

PAPER

Emotion-Aware and Context-Driven Mobile Game-Based Learning: A Machine Learning Approach

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Tafila, JordanAimanAwwad@ttu.edu.jo**ABSTRACT**

Mobile learning has transformed the way educational content is delivered, enabling learners to access materials anytime and anywhere through portable devices. This flexibility enhances engagement and supports personalized learning experiences. Therefore, this paper proposes a mobile game-based learning (GBL) framework that integrates engaging gaming elements with educational content to promote learner engagement and motivation. By incorporating emotion, eye gaze, and context-driven adaptation through machine learning techniques, the proposed approach aims to enhance personalization and optimize the learning experience. In the experimental study, a small group of learners aged 8–13 engaged sequentially with both non-adaptive and adaptive versions of the educational game. Emotional analysis revealed that 70% of observed responses during the non-adaptive gameplay were negative, including anger (30%), sadness (10%), and disgust (30%). In contrast, 80% of participants reported greater satisfaction with the adaptive version, citing improved engagement as the reason. The experimental group demonstrated a 15% higher improvement in quiz scores and a 20% reduction in task completion time compared to the control group, which showed only a 10% improvement. Experiments conducted in this study demonstrate the effectiveness of emotion- and context-driven adaptation in GBL environments. The results showed that adaptive gameplay significantly reduced negative emotional responses by 50% and improved learner engagement and satisfaction (Cohen's $d > 1.2$). It also revealed that the adaptive group outperformed the non-adaptive group in quiz scores and task efficiency, with statistically significant gains and large effect sizes (Cohen's $d > 1.7$), highlighting the efficacy of emotion- and context-driven adaptation in GBL environments. Comparative analysis with prior studies confirms that emotion-aware adaptive GBL reduces negative effects by 50% and improves learning outcomes by 15–20%.

KEYWORDS

mobile learning, game-based learning (GBL), gamification, context-aware app, visual emotion, machine learning, adaptation

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1 INTRODUCTION

In today's digital age, mobile devices have become an integral part of everyday life, especially among younger generations [1]. With global smartphone usage projected to exceed 7.4 billion users by 2025 [2], these devices have fundamentally changed how people access information, communicate, and engage with entertainment [1, 3]. For Millennials in particular, mobile devices are indispensable; users in this demographic spend an average of four to five hours per day on mobile apps, with gaming accounting for a significant portion of that time [4].

The proliferation of smartphones has created an optimal environment for the expansion of mobile learning [3, 5]. Yet, even as mobile learning becomes more accessible and scalable, many platforms continue to adopt conventional teaching methods. While these traditional methods successfully convey foundational knowledge and maintain structured instruction, their inflexible design often leads to insufficient interactivity and poor student engagement [5, 6, 7]. This lack of flexibility ultimately undermines learner motivation, personalization, and adaptability. Over the past decade, the popularity of mobile learning has surged, fueled by breakthroughs in mobile internet and machine learning technologies. The integration of machine learning algorithms has significantly advanced mobile learning, particularly in the realms of mobility and big data [3, 8, 9].

Machine learning utilizes algorithms and statistical models that enable computer systems to learn from large datasets and continually enhance their performance over time. When applied to mobile learning platforms, this technology allows for the delivery of personalized and adaptive educational experiences. By harnessing the capabilities of machine learning and big data analytics, these platforms can assess individual learning behaviors, preferences, and performance. This insight allows for the customization of content and activities to meet each learner's specific needs [3, 10].

On the other hand, gamified applications have transformed mobile learning into a more personalized, on-demand experience, accessible anytime and anywhere. To fully unlock its potential, however, mobile learning requires thoughtful improvements in design, implementation, and learner engagement strategies [11, 12]. The growing integration of game elements in educational content presents new opportunities, particularly in a smartphone environment. Smartphones equipped with interactive features, portability, and built-in sensors such as touchscreens and accelerometers are well-suited to support mobile game-based learning (GBL). These capabilities enable the delivery of engaging, immersive, and context-aware learning experiences [12, 13].

To fully harness these benefits, it is essential to consider the emotional dimension of learning. Traditional systems that do not consider learners' emotional states and eye gaze patterns may struggle to deliver personalized and effective learning experiences [6, 9]. Emotion, often characterized by personal feelings, mood fluctuations, and expressive behaviors, plays a critical role in the learning process by enabling systems to adapt more effectively to individual learner needs [14, 15]. Similarly, eye gaze orientation reveals valuable insights into learners' attention and cognitive engagement, making it a vital tool for adaptive learning interventions [16].

This study integrates principles of affective computing, adaptive learning, and mobile learning to design an intelligent GBL platform. By analyzing emotional and contextual data collected from mobile devices, the system advances the fields of intelligent tutoring and ubiquitous learning, offering personalized and adaptive educational experiences. Grounded in the foundational work on affective computing [17], the system employs real-time emotion recognition to enhance learner engagement and improve learning outcomes. By identifying learners' emotional states, the game dynamically adjusts its content and difficulty levels to sustain motivation and reduce frustration.

In line with adaptive learning principles, the game continuously modifies content based on learners' emotional states and situational factors [18]. Powered by machine learning, these adaptations enable a customized learning journey that balances intellectual and affective demands. Based on mobile learning theory [10], which highlights the importance of contextual learning, the proposed system leverages the platform's mobility to continuously gather data, including device interactions, location, and time. In line with adaptive learning principles [18], the platform constantly tailors learning experiences based on both emotional feedback and contextual information. Drawing on mobile learning theory [10, 19], which emphasizes the value of contextualized, on-the-go learning, the system leverages the mobility of devices to collect rich contextual data, including user interactions, location, and time.

Therefore, this study aims to develop a framework that integrates visual emotion recognition, eye gaze, and context-aware adaptation to create more intelligent and responsive GBL environments. We present a framework that addresses a learner's negative emotions and level of attention (i.e., eye gaze orientation) in real-time mode. The proposed framework will be immediately adapted to the learner's context to overcome these negative visual emotions by utilizing a machine learning algorithm. The effectiveness of the proposed context-aware GBL lies in carefully designing the game content, layout, and mechanics to align with the learner's needs and the specific context, while also providing a fun and engaging experience. This requires a deep understanding of the user's motivations, attitudes, and preferences, as well as a solid knowledge of game design principles and mechanics.

2 LITERATURE REVIEW

The rapid advancement of intelligent technologies has significantly transformed the landscape of digital learning environments. Notably, innovations in emotion recognition, contextual awareness, and mobile game-based strategies have created new opportunities for adaptive, personalized, and immersive educational experiences. This literature review investigates critical domains in the evolution of intelligent learning systems.

2.1 Visual emotion-aware system

The visual emotion-aware system aims to develop models to detect and respond to human emotions depicted in images or videos [20, 21]. This field encompasses various techniques, including computer vision technologies, machine learning methods, and deep learning approaches, to detect and understand emotions [15, 16]. By identifying emotions, such systems can enhance user experiences, improve user engagement, and provide valuable insights into individual behavior [20]. These systems could help applications in areas such as emotional computing, where they enable applications to be adaptable and respond correctly to individuals' emotions, as well as in market research, where they provide useful information about customers' behaviors toward goods, services, or advertisements [14, 21]. They can also be employed in gaming and virtual reality applications to deliver interactive and emotionally engaging experiences [14].

It is worth noting that despite the significant progress made in visual emotion-aware systems, they remain an active research area, and there are continuing efforts to enhance their accuracy, robustness, and actual applicability in the world. Typically, a visual emotion-aware system includes the following steps [22]:

1. Detection of Human Face: Find and identify the area of a human face within a photo or video.

2. Detection of Facial Landmark: Recognize facial features such as eyes, mouth, and nose.
3. Extraction of Feature: Extract relevant visual landmarks, such as facial expression, head position, and gaze orientation.
4. Classification of Emotion: Using deep learning techniques to categorize the extracted features into various emotion types, such as joy, sorrow, fury, fear, surprise, and disgust.
5. Analysis of Emotion: Analyze the emotions detected to acquire insights into humans' emotional condition and possibly predict their behavior or reactions.

2.2 Context-aware computing

Context-aware computing involves technology that can detect, understand, and respond to elements of its environment and adjust its behavior based on contextual information. This approach is essential in mobile and ubiquitous computing, where devices are often used in real-world and dynamic environments [15, 20]. Systems can deliver more relevant, personalized, and efficient interactions by recognizing context, such as a user's location, time, nearby people or devices, and physical activity, as illustrated in Figure 1.

