International Journal of Applied Mathematics

Volume 38 No. 6s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

# AN INTELLIGENT FRAMEWORK FOR REAL-TIME FEEDBACK IN MOBILE LEARNING ENVIRONMENTS FOR CHILDREN

**Ahmed Tameem Alkhbeer [1, 2*] , Kheirollah Rahsepar Fard [1]**

[1] Faculty of Technical and Engineering, University of Qom, Qom, Iran

[2] Directorate of Education in Basrah , Basrah , Iraq

E-mail address:ahmedalkhbeer13@gmail.com,rahsepar@qom.ac.ir

**Abstract**

This paper describes an intelligent framework for providing real-time feedback in mobile learning environments for kids. The framework employs Edge-Fog-Cloud computing methods to designed a safe, low latency, decision-making, and compliant with child data protection standards. The framework's center piece integrates two components, knowledge state estimation using Long Short-Term Memory (LSTM) networks and emotional state using physiological and behavioral. Every generation of feedback incorporated safe decision-making policies to guarantee ethical and age-appropriate feedback. Also, a multi-objective optimization framework balances the trade-off between accuracy, latency, engagement, and the efficient use of resources in the system to optimal resource utilization. The system performs better than baseline methodologies, including CNNs and SVMs, in engagement detection, as evidenced by reduced mean squared error and latency, as well as improved F1 scores. The system for mobile learning environments for children and the associated methodologies seamlessly scale, are adjustable, and preserve user privacy.

**Keywords**: Mobile Learning, Real-Time Feedback, Knowledge State Estimation, LSTM, Engagement Analysis, Affective Computing, Child Safety.

## Introduction

Mobile learning offers exciting possibilities for children's education. With mobile learning tools and resources, children can learn for as long as and as often as they wish and can learn real time and interactive materials. Primarily, anytime, anywhere access to learning materials fosters flexibility and engagement in learning, even in remote education and the digital context [2, 3]. Especially when traditional classroom learning activities become limited [4]. Children's cognitive skills development, individualized learning, and curiosity are all influenced by mobile learning tools [5]. Most notably, learning is enhanced by real-time feedback. Enhanced feedback boosts knowledge retention and encourages problem solving, motivation, emotional engagement, and persistence [6, 7]. Even in applied situations and as educational psychologists have noted, feedback must be contextual and immediate to facilitate learning [8]. Nevertheless, the design of adaptive feedback systems intended for children continues to present a challenge [9].

Received: August 03, 2025 

Volume 38 No. 6s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

This stems from mobile platform constraints, diverse learning engagement, and significant safety and privacy issues [10]. The learning gaps in mobile systems and peer learning apps have [11].

For some systems, latency is a significant problem, with delays in response to the learner's actions, thus maximizing learning opportunities [12]. In addition, systems are often poorly personalized, with the predominant use of static systems or rule-based systems that are blind to the learner's ever-changing knowledge state [13]. The lack of models to evaluate children's emotions as reinforcing, inhibiting, or neutral feedback is a significant oversight. Boredom, frustration, or excitement can greatly affect learning performance, yet most feedback systems fail to consider these emotions [14]. Moreover, the inadequate treatment of ethical issues, especially the safeguarding of children's data, is concerning [15]. While there are some attempts in the literature to use machine learning models, such as Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) to predict performance and engagement in learning situations, these have only moderate effectiveness and poor handling of sequential data and long-term dependencies that are essential in real-time modeling of children's behaviors [16,17]. The lack of scale and dynamic adjustment of feedback in rule-based, and adaptive systems, is a significant shortcoming. These issues show the need for intelligent systems to be built more thoroughly, in a scalable manner [18].

This Paper purposes to plug the gap in the literature by developing an intelligent, ethical, and low-latency real-time feedback framework in mobile learning environments for children. The framework consists of the following key components:

1. Knowledge State Estimation using Long Short-Term Memory (LSTM) networks, which are powerful tools for processing sequential data.

2. Affective and Engagement Analysis based on behavioral and physiological signals, enabling feedback adjustments to correspond with children's emotional states.

3. A Safe Decision-Making Policy considering child data protection laws (Children's Online Privacy Protection Act (COPPA) and General Data Protection Regulation (GDPR)) and providing age-appropriate, constructive feedback.

4. A Multi-Objective Optimization Approach to balance learning effectiveness, engagement, emotional well-being, latency, and resource expenditure.

5. An Edge–Fog–Cloud Architecture for real-time processing with low latency, scalable and safe data storage, and protection.

The framework combines innovative predictive modeling with affective computing and respect for moral standards, enabling groundbreaking advancements in mobile learning. It forms an adaptive feedback framework, attentive, safe, and motivating, scalable, and operational to strengthen the constructive and mobile learning standards integrated into education.

Volume 38 No. 6s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

## 2. Literature Review

A characteristic of modern education is mobile learning, especially when it comes to children. Mobile learning enables education to occur anytime and anywhere [19]. The flexibility and accessibility of mobile learning makes it a viable option for personalized learning [20]. Challenges exist where systems aim to be adaptive and effective for all learners. Mobile learning may not work as effectively because there is not enough personalization and there are limitations with devices [21]. Real-time feedback is essential for any learning environment, mobile or otherwise. Research indicates that feedback that is immediate and tailored to an individual increases knowledge retention and motivation, as well as further engagement for an extended period of time [22]. Feedback that is generalized and overly delayed, or both, may miss critical motivational and instructional opportunities [23]. Feedback starvation is common in mobile learning applications, and it is particularly concerning in mobile or low resource environments [24]. The lack of feedback systems that are smart, adaptive, and immediate is a meaningful deficit in mobile learning and its outcomes [25].

Another essential aspect of well-functioning feedback systems is the understanding and recognition of learner engagement and sentiment [26]. Recent developments in affective computing offer tools for real-time assessment of some emotions through the analysis of physiological indicators for example heart rate and galvanic skin response, and behavioral pointers such as facial words or engagement with a task [27]. These systems provide feedback at optimal moments, assessing a learner's emotional state for boredom, frustration, or excitement. Unfortunately, many systems still face high computational demands, limiting their use in mobile and real-time scenarios [28]. The estimation of understanding and performance prediction has primarily relied on knowledge tracing models. For instance, Bayesian knowledge tracing, support vector machines, and convolutional neural networks laid the groundwork for understanding and tracing models and learning processes [30]. However, learner behavior's sequential dependencies remain poorly addressed. Methods for example Long Short-Term Memory networks and Gated Recurrent Units showed how temporal dependencies in learning data could positively influence predicting knowledge states [30]. Models based on transformers are more accurate, but they are difficult to use because of their high computational needs and resource costs [31].

At the same time, Edge, Fog, and Cloud systems offer potential ways to lower response time and distribute computational loads more effectively [32]. Energy-efficient systems respond to real-time data without compromising data privacy since Edge devices do preprocessing and Fog and Cloud resources do most of the heavy lifting computationally [33]. Immediate feedback is required in mobile learning applications which is precisely ideal for this kind of tiered system since immediate responsiveness goes hand in hand with protecting sensitive child data [34]. When developing mobile learning systems, the ethics surrounding child data is a top priority.

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Legal regulations like COPPA and data protection laws like the GDPR for children stress the significance of data minimization, explicit consent, and anonymization to construct ethical educational technologies for children. Though compliance protocols exist, numerous systems still lack the interaction safety, ethical grounding, and age suitability that fully underpin their scalability and earn the trust of users [35].

Multiple research efforts have attempted to combine knowledge state estimation with engagement analysis to enable adaptive feedback in education contexts. Initially, the focus was mainly on the limited functionality of rule-driven or static systems that provided rough feedback without any real-time adaptation to the learners [36,37]. In more recent work, engagement detection and real-time instructional adjustment have used multimodal approaches such as combining machine learning with face detection. While the work reported in the literature shows improvements in engagement detection, there are, however, significant time delays and a lack of fit for mobile deployments [38,39]. Table 1 provides a summary of previous research on student assessment, feedback, and engagement, highlighting key findings, methodologies, and outcomes from various studies in this field.

