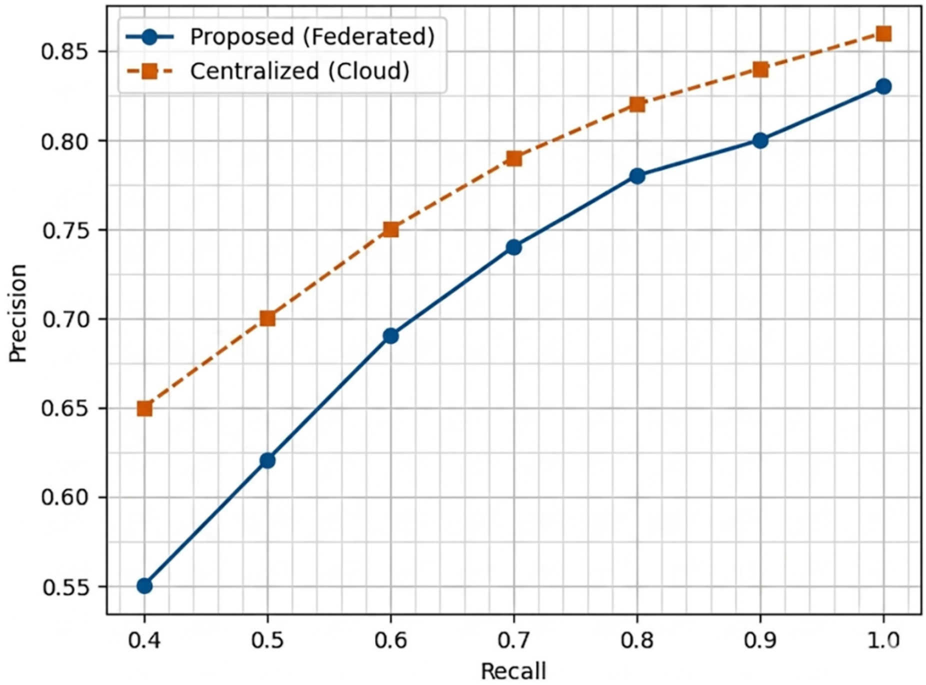

Fig. 3. PR analysis of the proposed model

4.3 Communication cost

Communication cost is a real limitation in FL systems that are implemented across universities with different infrastructures. We used three relevant educational datasets (Datasets A, B, and C) to estimate the average bandwidth consumption per client under various training procedures in order to assess this. The suggested approach consistently shows the lowest communication cost in all situations, as shown in Figure 4.

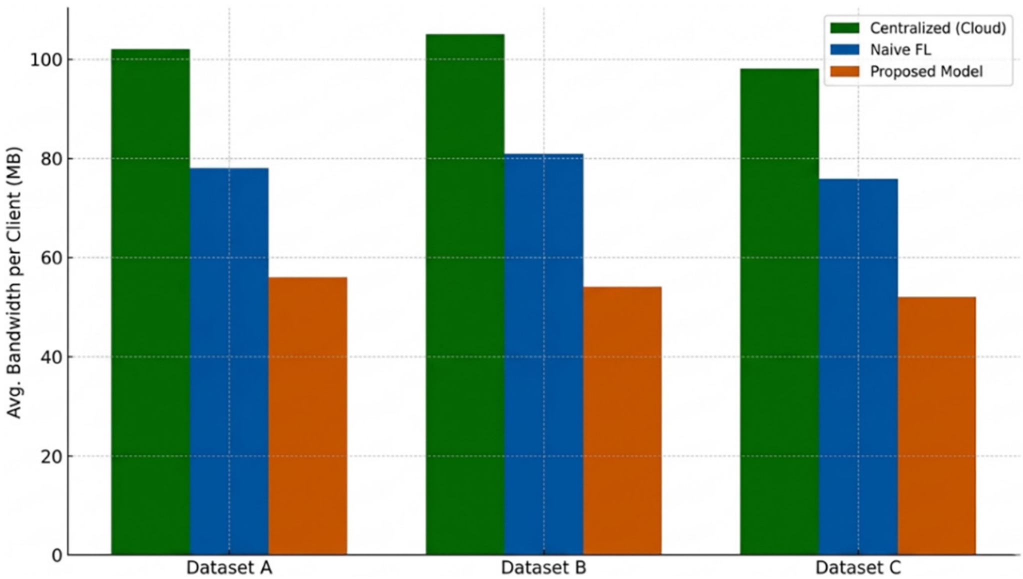

Fig. 4. Communication efficiency of the proposed model

Compared to centralised training, which necessitates full raw data transmission, the proposed approach delivers 50–60% lower average per-client bandwidth utilization. Additionally, it uses less bandwidth than naïve FL by more than 30% due to two primary factors: adaptive client involvement and gradient sparsification. With fewer communication cycles and more effective data encoding, these improvements enable our system to maintain learning quality.

The naive FL model, on the other hand, has significantly higher transmission costs since it sends dense model updates without compression or dropout methods, despite being decentralized. Because total data centralization is required, the centralized oracle naturally has the largest bandwidth load. These findings show that our approach facilitates scalable implementation in academic settings with limited bandwidth while maintaining accuracy and privacy.

4.4 Discussions

The results of the experiment support the efficacy of the developed FL architecture for collaborative and privacy-enhanced modeling in computer-assisted education. In particular, the proposed system prioritizes student data privacy while demonstrating strong generalization performance across decentralized and diverse environments. The proposed framework can also effectively function as a viable alternative to centralized learning in educational environments whose operations are constrained by privacy regulations and infrastructure fragmentation, as demonstrated by the consistent accuracy improvement over communication rounds (see Figure 2) and the good PR tradeoff (see Figure 3).

Scalable deployments are also made possible by our system communication efficiency. We used gradient sparsification and adaptive client scheduling to significantly reduce the cost of transmission in each round, taking inspiration from bandwidth-conscious protocols used in energy trading and medical imaging.

Compared to previous work that assumed consistent high-bandwidth connectivity, this makes compatibility with edge servers and mobile learning setups easier. The approach can readily be applied to various educational AI use cases, such as intelligent tutoring systems, learning resource recommendation, and mental well-being prediction, even though our tests focused on engagement prediction as a baseline job. The system may be used in K–12 education, e-learning course platforms, and even international collaborative research with the appropriate domain adaptation and privacy tuning.

5 CONCLUSION

In this study, we explore the integration of AI, edge computing, and federated learning to develop an efficient and privacy-preserving personalized learning framework for mobile applications. The suggested system analyses learner behavior, preferences, and performance in real time using on-device AI models that are deployed via edge computing. Federated learning ensures improved privacy and security by facilitating cooperative model training across several devices without sending private user information to centralized servers. The system lowers communication overhead, speeds up reaction times, and keeps recommendations customized for each learner by fusing distributed learning methods with local data processing. When compared to traditional cloud-centric approaches, experimental research shows that the suggested framework increases system efficiency, learning engagement, and recommendation accuracy. The study emphasizes the promise of FL and edge-based AI as a scalable solution for future intelligent mobile learning environments. The suggested design can support multimodal learning environments, is adaptable to different teaching situations, and is robust across a variety of platforms. Future research will focus on blockchain-incentivized models, fairness-aware optimization strategies, and broader applications across national academic networks.

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