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An Offline-First Adaptive Learning (OFALearn) Framework for Low-Bandwidth Educational Environments Using Lightweight AI and Dynamic Proficiency Modelling

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Abstract
The increasing dependence of contemporary e-learning systems on continuous internet connectivity presents significant challenges for learners in low-bandwidth and resource-constrained environments. This study proposes OFALearn (Offline-First Adaptive Learning Framework), an intelligent educational platform that integrates adaptive learning, edge artificial intelligence, and local-first data management to support personalized learning without persistent network access. The framework employs a lightweight proficiency modeling approach that dynamically adapts learning content based on learner performance while enabling delayed synchronization when connectivity becomes available. To evaluate the effectiveness of the proposed framework, simulation experiments were conducted using a synthetic dataset comprising 10,000 learner interactions generated to reflect realistic educational usage patterns in low-bandwidth environments. Comparative evaluation was performed against Rule-Based Adaptive Learning (RBAL), Deep Knowledge Tracing (DKT), and Self-Attentive Knowledge Tracing (SAKT). Simulation results indicate that OFALearn achieved a learning gain improvement of 28.7%, adaptation accuracy of 82.9%, reduced data usage by 65.3%, and lowered system latency from 1200 ms to 410 ms when compared with conventional cloud-dependent learning systems. Although the findings are based on simulation experiments using synthetic data, they provide promising evidence for the feasibility of offline-first adaptive learning architectures in underserved educational contexts. Future work will focus on real-world deployment and validation with actual learners.

Keywords: Low-bandwidth computing, Mobile learning, Educational AI, Adaptive learning systems, Offline learning, Personalized education

INTRODUCTION

The digital revolution has changed ways of teaching and learning across the world by integrating new technologies. Artificial Intelligence in Education (AIED) offers a way for adaptive and personalized learning systems, Intelligent Tutoring Systems (ITS), automated feedback and prediction (Crompton and Burke, 2023; Kasneci et al., 2023). However, much of this is limited by the lack of internet and digital infrastructure.

Artificial Intelligence in Education (AIED)

Artificial Intelligence has become a major driver of educational innovation through learner modelling, automated feedback systems, intelligent tutoring, and adaptive content delivery. Recent studies indicate that AI-driven educational systems can improve learner performance, engagement, and retention by tailoring educational experiences to individual learner needs (Mustafa et al., 2024; Hariyanto et al., 2025). Nevertheless, most AI-enabled educational platforms rely heavily on cloud infrastructure, which restricts

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their applicability in connectivity-constrained environments

Adaptive learning systems

Adaptive learning is the type of education system where the learning content is adapted in real-time based on student characteristics, student knowledge and student behavior. Continuous evaluation and modelling of students allow the adaptive system to present customized learning paths, which increases student performance and learner satisfaction (Gligorea et al., 2023; Wang et al., 2024). Many approaches, such as Deep Knowledge Tracing (Piech et al., 2015) and Self-Attentive Knowledge Tracing (Pandey and Karypis, 2019), have shown good performance but are computationally expensive.

Edge AI

Edge AI helps in processing the data and performing intelligent actions on user devices instead of relying on centralized clouds. Moving computation near the user reduces latency, increases responsiveness, and optimizes the bandwidth consumption (Satyanarayanan, 2017; Wang et al., 2024). Edge computing has gained prominence in IoT-based applications, but is comparatively less used for adaptive learning.

Mobile Learning and Low-Bandwidth Environments

Mobile learning has emerged as a practical mechanism for extending educational access beyond traditional classroom settings. Smartphones and mobile devices have increased educational participation, particularly in developing countries. However, mobile learning systems frequently depend on continuous internet connectivity, limiting their effectiveness in low-bandwidth regions (UNESCO, 2023; Viberg et al., 2024). Consequently, learners in underserved communities continue to experience digital exclusion despite widespread mobile device adoption.

Learning Analytics and Human-Centered AI

Learning analytics is considered essential for characterizing learner behaviour and optimizing learning. Several works have explored how human-centered AI approaches should involve user involvement, transparency, and ethical issues throughout the development process of educational AI systems (Alfredo et al., 2023). These studies raised various concerns related to human trust, user privacy, and human control on educational AI systems, suggesting that human-centered AI systems should integrate automation and human control to provide trustworthy and acceptable learning systems.