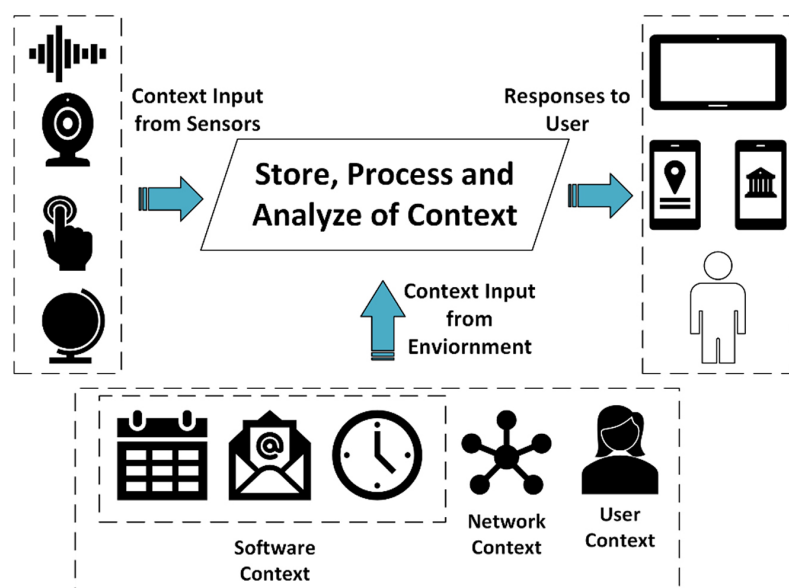


Fig. 1. Context-aware computing concept

The key components of context-aware computing consist of context acquisition, context modeling and interpretation, and context adaptation, described as follows [10, 21, 23]:

1. Sensing and Data Collection: Gathering information about the environment and the user through sensors (such as GPS, accelerometers, cameras, microphones, etc.)
2. Context Modeling and Interpretation: Structure and analyze raw sensor data to extract meaningful insights, such as determining whether the user is moving or stationary, whether the environment is noisy or quiet, or if the user is alone or with others.
3. Adaptation and Response: Adjusting system behaviors or interactions based on the interpreted context. This might involve adjusting a phone's display brightness according to ambient light, providing location-specific suggestions, or prioritizing messages in specific situations.

2.3 Mobile game-based learning

Mobile GBL is an educational method that incorporates game principles and mechanics to engage learners, creating a more interactive, motivating, and practical learning experience [9, 11]. It incorporates challenges and problem-solving activities that foster critical thinking, strategic planning, and decision-making skills. It includes motivational elements such as rewards, points, badges, or other incentives to motivate progress, alongside real-time feedback to reinforce learning. Progression and levels are also key features, providing the learner with a sense of accomplishment as they advance through stages that gradually increase in difficulty to match their growing skills. Progress tracking allows learners to monitor their achievements and development through scores, levels, or badges [11].

Mobile GBL incorporates features that enhance engagement and motivation, such as compelling stories, characters, and immersive environments that capture learners' attention. It also provides opportunities for reflection and assessment, allowing learners to evaluate their decisions and outcomes, which helps reinforce the learning objectives. These components create a well-rounded GBL experience that fosters fun and effective learning outcomes [11, 13].

Mobile GBL provides instant feedback, enabling learners to understand the results of their actions and continuously adjust and improve. It gives adaptability by adjusting the difficulty or pace of content to suit individual abilities, ensuring a personalized learning experience. Emphasis is placed on cooperation and social interaction, encouraging group activities, teamwork, and the development of communication skills. Additionally, it sets goals that are challenging enough to promote effort while keeping them achievable to avoid frustration [11, 12]. These features help make GBL an engaging, effective, and adaptive educational approach that can enhance motivation and maintain learning continuity, as illustrated in Figure 2.



Fig. 2. Game-based learning components

2.4 Related works

The adoption of digital technologies in education has fueled increasing interest in innovative teaching strategies such as GBL, gamification, and mobile-assisted learning. These approaches seek to boost student engagement, motivation, and academic performance by utilizing interactive and adaptive digital tools. Extensive research has investigated how these methods can advance educational outcomes across different fields, especially in mathematics and computer science. In this section, we analyze and consolidate key studies on the design, application, and effectiveness of GBL, gamification, and mobile learning systems, highlighting their role in personalized education, skill enhancement, and their connection to global initiatives such as Sustainable Development Goal 4 (SDG 4).

Vankúš [24] explored the preparation of prospective mathematics teachers for integrating GBL and gamification into their future teaching. To support this aim, a university-level course was developed to introduce pre-service teachers to the foundational principles of GBL and gamification, while also offering hands-on experience with these approaches. The study details the course structure and presents findings from a survey conducted with 115 participants using an online questionnaire. Results indicated a generally positive reception to the course, with students expressing appreciation for the exposure to GBL and gamification tools. These outcomes suggest the course effectively fostered openness toward incorporating such technologies into future teaching practices. However, the study was limited to a single institution, prompting a recommendation for broader investigations across diverse educational contexts. Future research could also include pre- and post-course assessments to better understand the evolution of students' attitudes and beliefs regarding GBL and gamification.

Mahamarowi et al. [25] developed a 3D game designed to promote historical learning among schoolchildren by immersing them in the cultural and historical heritage of Ancient Malay civilization. Their study employed a qualitative approach to explore students' perceptions of history learning. It aligned its objectives with the fourth goal of the United Nations' SDGs, which advocates for inclusive and equitable quality education. The game was designed not only to engage learners through interactive storytelling but also to foster interest in Malay history through third-person gameplay. Findings suggest that this form of digital engagement offers an immersive educational experience, enabling students to interact with historical artifacts, landmarks, and cultural traditions in a virtual environment. The study highlights the game's potential to enhance historical understanding and cultural appreciation among young learners. The authors proposed that future research could expand the game's narrative depth, diversify character attributes, and incorporate comparative analyses to evaluate the impact of 3D GBL relative to traditional history instruction. They also recommend developing robust assessment tools to measure knowledge retention, student engagement, and overall learning outcomes associated with this educational approach.

A comprehensive study exploring the role of gamification and GBL in supporting SDG 4 was conducted [26], which aims to ensure inclusive, equitable, and quality education. Anchored in constructivist learning theory, Self-Determination Theory, and Flow Theory, the study investigated how educational games enhance student learning, particularly in mathematics education. A systematic qualitative review of literature from 2010 to 2023 was performed across databases such as ERIC, PsycINFO, and Scopus, using thematic coding and the CASP qualitative checklist to ensure analytical rigor. The review revealed that gamification elements, such as points, badges, and rewards, significantly boost student motivation, engagement, and academic performance. It also highlighted

the growing relevance of emerging technologies such as virtual reality (VR) and artificial intelligence (AI) in enriching GBL environments. Nonetheless, the study acknowledged persistent challenges related to equitable access to technology and the integration of games within formal curricula. The findings emphasize that well-designed educational games, characterized by clear goals, immediate feedback, and adaptive difficulty, can foster lifelong learning skills and contribute to reducing educational disparities.

Limitations in current educational assessment research were addressed by Huang et al. [27], which often concentrates on data collection and analysis but lack methodological breadth and practical application. Their study investigated the integration of mobile technology into teaching and assessment, aiming to introduce innovative perspectives and data-driven strategies that modernize assessment practices. By leveraging mobile-based learning analytics, the authors demonstrated the potential of mobile technology to enhance both the precision of teaching assessments and the personalization of educational experiences. The study is divided into two key components: the first examines a variety of data collection methods, showing that the proposed mobile-based approach significantly outperforms traditional techniques, particularly in capturing rich learning behavior and contextual data. This comprehensive and efficient data gathering offers a stronger foundation for meaningful assessment. The second component evaluates the performance of different algorithms, concluding that specific models (notably IMF5 and IMF6) achieved higher accuracy and lower error rates after data fitting and normalization. Future work could expand on these aspects to further validate and operationalize mobile-assisted assessment strategies across diverse educational settings.

Bourekache et al. [6] proposed a mobile learning system designed to improve the educational experience of computer science students, with a particular focus on foundational courses such as C programming and databases. The system incorporates adaptive strategies designed to address the diverse needs of learners with varying backgrounds and proficiency levels. Implemented as an Android application, the tool supports ubiquitous learning by allowing students to engage with course materials anytime and anywhere, thereby complementing in-class instruction. The study, which involved second-year undergraduate students, reported notable improvements in learning outcomes and comprehension levels. The mobile platform also facilitated interactive knowledge exchange and dynamic learning experiences. Survey results from the student cohort revealed strong interest in mobile-assisted learning and affirmed the relevance of focusing on the C programming language as a core subject due to its foundational role in computer science education. The application was developed using a suite of tools, including Android Studio, SQLite, Java, and Genymotion. The findings underscore the potential of mobile learning systems to reinforce classroom instruction and promote personalized, accessible learning environments for computer science education.

Papadakis [28] conducted a literature review of empirical studies examining mobile applications that claim to support young children's learning of computational thinking (CT) and coding skills. The review revealed that, despite the abundance of "self-proclaimed educational" apps, a significant gap remains in the availability of developmentally appropriate tools specifically designed to foster CT concepts and coding abilities in early childhood. The study highlights that young children can develop foundational STEM and coding skills through well-designed, playful learning experiences on smart mobile devices, thereby contributing to the emerging body of research on technology-mediated early coding education.

Mobile applications designed to promote CT concepts and coding skills among preschool and pre-primary school children were examined by Papadakis [29]. The chapter analyzed the design features, pedagogical underpinnings, and developmental

appropriateness of various apps, identifying those that effectively integrate playful learning experiences with early STEM education. Findings underscored the importance of age-appropriate interface design, engaging game mechanics, and scaffolding strategies to support young learners' acquisition of fundamental CT and coding skills. This work adds to the growing body of literature on mobile learning in early childhood, highlighting the potential of carefully designed apps to serve as effective tools for introducing computational concepts at an early age.