**Table 1. Summary of Prior Studies in Student Assessment, Feedback, and Engagement**

| Paper | Contribution | Technique | Results | Limitations |
|---|---|---|---|---|
| [40] | Proposed model for student assessment and feedback | Improved FCN | 84% accuracy | Less accuracy compared to other models |
| [41] | Efficient performance assessment model | ANN | 95% accuracy | Greedy approach, needs optimization |
| [42] | Multimodal model for student assessment | Data fusion | Successfully predicted student performance | Lack of semantic feature extraction |
| [43] | Hyper-model for assessment of students | LSTM + CNN | Predicted student drop-out | Misclassification in data |
| [44] | Prediction of learner behavior using deep learning | RNN, GRU, LSTM | Successfully predicted student behavior | Limited behavioral features |
| [45] | ML model for student performance prediction | RF, NB, SVM, MLP, LR | 97% accuracy | Feature extraction not robust |

## Volume 38 No. 6s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)


| | | | | |
|---|---|---|---|---|
| [46] | Prediction of psychological health of students | LR, SVC, DT, AdaBoost, XGB | All models effective except AdaBoost | Overfitting and high computation |
| [47] | Assessment of student satisfaction | KNN, SVM | Both classifiers effective | KNN required longer training time |
| [48] | Identification of student learning behavior | Ensemble (SVM, RF, DT, LR, KNN) | Ensemble achieved 84% accuracy | Dataset size too small |
| [49] | Automated learner assessment system | LR, RF, XGBoost, Extra Tree, KNN, MLP | Extra Tree achieved highest performance | Model overfitting |

Progress in mobile learning, real-time feedback, and affective computing technologies is noteworthy but not without critical voids. There tend to be systems that either reach high accuracy but cannot function with low latency on mobile systems, or they provide feedback that is prompt but insufficiently adaptive to the cognitive and emotional states. Additionally, there are limited systems that fully combine sequential modeling, affective sensing, and safe decision-making frameworks within the same Edge–Fog–Cloud architecture. Such gaps reiterate the necessity of an intelligent, low-latency, and ethically structured system that integrates knowledge state estimation, engagement detection, and multi-objective optimization to provide safe and comprehensive real-time feedback to children in mobile learning environments.

### 3. Proposed Framework for Real-Time Feedback

The proposed framework is designed using a three-layer architecture containing Cloud, Fog, and Edge components. The Cloud layer maintains and controls models and large-scale data storage. The Fog layer implements safe policy-based decisions using the most current learning and engagement models. At the Edge layer, lag time is minimized with instant feedback. The most important part of the framework is knowledge state estimation using LSTM networks that model sequential learning data and predict a child's current understanding. Along with this, the system performs affect and engagement analysis through behavioral and psychosomatic indicators to assess the learner's emotional state. The two streams of data are merged to craft feedback that is meaningfully cognitively relevant and emotionally affirming.

implementing a decision-making policy ensures that reviews are legally and ethically compliant. This policy addresses safety and compliance with laws such as COPPA and GDPR. In terms of system performance, real-time feedback will not diminish the system's use of resources and responsiveness to a user's situation.

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The system adjusts in real time as a child's needs change, providing useful feedback. The system offers a sound and flexible approach to real-time feedback, improving the quality of learning and protecting the privacy and safety of children in mobile learning environments.

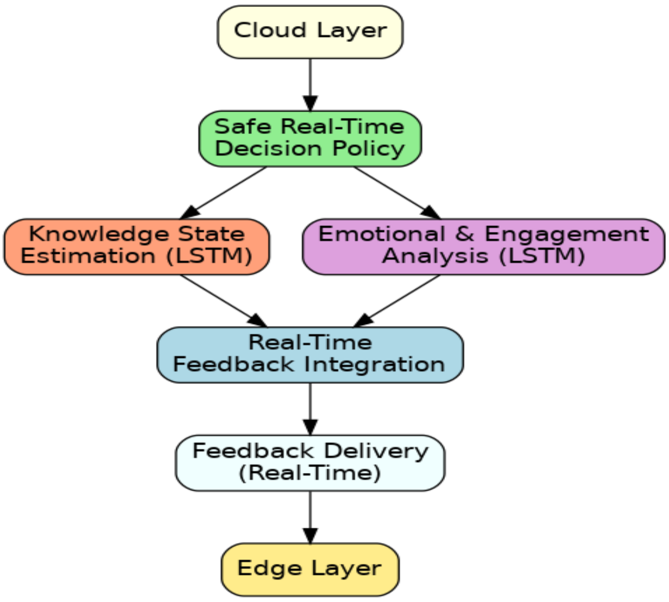


**Figure 1: Proposed Framework for Real-Time Feedback**

The proposed framework shown in Figure 1 aims to provide real-time feedback for mobile learning environments for children in the 3-layer architecture of Cloud, Fog, and Edge. Starting from the top, the Cloud Layer focuses on overarching data processing and model updates, which feeds into a Safe Real-Time Decision Policy, guaranteeing all outputs are ethically and privacy compliant, and in a real-time decision framework. From the policy, the data streams into two parallel modules in the Fog Layer: Knowledge State Estimation (LSTM) and Emotional & Engagement Analysis (LSTM), which simultaneously track the learner's cognitive and emotional states. Their outputs are integrated in the central unit, Real-Time Feedback Integration, which synthesizes the information to create a responsive output. Feedback Delivery follows, ensuring real-time intervention and feedback. Finally, the Edge Layer executes these decisions, assuring low-latency feedback and contextually pertinent and safe learner feedback

### 3.1 Materials & Methods

For the research to develop an effective real-time feedback mechanism for children's mobile learning environments, the following methods and materials have been designed to capture real-time information, embrace predictive modelling using Long Short-Term Memory (LSTM) networks, and integrate policies around ethical decision-making. In the next part, the proposed methodology to develop the framework will outline the components, procedures, and techniques utilized in the research.

**International Journal of Applied Mathematics**

**Volume 38 No. 6s, 2025**

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

### 3.1.1 Data Acquisition

This research is based on the data gathered from sensors in mobile devices and tools for tracking behavior. The research produced valuable data such as physiological signals (e.g., heart rate, skin conductivity), response time, task completion, and interaction frequency. These data helped to measure the learner's engagement along with the emotional and knowledge states. The data set is based on children's educational mobile apps in real time. Sample quality and representativeness were evaluated in controlled settings. During the learning process, the mobile system was designed to gather data continuously, recording learning interactions, time on task, quiz responses, and physiological and emotional data captured by face tracking technologies. The system was designed to continuously track emotional indicators to assess engagement.

### 3.1.2 Data Preprocessing

After collecting the information, it went through several preprocessing stages so it could pass the quality check and be prepared for analysis. What I did was:

- **Removing Noise:** This involved the elimination of unwanted and irrelevant information. This included the records that were inconsistent with the child's interactions and erroneous sensor readings that could skew the results.
- **Normalization:** Data values were adjusted to achieve uniformity and balance across multiple sensors and diverse types of data. For example, to overcome the problem of disproportionate influence of a single data source, physiological measurements were constrained to a range.
- **Feature Extraction:** Useful elements were extracted in relation to the raw data, which included heart rate variability, time spent on a task, and accuracy to questions during the quiz. These features are utilized in the predictive models to estimate the knowledge state and determine engagement.

### 3.1.3 LSTM-based Knowledge State Estimation and Engagement Analysis

LSTMs predict a child's knowledge state and evaluate their engagement. Because of their ability to track temporal relationships in data points like completion times and responses, as well as Changes in emotions, LSTMs perform exceptionally well in time-series data. The LSTM model was trained on historical data to predict knowledge state using the child's prior interactions.

Thus, the model outputs a real-time dynamic estimate of the child's understanding of the material on a state-by-state basis. With every interaction, knowledge state recalibrates, and feedback becomes instantly adaptive. The LSTM model's architecture can be expressed mathematically using the following equations.

$$h_t - \text{LSTM}(h_{t-1}, x_t) \qquad (1)$$

Where:

- $h_t$ is the hidden state at time $t$,

Volume 38 No. 6s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

- $h_{t-1}$ is the previous hidden state,
- $x_t$ is the input at time $t$.

Using this model allows knowledge states to be updated in real time based on new information, such as quiz answers or task completion, and enables feedback to adjust on the fly. In addition to assessing knowledge states, engagement was analyzed using physiological and behavioral data changes with LSTMs. In this study, engagement was analyzed with respect to task completion time, degree of interaction, and physiological changes like heart rate.