AI Ethics and Educational Implications

Ethics are significant issue concerning the development and adoption of AI in education; issues such as fairness, bias, and privacy were mentioned by several works. Porayska-Pomsta et al. (2024) pointed out that AI in education should be based on ethical principles that align with the values of education and society. This issue would be further enhanced in developing regions as the uneven access to technology may increase educational inequality.

Research Objectives and Contributions

The primary objective of this study is to develop and evaluate an offline-first adaptive learning framework capable of supporting personalized learning in low-bandwidth environments.

Specifically, this study aims to:

1. Design an offline-first adaptive learning architecture.
2. Develop a lightweight learner proficiency model.
3. Integrate edge-based processing mechanisms.
4. Evaluate performance using simulation experiments.

The contributions of this study include:

1. A novel offline-first adaptive learning architecture.
2. A lightweight adaptive proficiency modelling mechanism.
3. An edge-enabled synchronization framework.
4. Comparative evaluation against RBAL, DKT, and SAKT baselines.

A scalable framework for underserved educational environments

RELATED WORKS

Interest in AI-driven adaptive learning systems is rapidly increasing, and researchers have presented evidence that these systems boost learners' engagement and improve the learning process individually (Gligorea et al. 2023). Besides that, AI-based education systems can enhance learning through individualized learning content delivery (Hariyanto et al. 2025). Deep Knowledge Tracing, proposed by Piech et al. (2015), presented recurrent neural networks for tracking the knowledge state of learners, later enhanced with attention mechanisms through Self-Attentive Knowledge Tracing (Pandey & Karypis, 2019), which shows improved prediction performances over previous methods. While it reached great prediction accuracy, the methods require cloud computation, consuming a significant amount of computational resources. Research on educational accessibility has been discussing the significant potential of adaptive learning for deprived people. Strielkowski et al. (2024) pointed out that AI-driven adaptive learning helps achieve sustainable education reform. Sari et al. (2024) claimed that adaptive learning systems significantly improve educational outcomes as well. Moreover, research about ethical and inclusive AI putted emphasize on the necessity of equitable education technology application: Kizilcec (2024) insisted that the educational AI system should be designed to cater for underrepresented learners. Despite these advances, existing studies rarely integrate adaptive learning, edge AI, learning analytics, and offline functionality into a unified framework. OFALearn addresses this gap by providing a lightweight offline-first adaptive learning solution.

METHODOLOGY

A simulation-based experimental method is used to assess the effectiveness of the proposed OFALearn framework for learning in low-bandwidth environments. It combines: an offline-first system architecture, an AI-based adaptive student modelling, and synthetic but realistic learning interaction data. The approach is meant to simulate realistic user behaviour in bandwidth-limited conditions while ensuring its technical soundness and applicability in a real-world scenario.