3 FRAMEWORK ARCHITECTURE OVERVIEW

In this section, we present a framework for mobile GBL that leverages emotion and context-driven adaptation using machine learning. The proposed framework comprises multiple layers that detect changes in learner emotions, eye-gazing patterns, and context. It adapts the system's layout and content based on the learner's context. The system's primary goal is to detect and gather the learner's contextual information, delivering a tailored and suitable learning environment that aligns with the learner's needs and requirements. The proposed framework combines emotional and contextual data to personalize the mobile GBL experience.

3.1 Workflow of the proposed framework

In this framework, a learner begins playing a game while a video camera constantly captures their facial expressions and tracks eye movements to monitor gaze, assess attention, and engagement. The collected data is then processed by models that analyze emotions and gaze patterns. If learners encounter in-game situations that evoke emotions such as boredom or anger, or if their attention drifts away from the screen, their willingness to continue playing is likely to decrease. To mitigate these negative emotional states and improve the learner's attention and engagement, the game environment, including layout and contents, is adjusted based on the detected emotion and eye gaze patterns to deliver a more personalized experience. Figure 3 depicts the proposed framework workflow, components, and their interconnections.

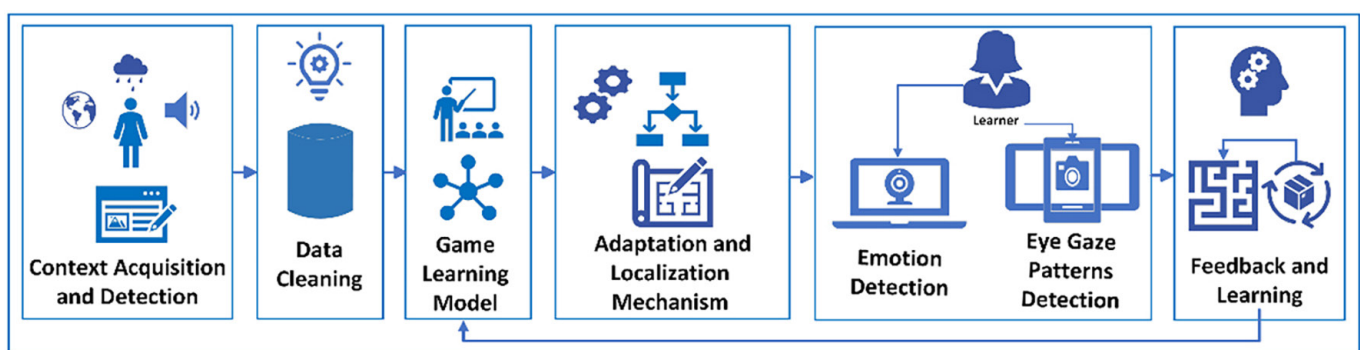


Fig. 3. The workflow of the proposed framework

3.2 Context acquisition and detection

The proposed system employs a multimodal sensing framework, integrating both physical and virtual sensors to capture real-time visual and contextual data. Mobile devices have various physical sensors, such as GPS, to determine the user's location,

while virtual sensors extract user-specific data from applications and services, including calendars, weather APIs, noise level, and the learner's identity [10, 21]. For example, a calendar can provide insights into a user's interests, location, preferred language, or cultural context (e.g., holidays). Learners define their settings and preferences, which can be tailored to individual users, and determine how the context-aware game system should act or respond in various situations. The main goal of this layer is to collect contextual information such as location (e.g., GPS), ambient noise levels (low vs. high), language, weather conditions, calendar events, and learner identity (see Figure 4).

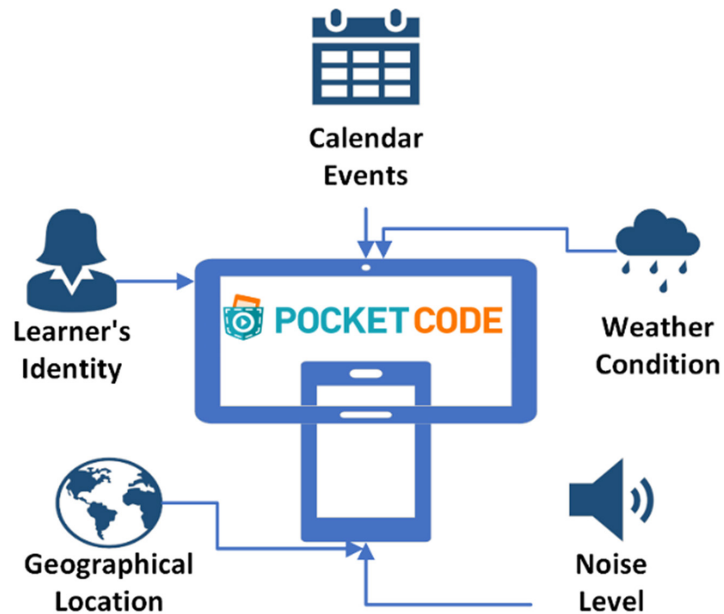


Fig. 4. Classifications of contextual information

3.3 Data cleaning and processing

The second step involves data cleaning and processing. Once contextual data is collected from various sensors, it must be thoroughly cleaned to ensure reliability and usability. Clean data refers to information that is free from errors, such as misspellings, redundancies, or irrelevant entries. Data cleaning is the process of transforming raw data into a format that is suitable for analysis. It involves removing duplicates, eliminating errors, addressing incompleteness, and resolving inconsistencies to ensure the dataset is accurate and reliable. This step is essential in data analysis, as the reliability of the results depends on the quality of the data used. However, in the proposed framework, the Pandas library is utilized in this layer, specifically to handle missing values. The `fillna()` function is employed to replace missing entries with default values, for instance, setting the default for ambient noise to "low." Conversely, the `dropna()` function is applied to remove rows or columns that contain missing values when appropriate.

3.4 Game learning model

Personalization in such cases is driven by contextual factors. These contextual factors are essential for adapting the game to suit individual needs and learning styles.

In the proposed adaptive mobile GBL framework, emotional and contextual data are combined to dynamically adjust both the game interface and contents. The design of an educational game should consider various learning models to accommodate diverse learner needs and preferences. Understanding learners and their context requires analyzing relevant information, a process supported by the development of a learning model powered by a machine learning algorithm, as illustrated in Figure 5. This model plays a critical role in integrating gaming elements that are not only engaging but also effective in enhancing the learning experience. It is responsible for selecting adaptable game content and creating a learning environment tailored to the learner's needs, progress, and preferences.

Learners engage with educational games in different ways depending on their backgrounds and preferences. For instance, one learner may respond more positively to a game environment that reflects their local culture, while another may be more motivated by a design that aligns with their gender identity. Smart devices play a key role in detecting environmental conditions, such as ambient noise levels and the presence of crowds, to assess the learner's surroundings. These factors influence cognitive performance; for example, high noise levels can impair concentration. To address this, the proposed framework dynamically modifies the content and complexity of tasks. In noisy environments, it presents simpler tasks, while in quieter settings, it introduces more challenging activities. However, if the learner is in a noisy room, the system automatically reduces the game's complexity to maintain engagement and ensure effective learning experiences. In the proposed framework, the game learning model contains the following components (see Figure 5):

- Input: Contextual information from surrounding environmental sensors (e.g., location, weather conditions, noise level, etc.)
- Machine learning algorithm: Context classification using decision trees.
- Output: Game learning model.

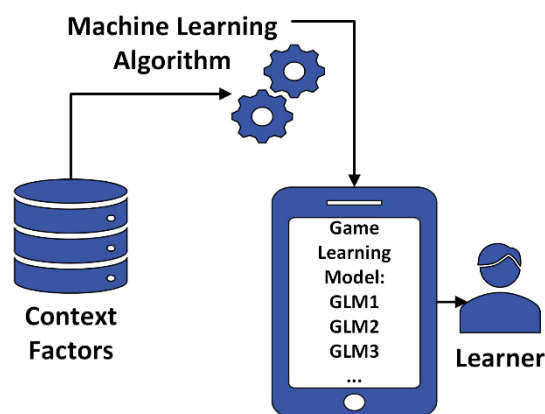


Fig. 5. The process of creating a game learning model using a machine-learning algorithm

The proposed system offers a “Software Flavor” feature, allowing for customized software versions designed to meet the preferences or needs of various user groups (i.e., gender-based flavor). Gender selection defines a learner's characteristics, behaviors, and experiences [10]. In a GBL system, these attributes are essential for shaping the learning model, as they influence how the game layout and contents are presented. Consequently, the system incorporates the learner's gender (female or male) into the target context to tailor the learning content and personalize themes

and colors accordingly (e.g., adapt the user interface to feature softer color palettes for a female player).

3.5 Adaptation and localization mechanism

The proposed framework employs machine learning algorithms to process and analyze real-time emotional and contextual data. The framework constantly tracks the emotional state, eye gaze, and movement of the learner and adjusts game parameters to enhance engagement and learning outcomes. Typically, this layer includes the following steps:

- **Adapt Content:** Change the displayed content according to the user's emotional state to make it more user-friendly.
- **Adapt Interface Layout:** Adjusting the game interface to reduce tension or increase engagement depending on contextual data. For instance, if the user is detected to be stressed, the framework may change the playing location or environment. If the user is happy, the framework may introduce more challenging tasks.
- **Localized Content and Layout:** Localization involves modifying a GBL system's content, including text, layouts, and visual elements, to align with a target region's language, cultural norms, and aesthetic preferences. This process ensures the application is linguistically and culturally appropriate for each supported market.