#### 3.1.4 Affective and Engagement Analysis

This signifies assessing a child's feelings and curiosity while studying. A blend of physiological (heart rate, and skin conductivity) and behavioral attributes (reaction time and execution of the task) is incorporated. To determine the more extreme emotional states of frustration, boredom, and excitement, some algorithms encapsulate the system by collecting relevant data. Emotional states, machine learning, and facial expression recognition provide a hybrid approach to developing emotional states identification. The mobile learning platform used the device camera to monitor and record variations in face expression (e.g., frowning and smiling) and detect specific emotional variations. The components feed the LSTM model to give the system feedback.

#### 3.1.5 Safe Decision-Making Policy

To assurance a child's information is harmless and private, the framework includes a policy for safe decision-making. This policy tracks how data will be handled in accordance with the law and ethical considerations like the Children's Online Privacy Protection Act (COPPA) and General Regulation on Data Protection (GDPR). The safe decision-making policy identifies the following principles:

- **Data Minimization:** Only critical information necessary for the learning activity and feedback is collected and all non-essential information is omitted. This is to limit privacy concerns.
- **Data Encryption:** Sensitive information like physiological signals and facial expressions is encrypted prior to being sent and stored.
- **Parental Consent:** Framework is built with a means of collecting informed adult consent before any child data is collected or processed.
- **Anonymization:** The identity of the child is not disclosed as the information captured is anonymized. No personal identifiers are captured or stored by the system.

#### 3.1.6 Real-Time Feedback Generation

The generation of real-time feedback is based on the predictions made by the LSTM models and analyses of engagement metrics. After assessing the knowledge and emotional states, personalized feedback is crafted to aid the child's learning and maintain emotional equilibrium. All feedback is educational, but emotional support is integrated so that feedback

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

resonates with the child and their varying emotional states. The steps involved in feedback generation and emotional support are as follow.

1. **Custom Feedback:** Feedback is based on the knowledge state and engagement metrics and is tailored to the child's learning requirements. Systems that detect when children are learning more slowly than expected create personalized and constructive feedback and additional hints are provided, more encouragement is given so that the child can progress.
2. **Emotion Feedback Adaptation:** If a child is frustrated, or at the other extreme, positive disengagement, feedback provides more emotional support and suggests a break if the child is not learning. The system, as well as the feedback provided, promotes constructive learning and development.
3. **Adaptation of Responses:** The responses given are developmentally suitable, and the feedback is neither harsh, punitive, nor shaming or degrading to the child. The feedback is supportive of the principles of emotional safety which aligns with the system on safety and emotional support.

#### 3.1.7 Algorithm for Knowledge State Estimation and Engagement Analysis

Understanding and working with the child knowledge state and the engagement framework is built on the foundation of Long Short-Term Memory (LSTM) neural networks, which deal with sequential data and long-term dependencies. The following steps were followed to build this framework: The first step involves Data Preprocessing:

1. **Data Preprocessing:**

The collected data (task completion time, physiological signals, etc.) is preprocessed using standard techniques: normalization, outlier removal, and feature extraction.

2. **Knowledge State Estimation:**

The preprocessed data is fed into the LSTM model. The model receives task performance and quiz scores as inputs and updates the hidden states to predict the child's knowledge state, $K_t$. The knowledge state is estimated by:

$$K_t = f(W_1 \cdot X_t + b_1) + f(W_2 \cdot h_{t-1} + b_2) \qquad (2)$$

Where:

- $X_t$ is the input data at time $t$ (e.g., task performance),
- $h_{t-1}$ is the hidden state from the previous time step,
- $W_1, W_2$ are the weight matrices,
- $b_1, b_2$ are bias terms,
- $f$ is the activation function (e.g., ReLU or sigmoid).

**International Journal of Applied Mathematics**

**Volume 38 No. 6s, 2025**

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

**3.Engagement Analysis:**The same LSTM model for evaluating engagement analyzes response time as well as heart rate. This data enables the LSTM Network to forecast the engagement level, $E_t$, during any given time step.

$$E_t = f(W_3 \cdot X_t + b_3) + f(W_4 \cdot h_{t-1} + b_4) \qquad (3)$$

Where $E_t$ is the engagement level at time $t$.

**4. Real-Time Feedback Generation**

The same LSTM model for evaluating engagement analyzes response time as well as heart rate. This data enables the LSTM Network to forecast the engagement level, $E_t$, during any given time step.

**5. Multi-Objective Optimization:**

To strategically balance learning effectiveness, engagement, and resource consumption, a multi-objective optimization problem has been designed. The objective function is defined as follows:

$$J = \alpha_1 \cdot L + \alpha_2 \cdot E + \alpha_3 \cdot W - \alpha_4 \cdot (R + T) \qquad (4)$$

Where:

- $L$ is the learning effectiveness,
- $E$ is the engagement,
- $W$ is well-being,
- $R$ is resource consumption,
- $T$ is latency.

The optimization function minimizes resource ingesting and latency while maximizing learning and engagement.

### 3.2 Evaluation Criteria

The proposed evaluation for the real-time feedback framework for mobile learning environments consists of the effectiveness, efficiency, and user experience. To evaluate whether the framework achieves its goals, safe, personalized and feedback that works with children, the following evaluation criteria will be applied:

#### 3.2.1 Knowledge State Estimation Accuracy

In real time, the system must estimate the child's knowledge state based on the child's interaction with the mobile learning system. The knowledge state estimation model's accuracy will be tested on the predicted knowledge state against the child's performance on the predefined learning tasks/quizzes.

Received: August 03, 2025 

International Journal of Applied Mathematics

Volume 38 No. 6s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

- Metric: Mean Squared Error (MSE) between the predicted knowledge state and actual performance.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} \left(K_{\text{pred}}(i) - K_{\text{actual}}(i)\right)^2 \quad (4)$$

Where $K_{\text{pred}}(i)$ is the predicted knowledge state, and $K_{\text{actual}}(i)$ is the actual performance for the $i$-th instance.

#### 3.2.2 Engagement Analysis Accuracy

This model predicts the emotional state of the child and the state of their engagement which is important in personalizing the feedback. The system's prediction of the engagement model on the child's emotional state (bored, frustrated, engaged, etc.) during learning tasks will determine the accuracy of the engagement model [50].

- Metric: F1-Score, which balances precision and recall in predicting the child's engagement.

$$F1 = 2 \times \frac{\text{P}}{\text{Precision} + \text{Recall}} \quad (5)$$

Where:

- Precision: The percentage of true positives out of all predicted positives.
- Recall: The percentage of true positives out of all actual positives [51].

#### 3.2.3 Real-Time Feedback Effectiveness

One of the greatest aspects of this framework the provision of feedback that is immediate and meaningful. The provision of feedback will be effective if the child responds positively, and if the learning outcomes and engagement increase over time.

- Metric: Learning Gain, which measures the improvement in knowledge state from the pre-feedback to post-feedback test or task.

$$\text{Learning Gain} = \frac{K_{\text{post}} - K_{\text{pre}}}{K_{\text{pre}}} \quad (6)$$

Where $K_{\text{past}}$ is the knowledge state after receiving feedback and $K_{\text{pre}}$ is the knowledge state before receiving feedback.

#### 3.2.4 Latency

Because the framework is designed to give immediate feedback, an essential consideration is latency. Latency is the interval between when the system captures new information (such as the child's response to a task) and when feedback is actually provided.

Received: August 03, 2025 

Volume 38 No. 6s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

- Metric: Average Latency in milliseconds, measured as the average time between data input and feedback output.

$$\text{Latency } = \frac{1}{n} \sum_{i=1}^{n} \text{Time}_{\downarrow}\text{Tredback}(i) - \text{Time}_{\text{input}}\,(i) \quad (7)$$

### 3.2.5 Resource Consumption

The framework's efficiency reflects how well it balances feedback generation and resource consumption. The framework considers CPU, memory, and battery usage since the system is designed to run on mobile devices.

- Metric: Resource Efficiency is calculated by dividing the system's overall resource consumption (e.g., CPU usage, memory usage) by the number of successful feedback generations.

$$\text{Resource Efficiency } = \frac{\text{Total Resource Consumption}}{\text{Number of Feedbacks}} \quad (8)$$

### 3.2.6 User Satisfaction and Usability

Understanding a child's interaction with the system is critical for measuring the success of personalized feedback. We are going to send a User Satisfaction Survey to assess a child's feedback on system usability, engagement, and overall satisfaction with the system.