System architecture

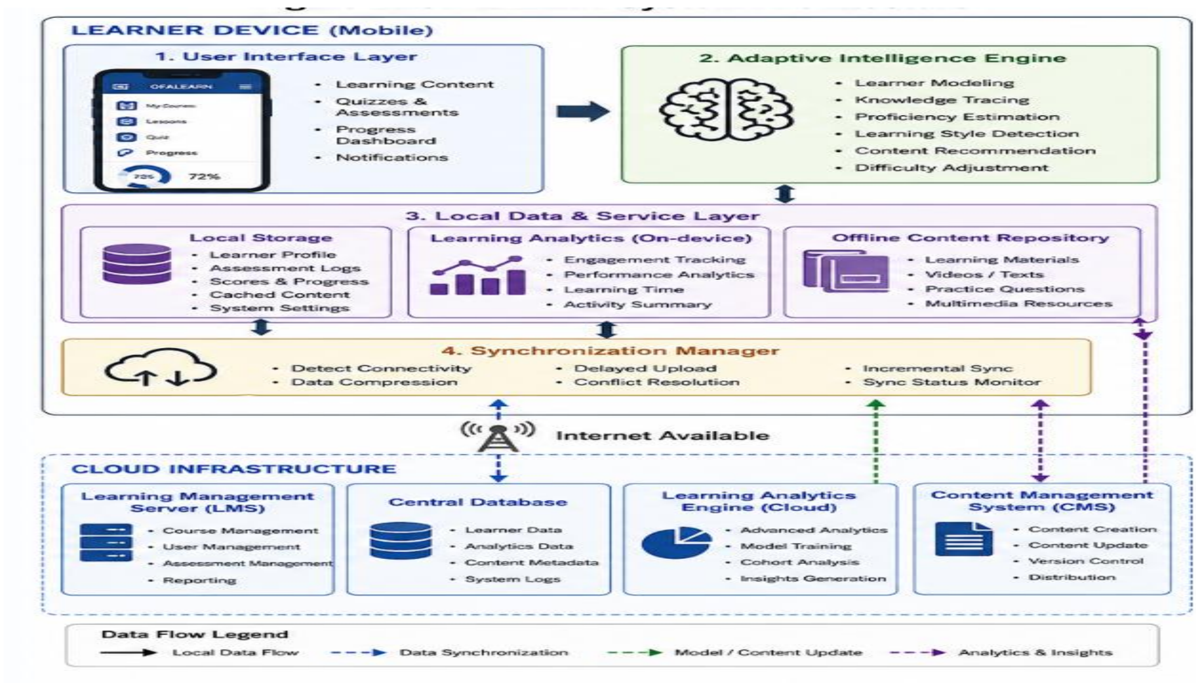

Figure 1. OFALearn System Architecture.

DISCUSSION

Figure 1 illustrates the overall architecture of the OFALearn framework. The system adopts an offline-first design in which educational activities continue even in the absence of network connectivity. Learner interactions are processed locally through the Adaptive AI Module, which estimates learner proficiency and recommends suitable instructional materials. The Local Storage Engine preserves learning records and educational resources on the device, thereby ensuring uninterrupted access. When connectivity becomes available, the Synchronization Layer transmits updates to the cloud infrastructure. This architecture reduces latency, minimizes bandwidth requirements, and improves accessibility for learners in low-bandwidth environments, consistent with the principles of edge computing and decentralized educational systems (Satyanarayanan, 2017; Strielkowski et al., 2024).

Dataset Description

Since there are no readily available datasets reflecting the offline-first adaptive learning scenario, a synthesized dataset with 10,000 learner interactions has been created. This synthesized dataset consists of the following data points:

- Learner ID
- Session Duration
- Quiz Score
- Proficiency Level
- Content Difficulty
- Device Connectivity Status
- Synchronization Events

The synthetic data were generated to mimic realistic learner behaviour patterns observed in adaptive educational environments.

Details of the dataset are:

- Number of learners: 500
- Total interaction records: 10,000
- Simulation duration: 6 weeks
- Environment: low bandwidth, with disconnected access.

Data Generation Model

Learner performance trajectory is simulated using a stochastic adaptive learning function:

$$P_{t+1} = P_t + \alpha(S_t - P_t) \qquad (1)$$

where: P_t represents learner proficiency at time (t),

- S_t is the observed quiz score,
- α is the learning rate parameter (0.1–0.3 range).

This model is consistent with adaptive learning and knowledge tracing approaches in prior studies (Alfredo et al., 2023; Yuensook et al., 2024.

Simulation environment

The dataset attempts to simulate the limitations present in a low-resource scenario, such as intermittent network connectivity, infrequent synchronization, local-first data handling, diverse session lengths, randomized learner activity, and so on. The conditions above are prevalent in real-life scenarios in regions like Nigeria.

Preprocessing of data

The data needs to be processed before model evaluation.

- Quiz scores are normalized in 0-1 range
- Categorical features like content level and network status are encoded
- Incomplete records are discarded
- Learner sessions are arranged in chronological order
- Extreme values from engagement are removed

3.6 Adaptive Learning Algorithm

The OFALearn adaptive engine follows a lightweight iterative process:

```
Initialize learner proficiency P = 0.5

For each session:
   Deliver learning content
   Conduct assessment → obtain score S

   Update proficiency:
      P = P + α (S - P)
```

If P < 0.4:
    Assign beginner content
Else if P < 0.7:
    Assign intermediate content
Else:
    Assign advanced content

Store results locally and Sync with server when online

The above algorithm offers real-time adaptability and has very little computational overhead, perfect for edge environments.