3.6 Emotion recognition

Mobile devices incorporate multiple sensors, including front-facing cameras capable of facial landmark recognition, to collect emotional response data from users. Emotion recognition identifies human emotions from visual inputs such as facial expressions, body language, and physiological signals. Here are the main steps and techniques used in emotion recognition:

- Capture continuously the user's face using the built-in camera.
- Extract facial landmarks (eyes, mouth, and eyebrows) and use a pre-trained machine learning model (i.e., Convolutional Neural Networks) to classify the user's emotional states (e.g., anger, happiness, boredom, sadness, and stress) and provide immediate feedback on the learner's emotional state.

3.7 Eye gaze detection

Gaze refers to the ocular movement and visual attention of a user toward specific objects or spatial coordinates within a given environment. This physiological phenomenon represents both the direction of eye movement and the focal point of visual fixation [16]. Measuring a user's gaze at a visualization typically entails using eye-tracking or observational techniques to uncover where the user looks, for how long, and in what order [16, 30]. Eye gaze serves as a valuable indicator of user engagement across various domains, including human-computer interaction, marketing, and educational research. By revealing where and for how long a person focuses their visual attention, eye gaze provides meaningful insights into their interest, comprehension, and overall involvement [16, 31]. As illustrated in Figure 6,

the proposed framework combines eye gaze tracking with visual emotion analysis to effectively evaluate user engagement and satisfaction.

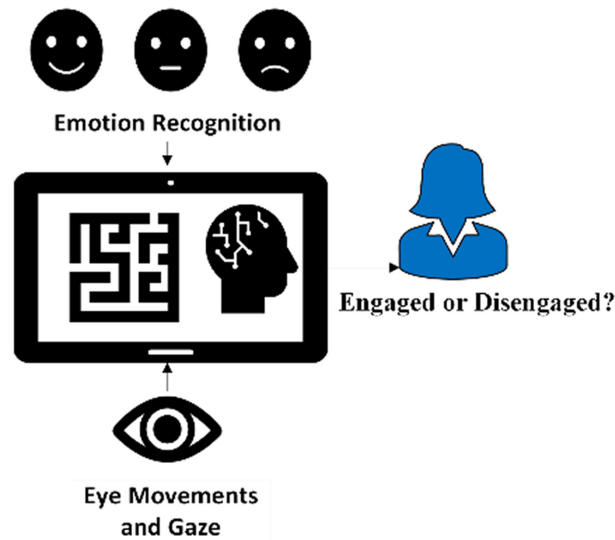


Fig. 6. Eye gaze and visual emotion as metrics for engagement and satisfaction

3.8 Feedback and learning

This layer observes learner behavior and interactions and collects feedback to improve the effectiveness of the adaptation process based on the two metrics (i.e., eye gaze and learner visual emotion). The collected feedback is analyzed to indicate user engagement with the adapted game. The model is constantly learned and updated based on new contexts.

4 SYSTEM PROTOTYPE IMPLEMENTATION

Developing a system prototype for GBL that leverages emotion- and context-driven adaptation through machine learning involves integrating several key components designed to enhance personalized learning experiences. The architecture of this system is structured into three primary layers, each playing a distinct role in delivering adaptive, emotionally responsive gameplay. The following overview outlines how these layers are implemented and interact to support an engaging and tailored learning environment.

4.1 Game layer

The initial game environment for learners is implemented using Pocket Code¹ (see Figure 7). Pocket Code provides tools for game development, including rendering, physics, audio, and scripting, making it suitable for creating 2D games with complex gameplay mechanics. Pocket Code is an integrated development environment (IDE) designed for the brick-based visual programming language (Catrobat) for smart mobile devices. Because it requires no prior knowledge of programming syntax,

¹ <https://catrobat.org/>.

Pocket Code is highly popular in programming education for children, teenagers, and students. The educational game, developed using Pocket Code, is designed to support learning outcomes across various subjects, including mathematics, science, and language learning. It features interactive puzzles and scenario-based challenges that engage learners in problem-solving activities [22].

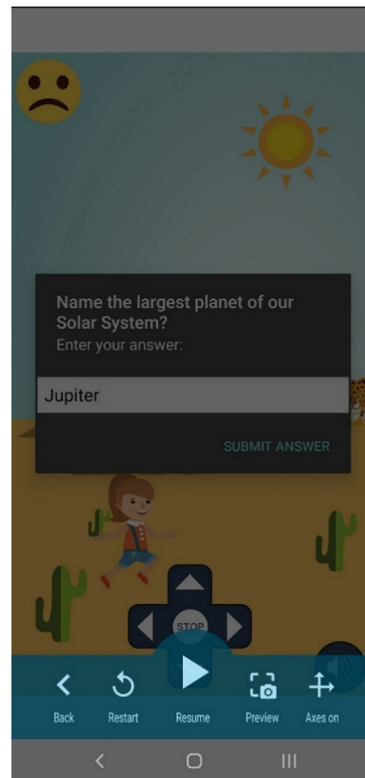


Fig 7. Screenshot of the proposed mobile GBL environment

4.2 Adaptation engine layer

The proposed system can efficiently gather and analyze contextual information to provide adaptive and personalized designs and content. Context factors encompass all relevant variables that affect a learning situation, and machine learning is employed to identify patterns and map these factors to predefined adaptive models. In our framework, the learning model dynamically adapts based on the learner's identity and real-time contextual data, including:

- **Demographic factors** (e.g., gender),
- **Environmental conditions** (e.g., weather, ambient noise levels),
- **Location information,**
- **Temporal context** (e.g., calendar events such as holidays).

In the proposed system, context data collected from various sensors in a smart device identifies different game delivery styles when the learner starts playing the game. Each unique combination of these factors defines a distinct game learning model (GLM), with six possible classifications (GLM1-GLM6, as detailed in Table 1).

Table 1. The value describes the GLM based on factors: Gender, weather conditions, noise level, and calendar events

Gender	Weather Conditions	Noise Level	Calendar Events	Game Learning Model
Male	Raining	High	Holiday	GLM1
	Sunny	Low	Birthday	GLM2
	Snowy	High	Holiday	GLM3
Female	Raining	High	Workday	GLM4
	Sunny	Low	No events	GLM5
	Snowy	High	Holiday	GLM6

For example, a male learner (gender) in a high-noise environment (noise level), during rainy weather (weather), on a holiday (calendar event) would trigger GLM1. To enable supervised learning, raw contextual data is preprocessed into structured features and labeled with the corresponding GLM class. The dataset is partitioned into training (80%) and testing (20%) subsets, and a decision tree classifier is applied due to its interpretability and efficiency in handling categorical variables, as shown in the Python code snippet.

```

data = {
    'Gender': ['Male', 'Male', 'Male', 'Female', 'Female', 'Female'],
    'Weather Conditions': ['Raining', 'Sunny', 'Snowy', 'Raining', 'Sunny', 'Snowy'],
    'Noise Level': ['High', 'Low', 'High', 'High', 'Low', 'High'],
    'Calendar Events': ['Holiday', 'Birthday', 'Holiday', 'Workday', 'No events', 'Holiday'],
    'Game Learning Model': ['GLM1', 'GLM2', 'GLM3', 'GLM4', 'GLM5', 'GLM6']
}
# Convert to DataFrame
df = pd.DataFrame(data)
# Preprocessing: Convert categorical variables to numerical
encoders = {}
for column in ['Gender', 'Weather Conditions', 'Noise Level', 'Calendar Events']:
    encoders[column] = LabelEncoder()
    df[column] = encoders[column].fit_transform(df[column])
# Separate features and target
X = df.drop('Game Learning Model', axis=1)
y = df['Game Learning Model']
# Split data (though small, we'll use all for training in this case)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Initialize and train Decision Tree classifier
dt_classifier = DecisionTreeClassifier(
    criterion='gini',
    max_depth=3,
    random_state=42)
dt_classifier.fit(X_train, y_train)

```

Furthermore, in this system, the player's location provides a game environment based on nearby points of interest. After enabling location services, the user can access the last known location of the smart device. When the game system integrates with these services, it can be adapted and customized based on the retrieved location.

4.3 Feedback and refinement layer

This layer automatically adjusts the game's difficulty level, layout, or content based on the player's emotions and eye gaze. The layer continuously assesses the user's performance and emotional state to adjust the game's difficulty level dynamically.

As previously noted, there are six learner models based on contextual factors. These models serve as the foundation for the adaptation layer, enabling the selection of adaptive learning content tailored to individual learners. For example, the system could lower the game's complexity when it detects signs of frustration in the learner.

As the learner's emotional state and performance evolve, the system may then generate new challenges tailored to their current level and mood. When the learner appears motivated, evidenced by facial expressions of happiness or sustained eye gaze indicating high engagement, the game can increase the difficulty to maintain an optimal learning pace.