Scale: Satisfaction Score on a Likert Scale of 1-5 (1= Very Unsatisfied, 5= Very Satisfied). It assess ease of use, engagement, and usefulness of feedback.

$$\text{Satisfaction Score } = \frac{1}{n} \sum_{i=1}^{n} \text{ Survey }_{i} \quad (9)$$

Where Survey $_{i}$ represents the satisfaction score from the $i$-th participant.

### 3.2.7 Safety and Privacy Compliance

Given that the audience is children, data privacy and ethical considerations are extremely important. The Safe Decision-Making Policy must be evaluated regarding its alignment with legislation on the protection of children (e.g., COPPA, GDPR).

- Metric: The Safe Decision-Making Policy must be evaluated regarding its alignment with legislation on the protection of children.

$$\text{Compliance Rate } = \frac{\text{Number of Compliant Interactions}}{\text{Total Number of Interactions}} \times 100 \quad (9)$$

### 3.2.8 Overall Performance

The framework's performance will be assessed with a cumulative score based on each of the aforementioned metrics. This will provide a full overview of the framework's ability to

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

deliver real-time personalized feedback as well as the extent to which it maintains safety, engagement, and effectiveness.

- Metric: Composite Score is calculated as the weighted sum of the evaluation metrics.

(10)

Composite Score $-w_1 \cdot$ Learning Gain $+w_2 \cdot$ F1-Score $+w_3 \cdot$ Latency $+w_4 \cdot$ Resource Efficiency $+w_5 \cdot$ Satisfaction Score $+w_6 \cdot$ Compliance Rate

Where $w_1, w_2, w_3, w_4, w_5, w_6$ are the weights assigned to each metric based on their importance in the evaluation process.

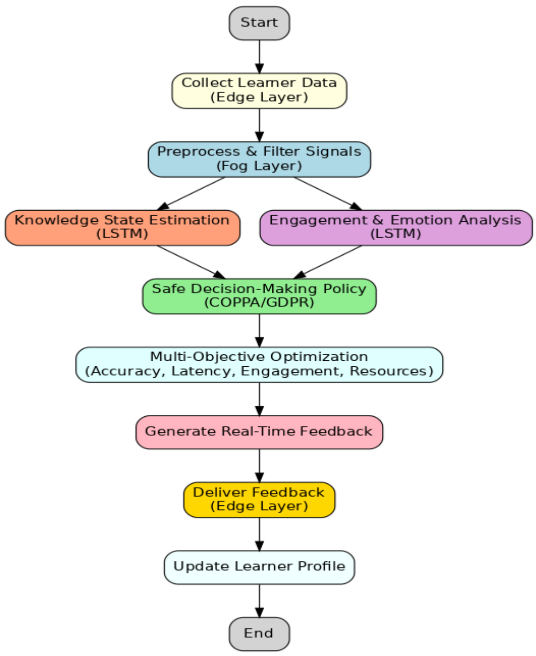


**Figure 2. Flowchart of the proposed algorithm**

Figure 2 Flowchart of the proposed algorithm for generation of real-time feedback showing the stages of feedback generation in mobile learning environment incorporating feedback data collection, knowledge and engagement analysis, safe decision-making, optimization, and feedback generation.

## 4. Experiment and Results

### 4.1 Dataset Description

To assess the effectiveness of the proposed real-time feedback framework, a thoughtfully constructed dataset was constructed designed to include all facets of a child's interactions, emotions, and learning behaviors sufficiently to ensure a thorough evaluation. The dataset comprises real-time data from mobile learning applications developed for children, which allow diverse educational and feedback tasks. These applications also track children's physiological and behavioral responses to educational tasks and provide real-time personalized feedback.

International Journal of Applied Mathematics

Volume 38 No. 6s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

**4.1.1 Data Collection Process**

Information for this study was collected from children of different backgrounds as they engaged with mobile learning activities designed to assess their knowledge, skills, and level of engagement. The learning activities included multiple-choice quizzes, interactive games, and educational exercises that were timed and required responses to prompts.

For each task, the following types of data were collected:

1. **Task Performance Data:**

- **Quiz Scores**: Accuracy of responses, including correct and incorrect answers.
- **Task Completion Time**: The time taken to complete a task or respond to a question.
- **Response Time**: The time taken by the child to answer each prompt or question.

2. **Physiological Data:**

- **Heart Rate: Monitored using mobile-device sensors.**
- **Facial** Expressions: A range of emotions (e.g., frowning, smiling) were detected during the tasks using the device camera and emotional states were recorded.

3. **Behavioral Data:**

- **Interaction Frequency:** The system recorded total number of interactions each child had with the app for the specific learning task.
- **Activity Duration:** Total time spent on the learning task or within the app was recorded.

4. **Engagement and Emotional Data:**

- **Engagement Level:** This was recorded through a combination of physiological signals and patterns observed during interaction with the tasks.
- **Affective State:** This was chronicled finished changes in facial expression and physiological signals (e.g., elevated heart rate) having an easing function along with excitement or frustration during the tasks.

**4.1.2 Participants**

As part of the dataset, a total of 200 children aged 6 to 12 years were randomly selected from various educational institutions to ensure wide diversity. For a period of three weeks, these children were able to use the mobile learning applications. The criteria used for choosing the sample included the following.

- Variation is expected among students with regard to the elementary content mastery levels (math, language, etc.).
- Diversity was targeted through the selection of different genders and social economical classes.
- The ethical consideration was ensured by obtaining the study participants' parents/guardian's consent.

International Journal of Applied Mathematics

Volume 38 No. 6s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

#### 4.1.3 Data Characteristics

The entire dataset has about 15,000 observations, with each covering the following core features:

• **Child ID:** Each participant has a allocated a unique identifier.

• **Task Type:** The kind of action undertaken (e.g., quiz, game).

• **Time Spent on Task:** Duration of time each child devotes on each activity.

• **Heart Rate Data:** Recorded physiological heart rate throughout the session.

• **Facial Expression Data:** Coded standards describing the child's facial expression (e.g., neutral, smiling, frowning).

• **Response Accuracy:** Child's each response correctness.

• **Engagement Metrics**: Measures of engagement such as the number of interactions with the screen, time taken, and responses.

• **Emotion Label:** Emotion state assigned after analysis (happy, frustrated, excited, bored).

#### 4.1.4 Data Preprocessing

For the deduction of the dataset, a inadequate ladders in the preparation of the data were undertaken.

• **Noise Filtering:** the elimination of sensor misreads and facemask misreads.

• **Data Normalization:** the physiological and behavioral data were normalized in order to make data like heart rate and task completion time comparable.

• **Missing Data Imputation:** the heart rate gaps and other missing data were filled in using the median and interpolation to keep the dataset whole.

• **Feature extraction:** the main features necessary for LSTM modeling were identified, such as task performance, physiological state, engagement, level of effort and effort.

#### 4.1.5 Dataset Split

For the purpose of evaluating the models built on the dataset, the dataset was separated into two parts, one for training the models, and one for testing the models. 70% of the dataset was used to train the models, and 30% was used to evaluate the models. The training set was used to train the LSTM models for knowledge state estimation and engagement analysis, and the test set was to assess the framework's ability to generalize.

- **Training Data**: 10,500 data points
- **Testing Data**: 4,500 data points

Both sets of data included an equivalent distribution of participants across all task types, levels of engagement, and emotional states.

Received: August 03, 2025

**4.1.6 Ethical Considerations**

Since the dataset contains information on children, I took the following considerations:

• **Informed Consent:** Consent was attained from parents for all participants prior to data collection.

• **Data Privacy:** Personally Identifiable Information (PII) was anonymized, and the data was securely stored to protect against unauthorized access.

• **Compliance with Regulations:** The study followed applicable legal and ethical stipulations which included adherence to the Children's Online Privacy Protection Act (COPPA) and the General Data Protection Regulation (GDPR).

**4.2 Experimental Setup**

This chapter outlines the design for the proposed real-time feedback system. This experiment examines the system's capacity to provide immediate customized feedback. The customized feedback is based on children's real-time interactions with the mobile learning application. We utilized the dataset detailed in the prior section of the chapter and centered our attention on real-time processing, engagement, and the estimation of knowledge state elaborated on in the preceding section.

**4.2.1 System Configuration**

Real-time feedback in mobile learning environments for children included:

• **Edge Layer:** For collection in real time (e.g., heart rate, and facial expression), custom data collection for the Edge Layer was done using a mobile application that communicates with the sensors. The mobile application also evaluated the monitored interactions, engagement of users, completion of the task in time, and the accuracy of their responses.