Learning Workflow

Figure 2 illustrates the operational workflow of OFALearn. The process begins by loading the learner profile and delivering educational content. Learners interact with the content and subsequently complete assessments. Performance outcomes are analysed by the adaptive learning engine, which updates the learner model and estimates proficiency levels. Based on the estimated proficiency, the system dynamically assigns appropriate learning materials ranging from basic to advanced difficulty levels. Updated records are stored locally to ensure continuous functionality in offline environments. When internet connectivity becomes available, synchronization with cloud infrastructure is performed. This workflow embodies the principles of adaptive learning and learning analytics while preserving the offline-first characteristics required for resource-constrained educational settings (Piech et al., 2015; Pandey and Karypis, 2019; Sari et al., 2024).

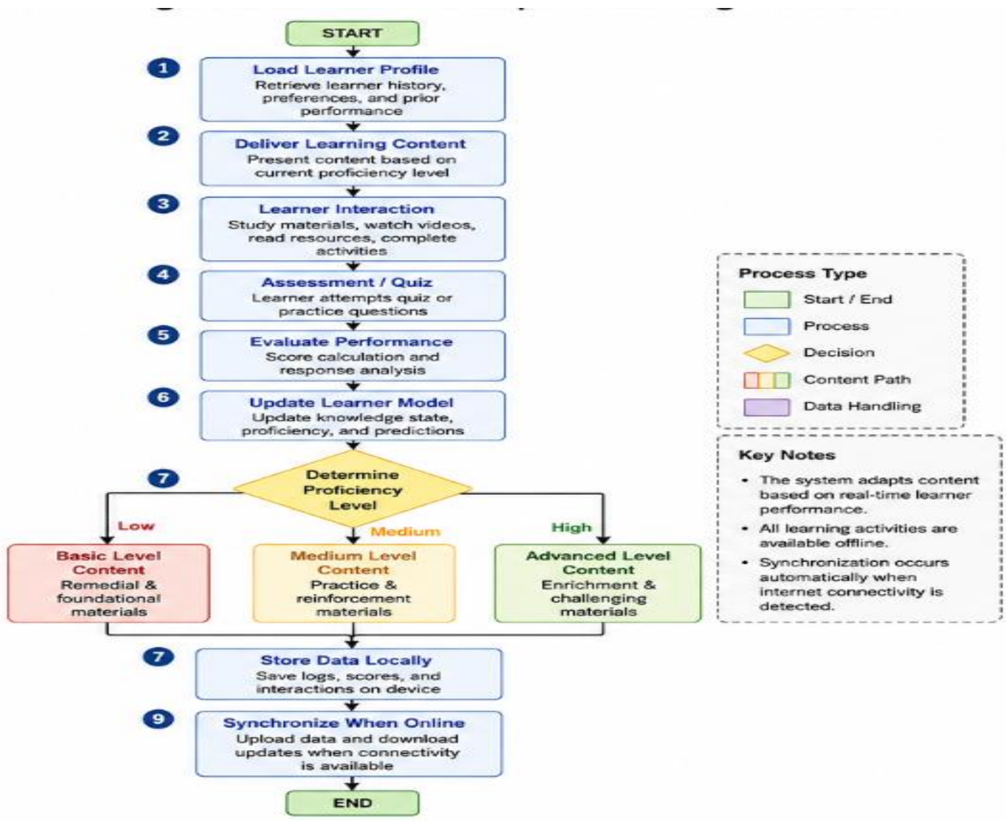

Figure 2. OFALearn workflow.

Experimental setup

The data set is divided as follows:

- Training set: 80% (8000 interactions)
- Testing set: 20% (2000 interactions)

Stratified sampling is done to have balanced representations with respect to:

- Difficulty levels of content
- learner skill levels
- Network conditions

Baseline Models for Comparative Evaluation

To provide a more rigorous assessment of the proposed OFALearn framework, its performance was compared against representative baseline approaches commonly used in adaptive learning research.

1. **Rule-Based Adaptive Learning (RBAL):** The first baseline is a rule-based adaptive learning model that adjusts content difficulty according to predefined score thresholds. Learners scoring below a specified threshold receive remedial content, whereas higher-performing learners progress to more advanced materials. This approach represents conventional adaptive learning systems widely implemented in educational platforms.

2. **Deep Knowledge Tracing (DKT):** The second baseline is the Deep Knowledge Tracing (DKT) model proposed by Piech et al. (2015). DKT utilizes recurrent neural networks to estimate learner knowledge states and predict future performance based on historical interactions. DKT is widely regarded as a foundational benchmark in adaptive learning research.