The refinement layer in the proposed framework is designed using a neural network. This layer takes in emotion and attention level indicators. It is implicitly derived from emotional and eye gaze data to dynamically adjust the game's difficulty, layout, or content. The neural network architecture consists of an input layer with two nodes, where emotion is labeled with encoded values (e.g., "Anger = -1") and attention level is labeled with "Low = 1, High = 2"; followed by a fully connected hidden layer with six neurons using ReLU activation, and finally an output layer with 4 nodes using Softmax activation to classify the difficulty level into categorical outputs: 0 (Very Easy), 1 (Easy), 2 (Normal), and 3 (Hard), visually depicted as four labeled output nodes corresponding to each difficulty level (see Figure 8).

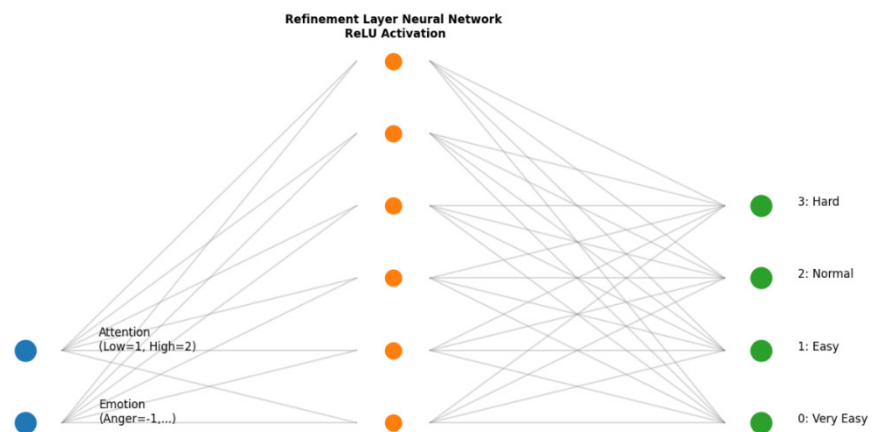


Fig. 8. Refinement layer neural network for difficulty level

Emotion recognition. In the proposed framework, user emotions are detected through a machine learning-based emotion recognition component. Facial expressions captured by the camera sensor serve as input, which is then processed using convolutional neural networks (CNNs) trained on facial expression datasets. These models classify the user's emotional state (e.g., joy, confusion, anger) with the support of computer vision tools such as OpenCV. Furthermore, TensorFlow is employed to train and optimize the emotion detection models, ensuring accurate recognition and real-time responsiveness. The proposed machine learning model for emotion detection includes the following components:

- Input: Live video stream.
- Model: For facial emotion recognition, a CNN trained on a labeled dataset (FER 2013 [32]).
- Output: Recognized emotions, such as happiness, sadness, frustration, etc.

In this model, we propose a facial emotion detection system capable of recognizing five human emotions: anger, disgust, happiness, sadness, and surprise. The system

employs a multi-class classification approach using a CNN composed of five layers: two convolutional layers, a flattening layer, a dense layer, and an output layer. Training and evaluation were conducted on the FER-2013 dataset, which contains labeled samples of the five target emotions (see Figure 9). The model achieved an accuracy of 93.42%. To enhance efficiency and portability, we leveraged TensorFlow Lite, which offers a wide range of pre-trained models. By running the model directly on edge devices, the system eliminates dependency on cloud or Internet connectivity, thereby ensuring consistent and reliable performance across environments. In the proposed framework, each detected emotion is classified into one of the five categories, with corresponding integer values assigned to each state, as summarized in Table 2.



Fig. 9. Samples of five emotions from the FER-2013 dataset [32]

Table 2. The values of the learner's emotional classes

Emotion	Value
Anger	-1
Disgust	-2
Happy	-3
Sad	-4
Surprise	-5

Eye gaze. In educational games, eye-tracking can reveal which elements attract and hold players' attention, offering valuable insights for designing more engaging and immersive learning experiences. Monitoring eye movements during gameplay can determine the level of attention learners give to essential content. Eye-tracking technology offers valuable insights into which game elements capture and retain the player's attention, thereby informing the development of more immersive and effective game design. By monitoring eye movements during gameplay, it is possible to assess the amount of attention a learner devotes to the main educational content. Based on this data, two distinct levels of player attention are identified, as outlined in Table 3.

Table 3. The values of the attention level

Attention Level	Value
Low	1
High	2

In the proposed framework, a machine learning model for eye gaze movement is developed to analyze patterns and gain insights into user engagement. We utilized the GI4E dataset to detect eye gaze, which comprises 1,339 images captured using a standard webcam. The dataset contains 103 different subjects, each represented by 12 images. Images are in lossless PNG format with a resolution of 800×600 pixels [33, 34]. The dlib library is utilized to identify the region of interest (ROI) focused

on the eyes. Each image is cropped to include only the ROI, with dimensions set to 150 pixels wide and 50 pixels high, as shown in Figure 10. These processed images are then fed into a CNN model for classification.



Fig. 10. The 12 samples for ROI

Convolution neural network for eye gaze. Designing neural network architecture is a crucial step in building a CNN model. This involves specifying the number of convolutional layers, pooling, and fully connected layers, and selecting the activation functions to use. During model training, parameters such as learning rate, batch size, and number of epochs must be carefully considered. To address this, we developed a customized CNN architecture for facial emotion recognition, as illustrated in Figure 11.

The first layer in this architecture is an input layer specifically designed for the dimensions of the preprocessed images (150 pixels wide, 50 pixels high, and 3 color channels). The layer has 32 filters with a 3×3 kernel and uses the ReLU activation function. This is followed by a max-pooling layer to decrease spatial dimensions and computational complexity. Subsequent layers consist of two convolutional layers, each with 64 filters and ReLU activation, followed by a max-pooling layer. Following the convolutional base, the network flattened the spatial data for classification, which was fed into a fully connected layer containing 64 neurons. The output layer contains 103 neurons, corresponding to the number of unique subjects, and uses a Softmax activation function to generate a probability distribution across the classes.

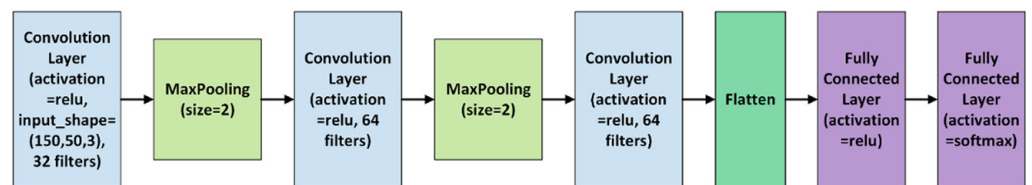


Fig. 11. CNN for the eye gaze detection model

The dataset was divided into training and testing subsets using the *train_test_split* function from the scikit-learn library, with 80% allocated for training and 20% for testing. The CNN model trained on this data achieved an accuracy of 94.2%. The model was implemented using TensorFlow, with a focus on designing a simple yet efficient CNN architecture. To enable deployment on mobile and embedded systems, the TensorFlow Lite Converter was used to transform the standard TensorFlow model into TensorFlow Lite format (see Figure 12) [35, 36]. This conversion substantially reduced the model size while optimizing its performance for resource-constrained devices. For mobile deployment, the trained TensorFlow Lite model was integrated

into the Pocket Code application, enabling execution on the Android platform with Google TensorFlow support [35, 37].

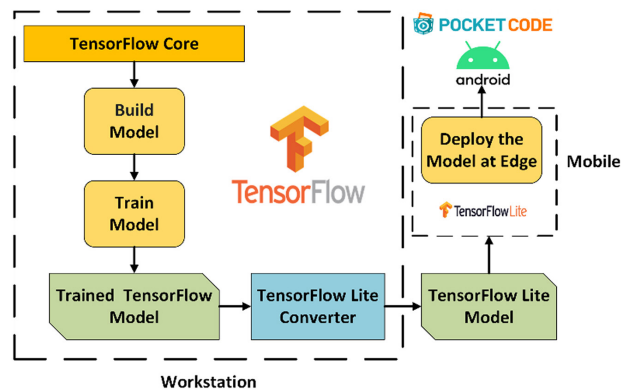


Fig. 12. Model conversion workflow in TensorFlow Lite [37]

5 EXPERIMENTAL RESULTS AND DISCUSSION

An empirical evaluation was conducted using Pocket Code to assess the feasibility of the proposed emotion and context-aware GBL framework. Apps such as Pocket Code provide an opportunity to utilize mobile devices in valuable and enjoyable ways without requiring professional development skills. The “Lego-style” visual programming framework enables anyone to design their apps. Using Pocket Code, a GBL app is designed to combine education and entertainment [38]. The system employs emotion recognition, eye gaze, and contextual sensors, powered by machine learning, to dynamically adapt the gameplay experience in the Pocket Code environment (see Figure 13).