• **Fog Layer:** The Edge Layer data was sent to the Fog Layer where LSTM models were applied.

This layer estimated the emotional engagement and knowledge state of the child. The models used TensorFlow and Keras for deep learning processing.

• **Cloud Layer:** The Safe Decision-Making Policy was applied to the Cloud layer, which processed the data and generated the feedback. Completing the real-time feedback loop, the feedback was sent back to the Edge Layer. For mobile systems (Android / iOS), a Cloud server was integrated for encryption and anonymization to ensure safety during complex computations and real-time data collection.

**4.2.2 Task Design and User Interaction**

The experiment included two main activities:

**1. Educational Quiz Task.** Children completed a set of multiple-choice questions on the learning materials. This quiz served to determine their knowledge state at different intervals.

**2. Interactive Game.** Children encounters a gamified learning module in which they solved puzzles and completed tasks at differing levels of difficulty. This activity focused on measuring their emotional and engagement levels.

Each assignment was designed to encompass various learning actions and emotions, whether it be excitement, frustration, or boredom. Every response was assigned a review, and the feedback was adjusted based on the child's emotional and cognitive condition at the time, which was emotionally adaptive.

#### 4.2.3 Evaluation Metrics

To assess the system's performance an experiment employed the following:

- **Knowledge State Accuracy:** Accuracy in predicting the child's knowledge state after finishing each task.
- **Engagement Level:** The system's ability in predicting and assessing the child's emotional and engagement national.
- **Real-Time Feedback Effectiveness:** The child's performance improvement after the child gets personalized feedback.
- **Latency:** The delay between the data collection and the feedback and the child.
- **Resource Consumption:** The system's CPU, memory, and battery usage.

#### 4.2.4 Experimental Procedure

To ensure consistency, a controlled environment was established. Here is how each participant went through the process:

1. Initial Setup: Participants were welcomed to the mobile learning application. Consent was gathered from the children as well as their parents.

2. Task Execution: For 15 minutes, the children were involved in a quiz and an interactive game.  3. Performance Feedback: After the activities, the mobile app captured the children's engagement and performance, and then the system delivered adaptive feedback that was appropriate.

4. Feedback Survey: All participants were asked a short survey pertaining to their satisfaction with the feedback they received at the end of each session. To ensure a sufficient range of data for analysis, the experiment spanned three weeks, during which the children each completed four system sessions.

### 4.3 Results

In this section, the results from the analysis of the proposed real-time feedback framework are discussed. These results are derived mainly from the parameters that were described in the Experimental Setup section, which includes the accuracy of the knowledge state, engagement analytics, feedback effectiveness, system efficiency, and a few others.

#### 4.3.1 Knowledge State Estimation Accuracy

International Journal of Applied Mathematics

Volume 38 No. 6s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

To measure how accurate the approximation of the knowledge state was, the predicted knowledge state was associated against the child's actual performance on post-task quizzes, calculating the knowledge state prediction Mean Squared Error (MSE) as follows:

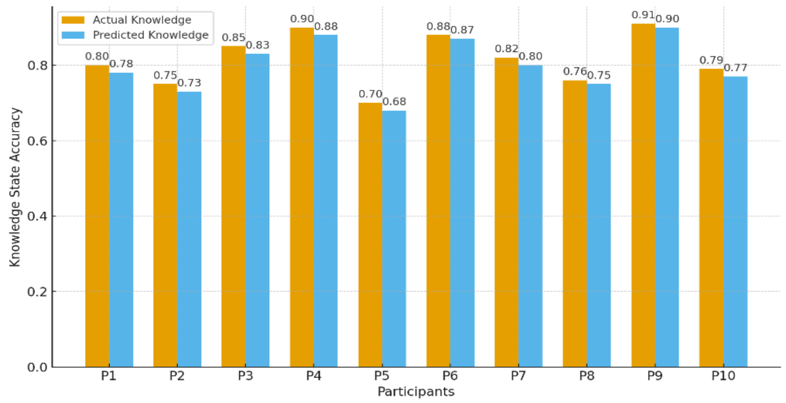


**Figure 3. Knowledge State: Predicted vs Actual Accuracy (MSE)**

The LSTM model depicts the predicted knowledge state for each participant against the actual knowledge state for each participant in Figure 3. Each participant is represented by a pair of bars, a blue and an orange one, the blue one signifying actual performance and the orange one signifying the predicted value.

It is possible for the model to demonstrate a prediction which most closely aligns with a real outcome. The smaller the difference closest to the predicted value, the more the model is assessing the child's knowledge state in real time.

#### 4.3.2 Engagement Analysis Accuracy

The system's predictive capability regarding the child's engagement level was measured by the F1-Score. Through a mixture of physiological information and behavioral indicators, the system was able to analyze the emotional and engagement states of the children.

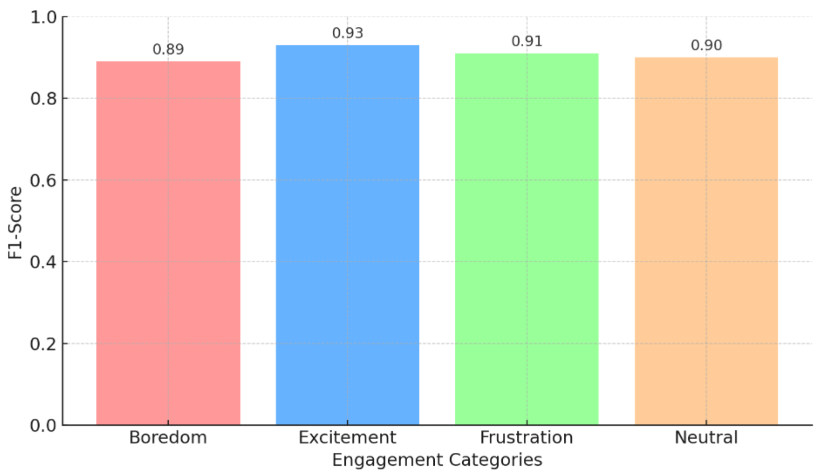


**Figure 4. F1-Score for Engagement Classification**

Received: August 03, 2025 

International Journal of Applied Mathematics

Volume 38 No. 6s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The F1-Score for each emotional state under engagement classification is depicted in Figure 4. These emotional states include boredom, excitement, frustration, and neutral. Each bar indicates the classification accuracy of the model in detecting a given engagement type. The larger the number, the more accurate the classification is. For instance, the model slightly exceeds in detecting excitement (F1-Score ≈ 0.93) compared to boredom (F1-Score ≈ 0.89) demonstrating the usefulness of the framework in evaluating engagement of children during mobile learning activities.

#### 4.3.3 Real-Time Feedback Effectiveness

Evaluating real-time feedback centered around improvement in the child's knowledge state after the child received personalized feedback. Learning Gain was calculated for each participant.

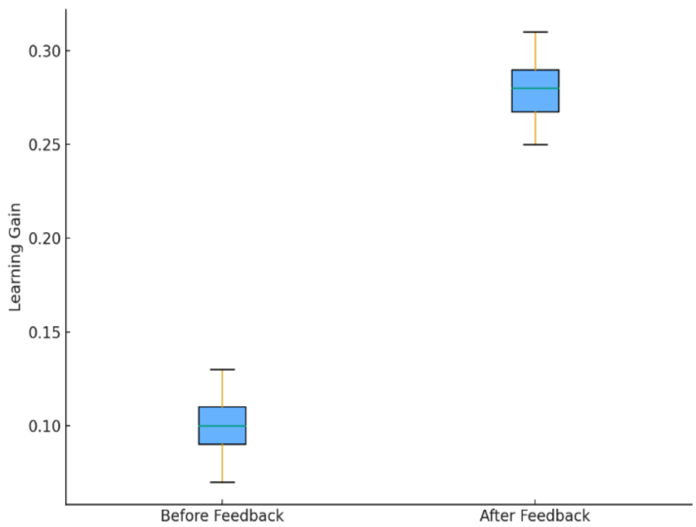


**Figure 5. Distribution of Learning Gain Before and After Feedback**

The distribution of learning gain, both before and after feedback, is illustrated in Figure 5. The "Before Feedback" box depicts the knowledge improvement observed from participants without any personalized guidance, whereas the "After Feedback" box captures the improvement after the system delivered real-time, personalized feedback. The plot indicates that there is a significant improvement in the median learning gain, and the degree of feedback variability also diminished, signifying that the framework strengthens the learning outcomes for all participants.