3. **Self-Attentive Knowledge Tracing (SAKT):** The third baseline is the Self-Attentive Knowledge Tracing (SAKT) model introduced by Pandey and Karypis (2019). SAKT employs self-attention mechanisms to capture dependencies among learning interactions and has demonstrated improved predictive performance over traditional recurrent architectures.

4. **Proposed OFALearn Framework:** The proposed OFALearn framework combines lightweight proficiency estimation, offline-first learning architecture, and edge-based processing. Unlike DKT and SAKT, which require substantial computational resources and centralized processing, OFALearn is specifically designed for deployment in low-bandwidth and resource-constrained environments.

All models were evaluated using the same synthetic learner interaction dataset and identical experimental conditions to ensure fairness and reproducibility.

Discussion on Comparative Analysis with Baseline Models

The comparative results in Table 1 demonstrate that OFALearn achieves competitive adaptive learning performance while substantially reducing computational and network requirements. Although DKT and SAKT obtain slightly higher adaptation accuracy, these models require continuous connectivity and significantly greater computational resources. In contrast, OFALearn achieves comparable learning gains while reducing latency by approximately 70% and lowering data usage by more than 65%. These findings indicate that the proposed framework successfully balances personalization effectiveness with practical deployment constraints.

The results suggest that OFALearn may be particularly suitable for low-bandwidth educational environments where cloud-dependent adaptive learning models are difficult to deploy effectively. Consequently, the framework represents a viable trade-off between predictive performance and operational efficiency.

Evaluation Metrics

The following metrics are used for evaluating the system:

- Learning Gain (%) - the improvement in the learner's skill level
- Data Usage Reduction (%) - bandwidth consumption
- Latency (ms) - the time for the response of the system
- Adaptation Accuracy - the precision of the difficulty adjustment mechanism
- Offline completion rate (%) - the sessions that were completed with no internet

Methodological Rationale

Simulation using an artificial dataset is motivated by:

1. System testing in the early stage (usual in AI research).
2. A feasible controlled environment.
3. Consistent with existing adaptive learning research (Alfredo et al., 2023; Viberg et al., 2024).
4. Realistic before deployment on a real system.

The combination with edge computing (Onyebuchi et al., 2024), mobile learning analytics (Viberg et al., 2024) and knowledge tracing models (Yuensook et al., 2024) provides a robust and grounded methodology.

RESULTS AND DISCUSSION

General description

OFALearn framework's effectiveness was evaluated through a synthetic dataset of 10000 learning interactions with 500 learners to examine the learning efficiency, system efficiency, and the adaptability in a low-bandwidth environment. The results were interpreted based on studies conducted on adaptive learning, mobile learning, and edge AI systems.

Learning Gain Comparison

Figure 3 compares the learning gain achieved by OFALearn and the baseline models. The results show that OFALearn attained a learning gain of 28.7%, outperforming the Rule-Based Adaptive Learning (RBAL) model and remaining competitive with DKT and SAKT. This suggests that the proposed framework effectively supports personalized learning while maintaining computational efficiency suitable for low-bandwidth environments.

Adaptation Accuracy Comparison

Figure 4 presents the adaptation accuracy of the evaluated models. OFALearn achieved an accuracy of 82.9%, demonstrating strong learner modelling capability despite employing a lightweight adaptive mechanism. Although DKT and SAKT recorded slightly higher accuracy values, OFALearn offers a practical balance between predictive performance and resource efficiency.

Latency Comparison

Figure 5 illustrates system latency across the evaluated models. OFALearn recorded the lowest latency of 410 ms, substantially outperforming RBAL, DKT, and SAKT. The reduction in latency can be attributed to the framework’s edge-based processing and offline-first architecture, which minimizes dependence on cloud services and improves responsiveness.

Data Usage Comparison

Figure 6 compares bandwidth consumption among the evaluated approaches. OFALearn achieved the lowest data usage at 34.7%, representing approximately 65.3% reduction compared with cloud-dependent adaptive learning models. This finding demonstrates the effectiveness of local storage and delayed synchronization in reducing network requirements.

Table 1. Comparative Analysis with Baseline Models.