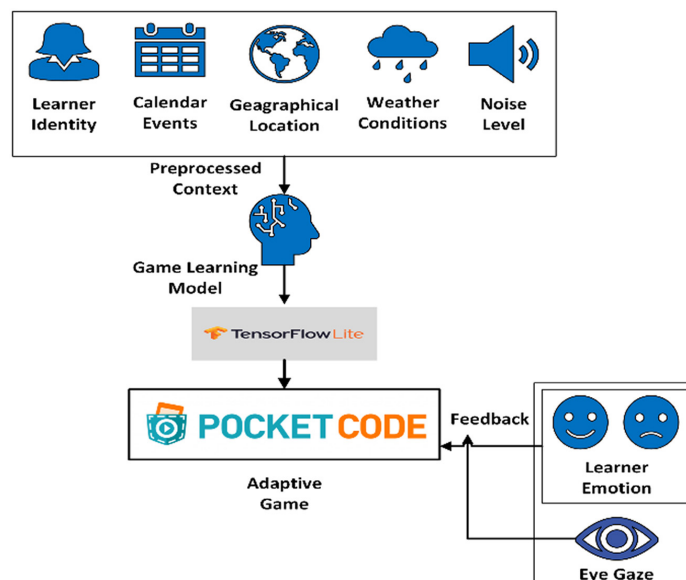


Fig. 13. Using emotion recognition and contextual sensors in Pocket Code, powered by machine learning

The educational game includes questions on math, science, and general knowledge, turning learning into an enjoyable and interactive experience. The game incorporates 15 interactive questions covering a range of topics, aimed at assessing players’ understanding while promoting active learning. The game app starts

with the “Use Camera” brick, which toggles between the smartphone’s front and back cameras. The camera constantly captures the learner’s facial expressions and tracks eye movements to monitor their gaze, and assess their attention, engagement, and reactions. When the system detects negative emotion or low player attention, the “Broadcast” block sends either a “NegativeEmotion” or “LowAttention” message. These signals are distributed to relevant subsystems within the game, prompting them to execute their corresponding scripts in response.

The game initiates communication by employing a “Broadcast” block, which sends a message to all other objects in the system. Consequently, the proposed system reacts to these messages using the “When you receive” block. This block detects incoming messages and triggers the execution of all blocks associated with the adaptation process, as illustrated in Figure 14.

Upon receiving the “NegativeEmotion” message, the game app initiates an adaptive scene with a new background, as shown in Figure 14a. The “Start scene” block transitions to a different scene within the game system and begins the adaptive scene from the start. By using this block (i.e., the “Start scene” block), we navigate to the customized scene and initiate it from the beginning to alleviate negative emotions and improve user engagement and experience. In response to the “LowAttention” message, the game app retrieves an image from a set path and applies a customized localized background to enhance player concentration, as shown in Figure 14b. The detection and analysis of a player’s visual emotion, eye gaze, and contextual information trigger adaptations in the game application, specifically, which is based on weather conditions and learner identity (see Figure 15).

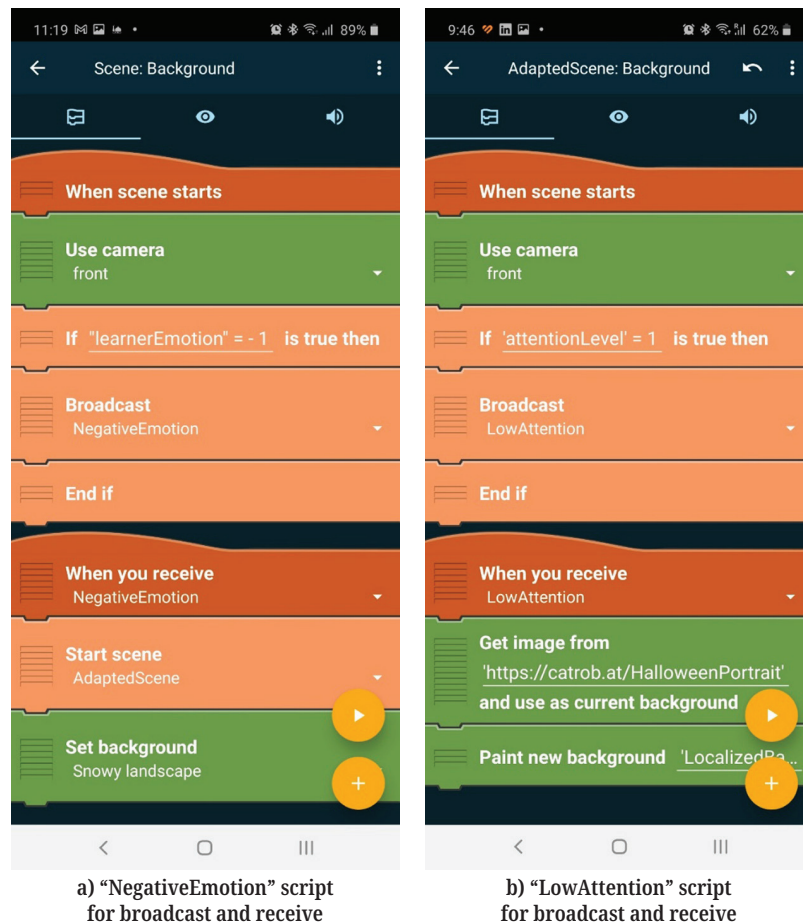


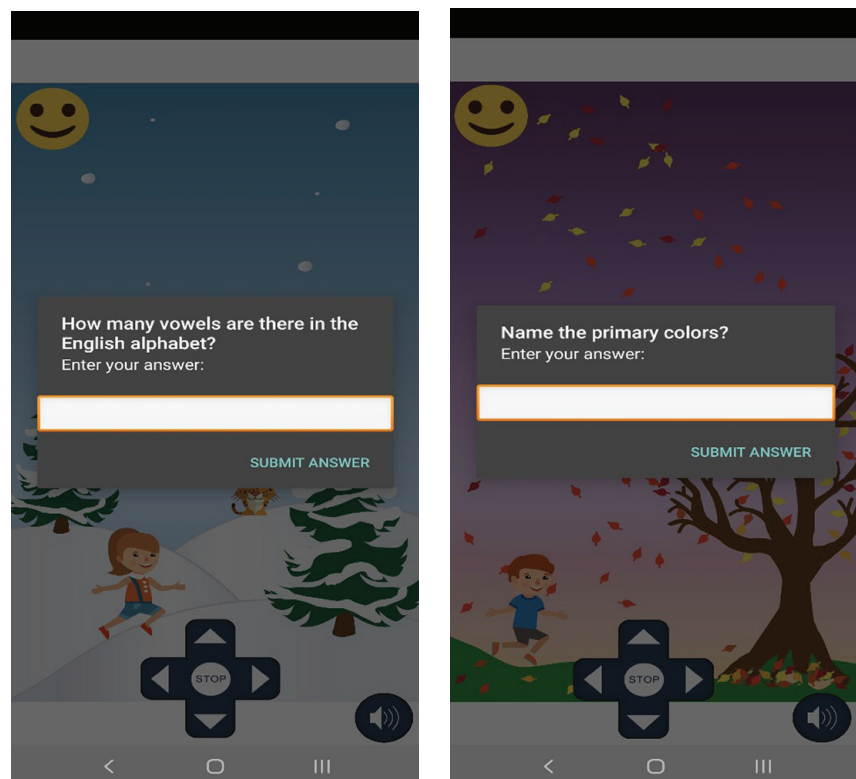
Fig. 14. Scripts for the proposed adaptive GBL system

To evaluate the quality of the proposed framework, a user study was conducted with 10 voluntary participants aged eight to 13. The learners were chosen based on their familiarity with block-based visual programming environments and coding education tools. This study adhered to ethical guidelines typically observed in educational research, with informed consent obtained from all participants. While no major ethical issues were encountered, the research emphasizes the importance of protecting student data privacy, especially due to the sensitive nature of self-reported information. Accordingly, all data were anonymized before analysis to ensure individual participants could not be identified.

Participants engaged in a 10-minute session with a non-adaptive and adaptive educational game, created on their smartphones using Pocket Code and its “Looks” elements. Table 4 presents the learners’ demographic characteristics. The study employed a series of three consecutive experiments to evaluate the effectiveness of the adaptive GBL system in comparison to its non-adaptive counterpart, as detailed below.

Table 4. Demographic characteristics of the participants

Variable	Description	Percentage
Gender	Male	50%
	Female	50%
Age	8–10	60%
	11–13	40%



a) Adaptive scene based on weather conditions with a positive emoji

b) Gender-based adaptive scene with a positive emoji

Fig. 15. Screenshots for the games adaptive scene

Experiment 1: Emotional Engagement and Adaptive Efficacy

Objective: To evaluate (1) the impact of non-adaptive gameplay on emotional engagement and (2) the effectiveness of adaptive GBL in mitigating negative emotional states and improving learning outcomes.

Setup

- **Participants:** The same small group of learners (aged 8–13) engaged sequentially with non-adaptive and adaptive versions of the educational game.
- **Emotion Tracking:** Emotional responses (happy, angry, sad, disgusted) were recorded via the smartphone's integrated video cameras during gameplay.
- **Feedback Collection:** Following post-adaptive sessions, participants rated the accuracy of adaptation and their perceived learning outcomes.
- **Ethical Considerations and Informed Consent:** Participants and their legal guardians provided informed consent before participation. Consent included explicit permission for the collection and analysis of facial expressions captured during gameplay for emotion recognition purposes. Participation was voluntary, and confidentiality and anonymity were ensured throughout the study.