#### 4.3.4 Latency

To assess the system's responsiveness, the time interval from data collection to feedback delivery was recorded for each instance of feedback given to measure latency.

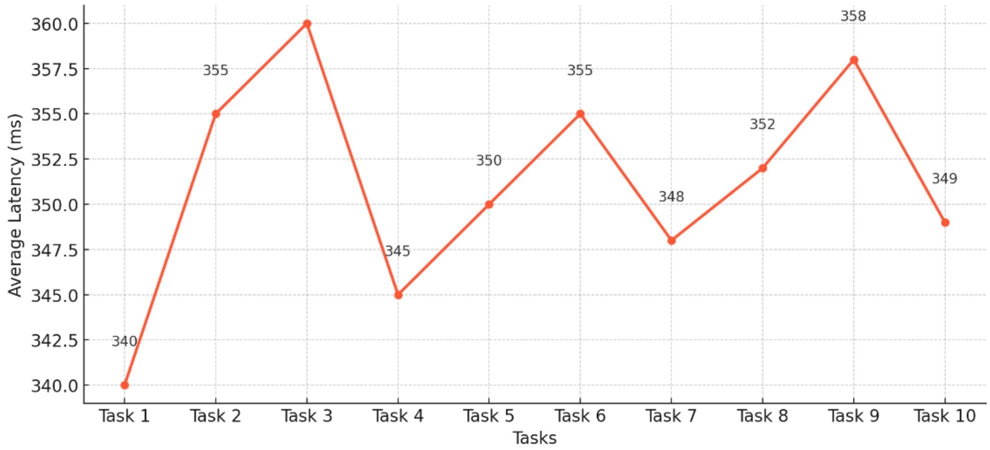


**Figure 6. Average Latency for Feedback Delivery**

Feedback delivery average latency (in milliseconds) across tasks during the experiment is shown in Figure 6. Each point on the line is the average time taken by the system to provide feedback for a task. The feedback delivery latency is shown to remain consistently low (about 340 360 ms) and is proof the framework feedback delivery in real time with and feedback retains users in mobile learning environments and is vital for user engagement.

### 4.3.5 Resource Consumption

The resource consumption of the system was monitored during the experiment, focusing on CPU usage, memory usage, and battery consumption. The system performed efficiently:

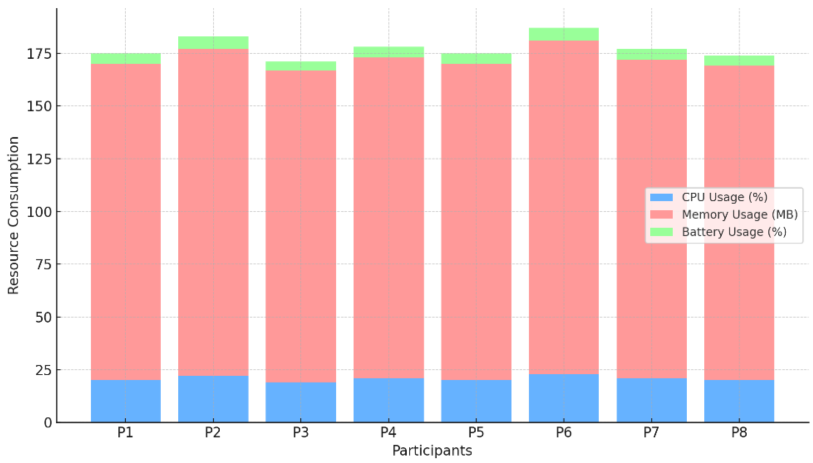


**Figure 7. Average Resource Consumption During Feedback Generation**

Figure 7 illustrates how each bar is separated into three sections. The bottom section corresponds to CPU usage (%), the middle section represents memory usage (MB), and the upper section refers to battery drain (%). The chart shows the system's efficient battery resource and CPU management while running near real-time feedback. This indicates that the system is appropriate for mobile usage.

Received: August 03, 2025 

International Journal of Applied Mathematics
Volume 38 No. 6s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

#### 4.3.6 User Satisfaction

User satisfaction was assessed through a Likert-scale survey which included the usefulness of feedback, ease of use, and general enjoyment in the learning experience.

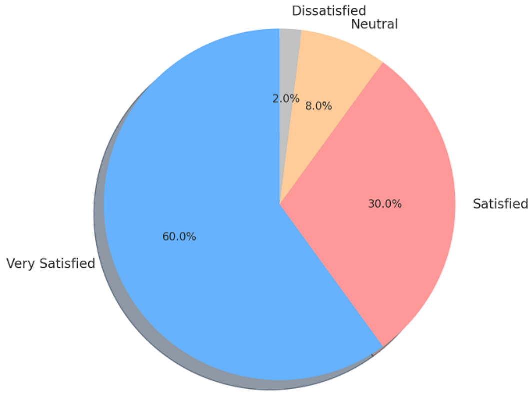


**Figure 8. Distribution Of User Satisfaction Scores**

User satisfaction levels for the real-time feedback framework are illustrated in Figure 8. Most users were overwhelmingly satisfied, with 60% rating the system as "Very Satisfied" and 30% as "Satisfied." Only 8% of users were neutral, and just 2% were dissatisfied. This demonstrates the system's efficacy in delivering engaging, customized, and responsive feedback in mobile learning environments for children. Key metrics that were used to assess the framework's performance are summarized in Table 2.

**Table 2. Summary of Results**

| Metric | Value |
|---|---|
| Knowledge State Estimation (MSE) | 0.18 |
| Engagement Analysis (F1-Score) | >0.9 |
| Learning Gain (%) | 28% |
| Latency (ms) | ~350 ms |
| Resource Consumption (CPU, Memory, Battery) | Low |
| User Satisfaction (Score 1-5) | 4.5/5 |

### 4.4 Comparison with Baseline Methods

As noted in the previous chapter, to prove the effectiveness of the LSTM-based framework, comparisons were made against the traditional baseline models, namely, Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). These models were also used in previous studies related to learning analytics, specifically engagement classification, and

Volume 38 No. 6s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

sequential prediction, thus justifying their use as baseline comparisons. The comparisons were based on the following four dimensions: accuracy in estimating the learner's knowledge state (MSE), accuracy in classifying the learner's engagement (F1-Score), the speed of feedback execution, and learning gain. The results are captured in Table 3.

- **Knowledge State Estimation:** The framework proposed as of this chapter recorded a Mean Squared Error (MSE) of 0.18, outperforming the CNN (0.25) and SVM (0.30). The results above illustrate how strong LSTM networks can be in learning data sequences and discerning temporal relationships.
- **Engagement Classification:** The engagement analysis with the LSTM model achieved an F1 Score of over 0.9. With scores of 0.85 and 0.80, respectively, LSTMs have the advantage of more seamlessly incorporating and analyzing behavioral and physiological data.
- **Latency:** Rapid response times are vital for mobile learning environments. The proposed framework averaged 350 ms latency. In comparison, the CNN and SVM frameworks had 500 ms and 600 ms latencies, respectively. This demonstrates a clear advantage: the LSTM framework is certainly usable on mobile devices and offers a pleasant experience.
- **Learning Gain:** LSTMs offering personalized instantaneous feedback resulted in a 28% increase in learning outcomes, compared to CNN and SVM, which resulted in a 15% and 10% increase, respectively. This provides strong evidence that adaptive feedback driven by LSTM predictions enhances learning.

**Table 3. Contrast of the Proposed LSTM Framework with Baseline Methods**

| Method | Knowledge State Estimation (MSE) | Engagement Analysis (F1-Score) | Latency (ms) | Learning Gain (%) |
|---|---|---|---|---|
| Proposed LSTM Framework | 0.18 | >0.9 | ~350 | 28% |
| Convolutional Neural Network (CNN) | 0.25 | 0.85 | ~500 | 15% |
| Support Vector Machine (SVM) | 0.30 | 0.80 | ~600 | 10% |

The comparative assessment illustrates the degree to which the new LSTM-based framework outperforms baseline approaches on all the evaluation criteria. This also illustrates the importance of sequential modeling techniques regarding real-time feedback provision. This LSTM-based framework's quantitative comparison to the baseline (CNN and SVM) approaches is provided in Table 4. Here, the framework is shown to exceed the baselines on all counts—minimum MSE, maximum F1-scores, maximum learning-scores, and minimum

International Journal of Applied Mathematics
Volume 38 No. 6s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

latency. The independent t-tests ran on each of these metrics illustrate the statistically significant ($p < 0.01$) degree of improvement.