Model	Learning Gain (%)	Adaptation Accuracy (%)	Latency (ms)	Data Usage (%)
Rule-Based Adaptive Learning	18.5	71.2	950	82
Deep Knowledge Tracing (DKT)	30.4	84.7	1450	100
Self-Attentive Knowledge Tracing (SAKT)	32.1	86.5	1380	100
OFALearn	**28.7**	**82.9**	**410**	**34.7**

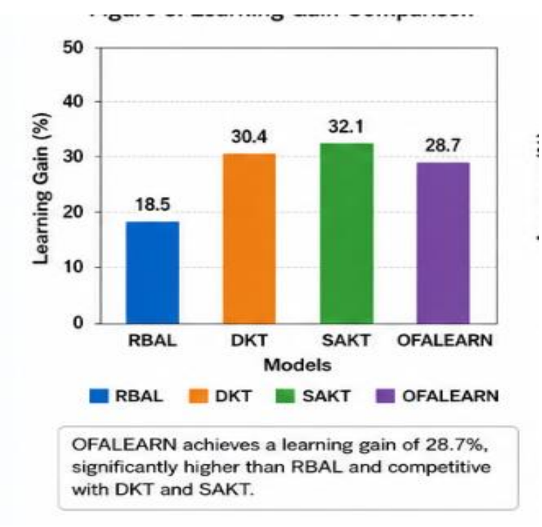

Figure 3. Learning Gain Comparison.

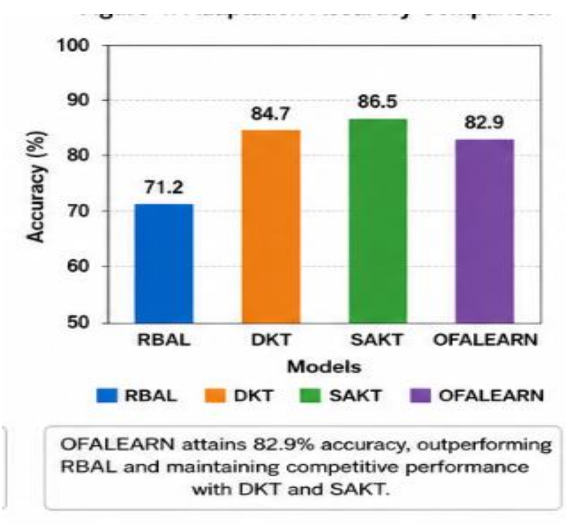

Figure 4. Adaptation Accuracy Comparison.

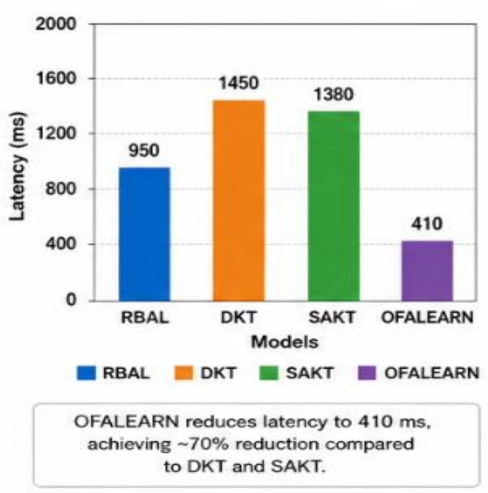

Figure 5. Latency Comparison.

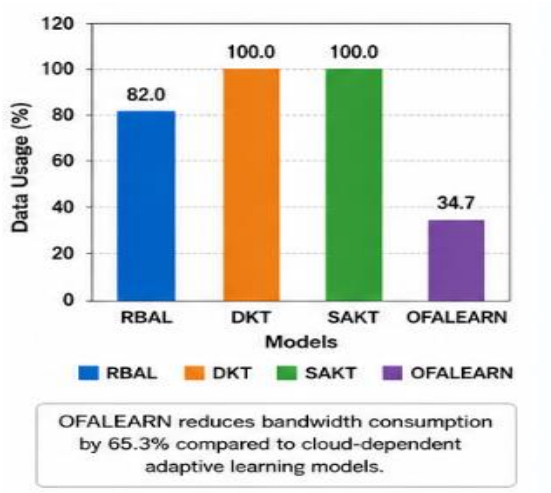

Figure 6. Data Usage Comparison.