Key Findings

1. Non-Adaptive Gameplay:

- 70% of observed emotional responses were negative (anger: 30%, sadness: 10%, disgust: 30%; see Figure 16).
- Participants exhibited frequent disengagement during challenging levels, indicating that the static design failed to account for emotional or contextual needs.

2. Adaptive Gameplay:

- 80% of participants reported satisfaction with the adaptive version, citing improved engagement.
- Adaptive mechanisms (e.g., dynamic difficulty adjustment) reduced negative emotional states by 50% (compared to non-adaptive play).

Implications

The findings highlight the importance of integrating context-aware adaptations into educational games. In contrast, the non-adaptive version consistently triggered negative emotions and player disengagement.

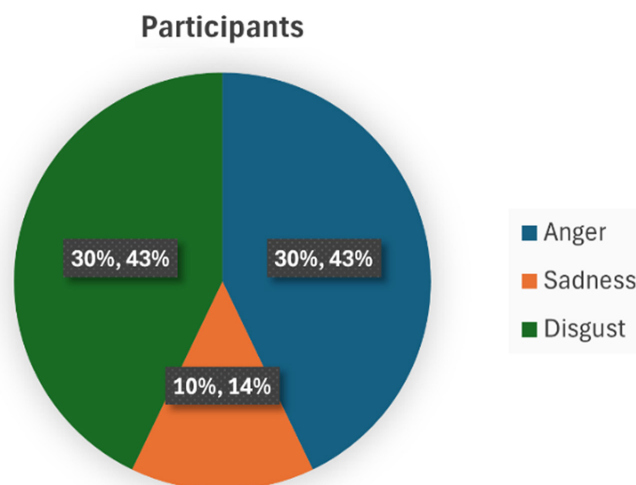


Fig. 16. Percentage of participants with negative emotions

Experiment 2: Efficacy of Adaptive GBL

Objective: To assess whether emotion- and context-driven adaptation improves learning performance compared to non-adaptive mobile GBL.

Setup: Ten learners were divided into a control group (non-adaptive mobile GBL) and an experimental group (adaptive mobile GBL). Both groups completed three 10-minute sessions of the same educational game, with the adaptive version dynamically adjusting difficulty based on real-time emotional feedback (e.g., reducing challenge during frustration).

Metrics: Quiz scores and task completion time.

Key Findings

- The experimental group showed a 15% greater improvement in quiz scores and a 20% reduction in task completion time versus the control group (10%).

Experiment 3: Learner Satisfaction and Perceived Efficacy of Mobile GBL.

Objective: To evaluate learners' subjective satisfaction with the adaptive GBL system.

Setup

- **Participants:** Learners from the experimental group (adaptive mobile GBL) completed post-session surveys.
- **Measures:**
 - **Enjoyment:** Rated on a Likert scale (e.g., "How enjoyable was the game?").

Key Findings

- **Motivation and Enjoyment:**
 - 90% of participants reported higher motivation to continue playing, attributing this to the adaptive gameplay's responsiveness to their needs.

Implications

Adaptive mobile GBL not only improves objective metrics (e.g., quiz scores, task time) but also enhances the subjective learning experience. The high satisfaction rates (90% motivation) suggest that localization and real-time adaptation are critical for sustaining engagement.

In summary, the study demonstrates that adaptive gameplay significantly enhances both emotional and learning outcomes compared to non-adaptive designs. By dynamically adjusting difficulty and responding to players' emotional states, the adaptive version not only reduced negative emotions by half but also improved engagement, motivation, and learning performance. These findings highlight the value of integrating emotion and context-aware adaptation into GBL environments to sustain learner motivation and optimize educational impact.

6 STATISTICAL ANALYSIS

To validate the claims presented in the proposed framework, statistical analyses, including t-tests, ANOVA, and effect size calculations, were conducted. Statistical analyses were performed in SPSS (v30.0.0). Differences in emotional responses, engagement, and perceived learning outcomes between non-adaptive and adaptive gameplay were assessed via paired samples t-tests. In contrast, emotional response types were

examined using repeated measures ANOVA. Effect sizes (Cohen’s *d* for *t*-tests, η^2 for ANOVA) were included to evaluate practical significance as presented in Table 5.

Claim 1: Non-Adaptive Gameplay Induced Negative Emotions: To compare the frequency of negative emotional responses (anger, sadness, disgust) between non-adaptive and adaptive gameplay, a repeated-measures ANOVA was performed. The analysis revealed a significant decrease in negative emotions during adaptive gameplay ($F(1, 9) = 15.34, p = 0.003, \eta^2 = 0.63$), with a large effect size. Follow-up paired *t*-tests indicated significant reductions in anger ($t(9) = 2.89, p = 0.018, d = 0.91$) and disgust ($t(9) = 3.12, p = 0.013, d = 0.98$). However, sadness levels were consistently low across both conditions and did not differ significantly ($t(9) = 1.21, p = 0.254$).

Claim 2: Adaptive Gameplay Increased Satisfaction and Engagement: A one-sample *t*-test was conducted to compare post-adaptive satisfaction ratings with a neutral midpoint (set at $M = 3$ on a 5-point scale). Results showed significantly higher satisfaction ($M = 4.2, SD = 0.63, t(9) = 5.57, p < 0.001$, with a large effect size (Cohen’s $d = 1.76$). Additionally, a paired *t*-test comparing engagement levels between adaptive ($M = 4.3$) and non-adaptive gameplay ($M = 2.7$) demonstrated a significant increase in engagement, $t(9) = 4.19, p = 0.002, d = 1.32$.

Claim 3: Learning Outcomes Improved After Adaptive Gameplay: Participants reported higher perceived learning outcomes after adaptive gameplay ($M = 4.1, SD = 0.7$) compared to non-adaptive gameplay ($M = 3.0, SD = 0.8$). A paired *t*-test revealed that this difference was statistically significant, $t(9) = 3.86, p = 0.004$, with a large effect size (Cohen’s $d = 1.22$).

Figure 17 presents key outcomes of adaptive gameplay implementation: (a) demonstrates a 50% reduction in negative emotional responses (from 70% to 35%), (b) reveals significantly higher engagement ratings, (c) shows satisfaction levels surpassing neutral baseline expectations, and (d) indicates improved perceived learning outcomes compared to non-adaptive approaches.

Table 5. Statistical analysis of emotional engagement and perceived learning outcomes in adaptive vs. non-adaptive gameplay (Experiment 1)

Comparison	Test	t/F	p-Value	Effect Size
Negative emotions (adaptive vs. non-adaptive)	ANOVA	$F(1,9) = 15.34$	0.003	$\eta^2 = 0.63$
Anger (adaptive vs. non-adaptive)	Paired <i>t</i> -test	$t(9) = 2.89$	0.018	$d = 0.91$
Satisfaction rating (vs. neutral)	One-sample <i>t</i> -test	$t(9) = 5.57$	< 0.001	$d = 1.76$
Engagement (adaptive vs. non-adaptive)	Paired <i>t</i> -test	$t(9) = 4.19$	0.002	$d = 1.32$
Perceived learning outcome	Paired <i>t</i> -test	$t(9) = 3.86$	0.004	$d = 1.22$

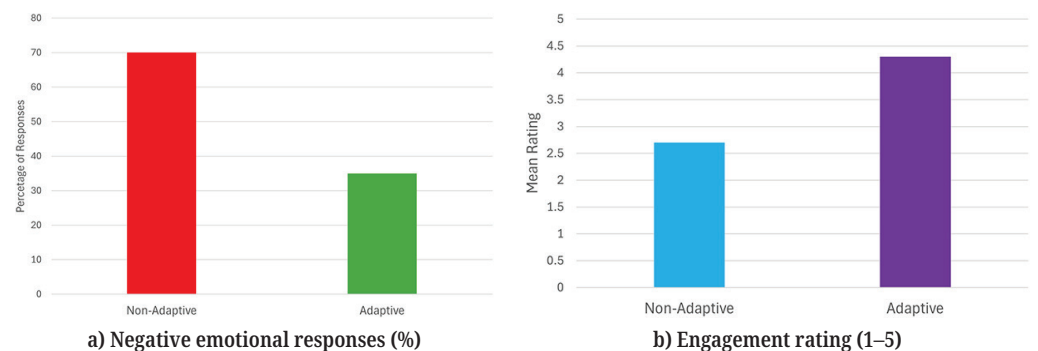


Fig. 17. (Continued)

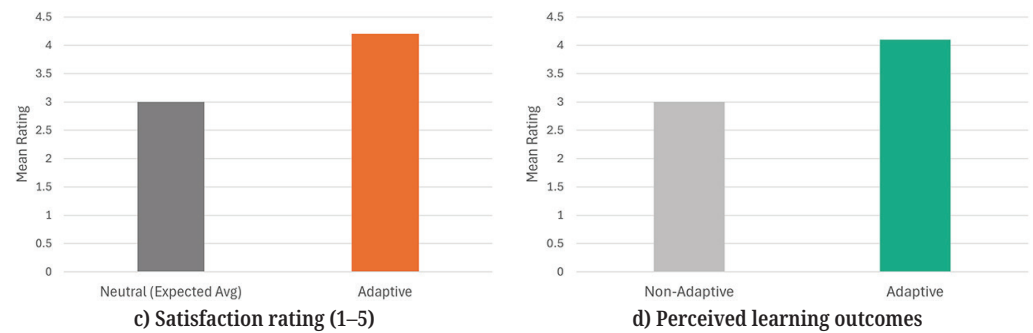


Fig. 17. Emotional engagement and adaptive efficacy

Claim 4: Adaptive GBL improves quiz scores and reduces task completion time: Independent sample t-tests were used to assess differences in quiz scores and task completion times between the non-adaptive (control) and adaptive (experimental) groups. To evaluate the strength of these differences, Cohen's d was employed as a measure of effect size, with benchmarks of 0.2 for small effects, 0.5 for medium effects, and 0.8 or higher for large effects.