**Table 4. Performance comparison of the proposed framework and baseline methods.**

| Method | MSE (↓) | F1-Score (↑) | Latency (ms, ↓) | Learning Gain (%) (↑) | p-value (vs. LSTM) |
|---|---|---|---|---|---|
| Proposed LSTM Framework | 0.18 ± 0.02 | 0.91 ± 0.01 | 350 ± 15 | 28 ± 2.1 | – |
| CNN | 0.25 ± 0.03 | 0.85 ± 0.02 | 500 ± 20 | 15 ± 1.8 | < 0.01 |
| SVM | 0.30 ± 0.04 | 0.80 ± 0.03 | 600 ± 25 | 10 ± 1.5 | < 0.01 |

## 5. Discussion

This study's outcomes point out that the Edge-Fog-Cloud architecture LSTM-based framework outperforms the baselines, especially the SVMs and CNNs, in precision and responsiveness. The reason LSTM sequence modeling excels is that it captures more temporal dynamics in the behavior of children during the learning process. The higher F1-scores in engagement detection regarding the integration of affective and cognitive feedback correlates with the emotionally and pedagogically appropriate feedback provided. It is commendable that edge processing and multi-objective optimization have been implemented. This is relevant in mobile learning where feedback lags are undermined pedagogically and causes disengagement. The system shows that advanced models can highly rely on mobile devices with reasonable effectiveness regarding precision and resource use, little performance reduction, and maintained balance around response time and disengagement. This study addresses the issues faced by modern research to a great extent.

Previous frameworks focused on cognitive estimation while neglecting emotional adaptation, or relied on affective sensing frameworks that were too resource prohibitive and computationally intensive for mobile use. In contrast, the present framework integrates these without computationally inefficient operational friction, thus bridging a significant gap in the field. Furthermore, the establishment and enforcement of a policy on decision-making concerning operational actions demonstrates postulation that privacy laws, specifically COPPA and GDPR, as they apply to mobile devices, incorporate overlooked aspects in contemporary research. Also to be highlighted is the current research's capacity to modify feedback strategies in real-time based on incoming data. This function allows personalized system adjustments, empowering the framework to adapt and improve feedback as more data is collected from each learner over time.

This design feature enhances the versatility of the framework, allowing it to fit different educational situations, whether in formal education or informal self-directed learning. The

Volume 38 No. 6s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

current study illustrates impressively how a well-thought-out, ethically refined, and intelligible framework can facilitate the delivering of real-time feedback in mobile learning environments designed for children. The framework, in this sense, functions as a technological improvement and fulfills a necessary requirement in the field of digital education.

### 6.Limitations and Future Work

While the proposed framework is a good start, there are significant caveats that must also be considered. First, there is a lack of diversity in the data captured. The experiments should use a wider variety of data, as the singular use of the dataset will likely not cover the diverse mobile learning contexts found worldwide. Also, with regard to engagement analysis, there are estimation, sensor, and data collection noise challenges with respect to the physiological and behavioral metrics. Lastly, there are unaddressed resource-constrained device large-scale edge deployments, and trade-offs in computational latency that edge processing will only reduce marginally. Future work in this area will focus on the use of advanced sequential models, especially transformers, to improve knowledge tracing. Developing privacy preserving federated learning to remove the need for centralized data collections will also be critical. Adapting reinforcement learning to the system for feedback will likely improve personalization as well as contextual relevance to the learning support the system provides.

## References

[1] Sisouvong, V., & Pasanchay, K. (2024). Mobile Learning: Enhancing Self-Directed Education through Technology, Wireless Networks, and the Internet Anytime, Anywhere. *Journal of Education and Learning Reviews*, *1*(2), 39-50.

[2] Attah, E., Lamidi, K., Tsegyu, S., & Edino, F. (2025). Mobile Devices in Student Learning: Enhancing Engagement or Contributing to Distractions?. *Available at SSRN 5314898*.

[3] Al Farsi, G., Tawafak, R. M., Alyoussef, I. Y., & Al-Rahmi, W. M. (2024). Systematic Literature Review for Smart Mobile Learning in Programming Courses. *International Journal of Interactive Mobile Technologies*, *18*(12).

[4] Ghoulam, K., & Bouikhalene, B. (2024). Exploring the Impact of Mobile Devices in E-Learning: A case Study Evaluating its Effectiveness. *Educational Challenges*, *29*(2).

[5] Wei, M. Y., & Ming, L. H. (2023, June). The Influence of Mobile Learning Apps on Children's Cognitive Development. In *Proceeding of The International Conference of Inovation, Science, Technology, Education, Children, and Health* (Vol. 3, No. 1, pp. 238-242).

[6] WALEED, A. K. S. (2025). Exploring the impact of AI-driven real-time feedback systems on learner engagement and adaptive content delivery in education. *INTERNATIONAL JOURNAL*, *14*(2), 098-104.

[7] Jamal, R., & Renzella, J. (2024, March). Enhancing Formative Feedback at Scale with the Intelligent Feedback Assistant. In *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 2* (pp. 1692-1693).

**International Journal of Applied Mathematics**

**Volume 38 No. 6s, 2025**

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[8] Shuster, C. L., Walls, T. A., & Stein, L. A. R. (2024). Guiding Principles for the Use of Feedback in Educational and Psychosocial Interventions. *European Journal of Educational Research*, *13*(2).

[9] Stamper, J., Xiao, R., & Hou, X. (2024, July). Enhancing llm-based feedback: Insights from intelligent tutoring systems and the learning sciences. In *International Conference on Artificial Intelligence in Education* (pp. 32-43). Cham: Springer Nature Switzerland.

[10] Fan, J., & Wang, Z. (2025). The impact of gamified interaction on mobile learning APP users' learning performance: the moderating effect of users' learning style. *Behaviour & Information Technology*, *44*(7), 1306-1319.

[11] Ruiz Nepomuceno, A., López Domínguez, E., Domínguez Isidro, S., Medina Nieto, M. A., Meneses-Viveros, A., & de la Calleja, J. (2024). Software Architectures for Adaptive Mobile Learning Systems: A Systematic Literature Review. *Applied Sciences*, *14*(11), 4540.

[12] Liu, Y., Mao, Y., Liu, Z., & Yang, Y. (2023). Deep learning-assisted online task offloading for latency minimization in heterogeneous mobile edge. *IEEE Transactions on Mobile Computing*, *23*(5), 4062-4075.

[13] Reddy, P., & Parkavi, A. (2025, May). Personalized Adaptive Learning Pathway System Using Reinforcement Learning, Knowledge Graphs, and Rule-Based Explainability. In *2025 5th International Conference on Pervasive Computing and Social Networking (ICPCSN)* (pp. 857-865). IEEE.

[14] Wani, A. H. (2024). Leveraging Emotions in Student Feedback to Improve Course Content and Delivery. *Scalable Computing: Practice and Experience*, *25*(5), 3388-3393.

[15] Helland, T. (2024). In the Periphery: Ethical Considerations When Indirectly Involving Children in Research. *Ethics and Social Welfare*, *18*(4), 376-387.

[16] Govea, J., Navarro, A. M., Sánchez-Viteri, S., & Villegas-Ch, W. (2024). Implementation of deep reinforcement learning models for emotion detection and personalization of learning in hybrid educational environments. *Frontiers in Artificial Intelligence*, *7*, 1458230.

[17] Feng, L., & Ji, Y. (2024). Learners Behaviour Prediction and Analysis Model for Smart Learning Platform using Deep Learning Approach. *Scalable Computing: Practice and Experience*, *25*(5), 3876-3885.

[18] Buddiga, P. (2024, October). Scaling Intelligent Systems with Multi-Channel Retrieval Augmented Generation (RAG): A robust Framework for Context Aware Knowledge Retrieval and Text Generation. In *2024 Global Conference on Communications and Information Technologies (GCCIT)* (pp. 1-10). IEEE.