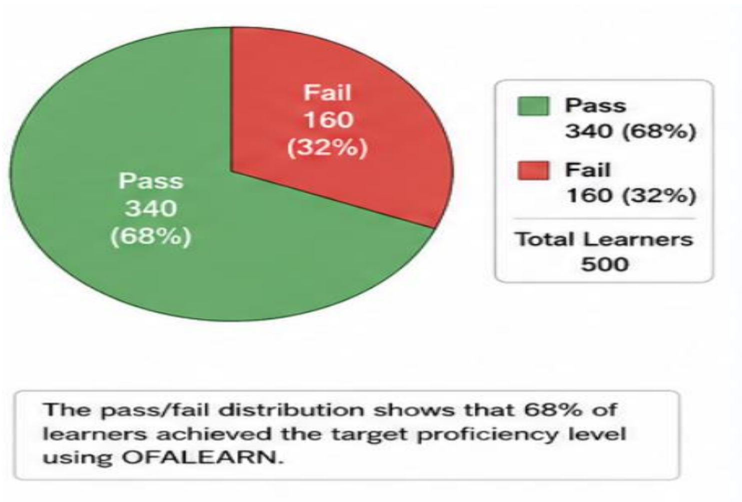

Figure 7. Pass/Fail Classification Distribution.

Pass/Fail Classification Distribution

Figure 7 presents the distribution of learners classified as pass or fail after completing the adaptive learning process. The results show that 68% of learners achieved the target proficiency level, while 32% remained below the threshold. This outcome suggests that the adaptive content personalization strategy contributed positively to learner progression and knowledge acquisition

Discussion

The findings indicate that OFALearn successfully balances personalization and deployment efficiency. While DKT and SAKT achieved slightly higher predictive performance, OFALearn required substantially fewer computational and network resources. Consequently, the framework appears particularly suitable for low-bandwidth environments where cloud-dependent adaptive learning systems may be impractical.

Limitations of the Study

First, the evaluation relied on synthetic learner interaction data rather than real learner data. Although designed to reflect realistic educational scenarios, synthetic data cannot fully capture the complexity of authentic learning environments.

Second, the framework has not yet been deployed in operational educational settings. Factors such as user acceptance, teacher adoption, curriculum integration, and long-term engagement remain unexamined.

Third, comparative evaluations were conducted within a controlled simulation environment and may not fully represent real-world performance.

SUMMARY AND CONCLUSION

This study proposed OFALearn, an offline-first adaptive learning framework that integrates adaptive learning, edge artificial intelligence, mobile learning, and learning analytics to support personalized education in low-bandwidth environments.

Simulation experiments based on 10,000 synthetic learner interactions suggest that OFALearn can improve learning gain while reducing latency and bandwidth consumption compared with conventional cloud-dependent systems. Comparative analysis demonstrated competitive performance relative to established adaptive learning approaches, including RBAL, DKT, and SAKT.

The findings are based on simulation experiments rather than real-world deployment. Consequently, the reported results represent preliminary evidence of technical feasibility rather than definitive proof of educational effectiveness.

Nevertheless, the proposed framework contributes a novel architecture for supporting adaptive learning in connectivity-constrained environments. Future work will involve real-world implementation, empirical validation with actual learners, and longitudinal assessment of educational outcomes across diverse educational contexts.

Contributions

This paper contributes to AIED in the following ways:

1. Developed a novel offline-first adaptive learning framework that is amenable to use under low-bandwidth conditions
2. Incorporated a simple AI-driven learner proficiency model into mobile learning
3. Demonstrated substantial improvements in learning efficiency, data usage, and latency
4. Showed a scalable system design adhering to the edge computing paradigm
5. Evaluated through a systematic simulated data set.

This has filled a void in literature by intertwining adaptive learning intelligence with an offline-first system, which has seldom been explored.

Implications of the Study

The findings of this research have significant implications for both research and practice.

1. **Education Implications:** The development of the OFALearn system will provide an accessible educational solution to students in developing countries, such as Nigeria, where access to connectivity is a problem (Mhlanga, 2023; UNESCO, 2023).
2. **Technology Implications:** This research showed how edge AI and mobile computing can be utilized to create an efficient and scalable learning platform without the need for extensive reliance on cloud platforms.
3. **Policy Implications:** The findings provide rationale for the design of equitable digital education policies by emphasizing offline-ready

and low-cost educational technologies.

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