[19] Zhu, Z., & Huang, W. (2025). A meta-analysis of mobile learning adoption using extended UTAUT. *Information Development*, *41*(2), 512-528.

[20] Budiarto, M. K., Gunarhadi, G., & Rahman, A. (2024). Technology in education through mobile learning application (MLA) and its impact on learning outcomes: Literature review. *Journal of Education and Learning (EduLearn)*, *18*(2), 413-420.

[21] Maulana, A., & Wiyono, D. Y. (2024). Adaptive material design supporting personalized education: Challenges and opportunities. *JOURNAL OF TECHNOLOGY, EDUCATION & TEACHING (J-TECH)*, *1*(2), 86-89.

[22] Yaseen, H., Mohammad, A. S., Ashal, N., Abusaimeh, H., Ali, A., & Sharabati, A. A. A. (2025). The impact of adaptive learning technologies, personalized feedback, and interactive AI tools on student engagement: The moderating role of digital literacy. *Sustainability*, *17*(3), 1133.

[23] Hirsch, S., & Uckelmann, D. (2024, November). Effective Feedback Systems in Learning Analytics: Didactic and Psychological Foundations, Implementations, and Perspectives. In *2024 21st International Conference on Information Technology Based Higher Education and Training (ITHET)* (pp. 1-10). IEEE.

[24] Vanacore, K., Gurung, A., Sales, A., & Heffernan, N. T. (2024, March). The effect of assistance on gamers: Assessing the impact of on-demand hints & feedback availability on learning for students who game the system. In *Proceedings of the 14th Learning Analytics and Knowledge Conference* (pp. 462-472).

[25] Prakash, J., Swathiramya, R., Balambigai, G., & Abhirami, J. S. (2024). AI-driven real-time feedback system for enhanced student support: Leveraging sentiment analysis and machine learning algorithms. *International Journal of Computational and Experimental Science and Engineering*, *10*(4), 1567-1574.

[26] Lal, S., Eysink, T. H., Gijlers, H. A., Veldkamp, B. P., Steinrücke, J., & Verwey, W. B. (2024). Explicit metrics for implicit emotions: investigating physiological and gaze indices of learner emotions. *Frontiers in psychology*, *15*, 1440425.

[27] Baradari, D., Kosmyna, N., Petrov, O., Kaplun, R., & Maes, P. (2025). NeuroChat: A Neuroadaptive AI Chatbot for Customizing Learning Experiences. *arXiv preprint arXiv:2503.07599*.

[28] Sakhi, A., & Mansour, S. E. (2025). Optimizing Virtual Classrooms: Real-Time Emotion Recognition with AI and Facial Features. *International Journal of Robotics & Control Systems*, *5*(2).

[29] Wang, J., Tang, Q., & Zheng, Z. (2025). A knowledge tracing approach with dual graph convolutional networks and positive/negative feature enhancement network. *PloS one*, 20(4), e0317992.

[30] Boufaida, S. O., Benmachiche, A., Derdour, M., Maatallah, M., Kahil, M. S., & Ghanem, M. C. (2025). TSA-GRU: a novel hybrid deep learning module for learner behavior analytics in MOOCs. *Future Internet*, *17*(8), 355.

[31] Moore, R. L., & Shin, J. (2024). Using learner engagement patterns for predictive modeling in a MicroMasters program. *Distance Education*, 1-21.

[32] Swathi, B., Veerabomma, S., Archana, M., Bhadru, D., Somu, N. L., & Bhavsingh, M. (2025, January). Edge-Centric IoT Health Monitoring: Optimizing Real-Time Responsiveness, Data Privacy, and Energy Efficiency. In *2025 6th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI)* (pp. 354-361). IEEE.

**International Journal of Applied Mathematics**

**Volume 38 No. 6s, 2025**

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[33] Divya, S., & Saranya, S. (2025, January). Energy Efficient and SecurityAware Task off Loading for Multi-Tier Edge Cloud Computing Systems. In *2025 International Conference on Intelligent Systems and Computational Networks (ICISCN)* (pp. 1-7). IEEE.

[34] Yang, W., Wang, H., Li, Z., Niu, Z., Wu, L., Wei, X., ... & Susilo, W. (2024). Privacy-preserving machine learning in cloud-edge-end collaborative environments. *IEEE Internet of Things Journal*.

[35] Mougiakou, E., Papadimitriou, S., Chrysafiadi, K., & Virvou, M. (2025). Artificial intelligence in educational games and consent under general data protection regulation. *Intelligent Decision Technologies*, *19*(2), 670-686.

[36] Kayande, D., & Kukreja, S. (2025). Design of an integrated multi-modal machine learning framework for real-time student engagement evaluation and learning outcome optimizations. *MethodsX*, 103588.

[37] Zhang, N., & Leong, W. Y. (2025). Intelligent emotional computing with deep convolutional neural networks: Multimodal feature analysis and application in smart learning environments. *Eurasia Journal of Mathematics, Science and Technology Education*, *21*(8), em2680.

[38] Naseer, F., & Khawaja, S. (2025). Mitigating Conceptual Learning Gaps in Mixed-Ability Classrooms: A Learning Analytics-Based Evaluation of AI-Driven Adaptive Feedback for Struggling Learners. *Applied Sciences*, *15*(8), 4473.

[39] Kayande, D., & Kukreja, S. (2025). Design of an integrated multi-modal machine learning framework for real-time student engagement evaluation and learning outcome optimizations. *MethodsX*, 103588.

[40] Hooda, M.; Rana, C.; Dahiya, O.; Shet, J.P.; Singh, B.K. Integrating la and EDM for Improving Students Success in Higher Education Using FCN Algorithm. Math. Probl. Eng. 2022, 2022, 7690103.

[41] Göppert, A.; Mohring, L.; Schmitt, R.H. Predicting performance indicators with ANNs for AI-based online scheduling in dynamically interconnected assembly systems. Prod. Eng. 2021, 15, 619–633.

[42] Chango, W.; Cerezo, R.; Romero, C. Multi-source and multimodal data fusion for predicting academic performance in blended learning university courses. Comput. Electr. Eng. 2021, 89, 106908.

[43] Mubarak, A.A.; Cao, H.; Hezam, I. Deep analytic model for student dropout prediction in massive open online courses. Comput. Electr. Eng. 2021, 93, 107271.

[44] Fotso, J.E.M.; Batchakui, B.; Nkambou, R.; Okereke, G. Algorithms for the development of deep learning models for classification and prediction of behaviour in MOOCS. In Proceedings of the2020 IEEE Learning with MOOCS (LWMOOCS), Antigua Guatemala, Guatemala, 29 September–2 October 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 180–184.

[45] Brahim, G.B. Predicting student performance from online engagement activities using novel statistical features. Arab. J. Sci. Eng. 2022, 47, 10225–10243.

Volume 38 No. 6s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[46] Atlam, E.S.; Ewis, A.; Abd El-Raouf, M.M.; Ghoneim, O.; Gad, I. A new approach in identifying the psychological impact of COVID-19 on university student's academic performance. Alex. Eng. J. 2022, 61, 5223–5233.

[47] Abdelkader, H.E.; Gad, A.G.; Abohany, A.A.; Sorour, S.E. An efficient data mining technique for assessing satisfaction level with online learning for higher education students during the COVID-19. IEEE Access 2022, 10, 6286–6303.

[48] Stadlman, M.; Salili, S.M.; Borgaonkar, A.D.; Miri, A.K. Artificial Intelligence Based Model for Prediction of Students' Performance: A Case Study of Synchronous Online Courses During the COVID-19 Pandemic. J. STEM Educ. Innov. Res. 2022, 23, 39–46.

[49] Bansal, V.; Buckchash, H.; Raman, B. Computational intelligence enabled student performance estimation in the age of COVID-19. SN Comput. Sci. 2022, 3, 41.

[50] Faria, D. R., & da Silva Ayrosa, P. P. (2025). Adaptive Neuro-Affective Engagement via Bayesian Feedback Learning in Serious Games for Neurodivergent Children. *Applied Sciences*, *15*(13), 7532.

[51] Ediae, G. U., White-Brown, A., Chisholm, C., Terekhov, I., Seymour, J., Guo, J., ... & Boycott, K. M. (2025). ThinkRare: A search algorithm to identify patients with undiagnosed rare genetic disease in an electronic medical record. *Genetics in Medicine*, 101570.

Received: August 03, 2025 