As presented in Table 6, the independent samples t-test showed that the adaptive (experimental) group achieved significantly higher post-game quiz scores ($M = 80\%$, $SD = 8\%$) than the non-adaptive (control) group ($M = 65\%$, $SD = 10\%$), $t(8) = 2.83$, $p = 0.022$, with a large effect size ($d = 1.79$). Additionally, the adaptive group completed tasks more quickly ($M = 7.2$ min, $SD = 1.0$) compared to the control group ($M = 9.0$ min, $SD = 1.2$), $t(8) = 2.72$, $p = 0.026$, $d = 1.72$, which also reflected a large effect. As shown in Figure 18a, the adaptive (experimental) group demonstrated significantly higher quiz scores compared to the control group. In contrast, Figure 18b shows a notable reduction in task completion time for the adaptive group.

Table 6. Comparison of quiz scores and task completion times between control and experimental groups (Experiment 2)

Group	Mean Quiz Score (%)	Mean Task Time (Minutes)
Control	65	9.0
Experimental	80	7.2

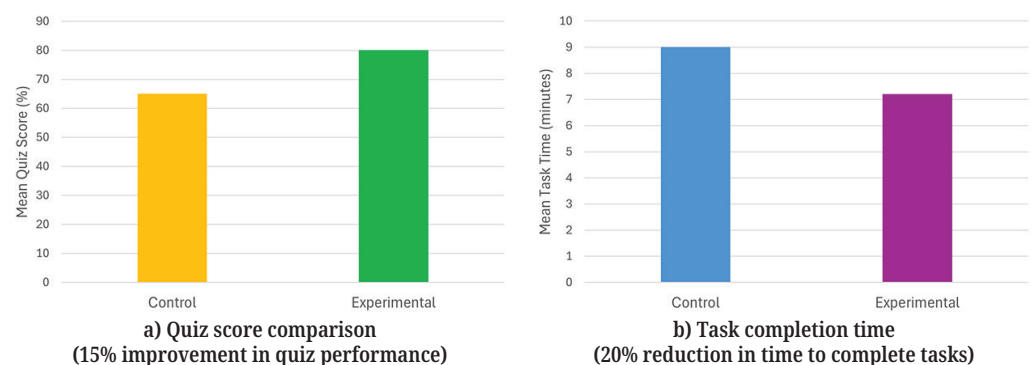


Fig. 18. The efficacy of adaptive GBL

Claim 5: Adaptive GBL significantly enhanced learner motivation: The findings indicate that learners perceived the adaptive mobile GBL environment

as both highly engaging and motivationally effective. Statistical analyses confirmed that user ratings significantly exceeded neutral benchmarks, with exceptionally large effect sizes. These results highlight the crucial role of real-time emotional and contextual adaptation in enhancing learner satisfaction and engagement.

Statistical analysis revealed significantly positive learner responses to the adaptive gameplay experience. A one-sample t-test indicated enjoyment ratings substantially exceeded the neutral midpoint ($M = 4.4$, $SD = 0.6$), $t(9) = 7.36$, $p < 0.001$, with a huge effect size ($d = 2.33$). Similarly, participants demonstrated markedly high motivation to continue playing ($M = 4.5$, $SD = 0.5$), $t(9) = 9.49$, $p < 0.001$, $d = 3.00$), reflecting a powerful motivational impact attributable to the adaptive game design as illustrated in Table 7.

Table 7. Descriptive statistics for learner enjoyment and motivation following adaptive gameplay (Experiment 3)

Measure	Mean	SD
Enjoyment	4.4	0.6
Motivation	4.5	0.5

7 COMPARATIVE EVALUATION OF EMOTION-AWARE ADAPTIVE GBL

To contextualize this study's findings within the broader discourse, a comparison with existing research on emotion-aware and context-driven mobile GBL proves insightful [39–45]. Previous studies have consistently highlighted the impact of adaptive gameplay on learners' emotional states, engagement, and performance. In non-adaptive environments, negative emotions, such as frustration, anger, and boredom, are prevalent, often compromising engagement and knowledge retention. In contrast, adaptive features (e.g., dynamic difficulty adjustment and context-aware scaffolding) have been empirically linked to reduced negative effects, heightened satisfaction, and measurable gains in both motivation and task performance. Aligning the present results with these established trends not only validates key findings but also clarifies the advantages of adaptive, emotion-sensitive designs over static, one-size-fits-all approaches as illustrated in Table 8.

8 SCALABILITY, CROSS-CULTURAL APPLICABILITY, AND LIMITATIONS

The scalability of the proposed GBL system is strengthened by its integration with Pocket Code. Pocket Code's intuitive, block-based interface allows users to customize and localize game content without requiring advanced programming skills. This accessibility makes the platform suitable for a broad range of users, including educators, students, and developers, regardless of their technical background, thereby supporting wider adoption and adaptation across diverse educational settings.

Table 8. Comparing the proposed GBL system with prior studies

Aspect	Proposed Approach	Supporting Literature
Adaptive Gameplay	<ul style="list-style-type: none"> – 80% satisfaction – 50% reduction in negative emotions – 15% higher quiz scores 	<ul style="list-style-type: none"> – Dynamic difficulty adjustment and emotion-aware AI in adaptive games improve engagement and reduce frustration [39] [40]. – Adaptive systems show better learning outcomes, and students in GBL had higher learning achievement than those in conventional learning [41] [42].
Motivation & Enjoyment	<ul style="list-style-type: none"> – 90% reported higher motivation due to adaptive features 	<ul style="list-style-type: none"> – Reward systems and flow theory in games enhance motivation (e.g., male students reported enjoying the game) [43]. – Positive emotions (e.g., enjoyment) correlate with creativity and persistence in problem-solving [44] [45].

This design approach enhances the system’s potential for widespread adoption across both formal and informal learning environments. Pocket Code’s mobile-first architecture leverages the ubiquity of smartphones, allowing for large-scale deployment with minimal hardware requirements. However, scalability is currently limited by the platform’s support for Android devices only, as well as its performance constraints when handling resource-intensive tasks such as real-time emotion recognition. To further improve scalability, future developments could focus on integrating cloud-based services and expanding compatibility with other platforms, such as iOS.

Cultural differences play a significant role in shaping emotional expression and learning behaviors, which can impact the accuracy of emotion recognition and the effectiveness of adaptive feedback. While the system incorporates context-awareness, its current emotion detection algorithms are trained on culturally homogeneous datasets, limiting their generalizability. To enhance cultural sensitivity and ensure more effective adaptations, future development should prioritize cross-cultural validation and validation of cultural sensitivity. This involves training and evaluating the model using data from diverse learner populations to support more accurate emotional interpretation and culturally appropriate game responses.

9 CONCLUSION

In this paper, we propose a mobile GBL framework that integrates engaging gaming elements with educational content to promote learner engagement and motivation. Mobile GBL proves to be an effective strategy for enhancing education by making learning more interactive, accessible, and enjoyable. Experimental results from a pilot study indicate significant improvements in learner engagement, motivation, and knowledge retention when compared to traditional GBL methods.

A small group of learners aged 8–13 participated in sessions with both non-adaptive and adaptive versions of the educational game. During the non-adaptive gameplay, 70% of emotional responses were negative, including anger (30%), sadness (10%), and disgust (30%), indicating a lack of engagement. In contrast, 80% of participants expressed satisfaction with the adaptive version, citing enhanced engagement and a more personalized experience. The experimental group also demonstrated a 15% greater improvement in quiz scores and a 20% reduction in task completion time compared to the control group. The findings from both experiments provide strong evidence for the effectiveness of emotion and context-driven adaptation in GBL environments.

Three experiments were conducted. Results from Experiment 1 showed that adaptive gameplay reduced negative emotional responses by 50% and significantly improved learner engagement and satisfaction, with large effect sizes supporting these outcomes (Cohen's $d > 1.2$). Similarly, Experiment 2 showed that learners in the adaptive group achieved higher quiz scores and completed tasks more efficiently than those in the non-adaptive group, with statistically significant improvements and large effect sizes (Cohen's $d > 1.7$). These results highlight the potential of adaptive GBL to foster both emotional well-being and academic performance. Furthermore, Experiment 3 showed that 90% of participants reported higher motivation to continue playing, attributing this to the adaptive gameplay's ability to respond to their emotional and contextual needs. These findings support the potential of emotion and context-aware adaptive mobile GBL to improve learning outcomes and motivation for learners.

While the integration of emotion recognition and eye gaze tracking holds promise for enhancing adaptive learning systems, it also presents significant ethical challenges that must be carefully addressed. The collection and analysis of sensitive biometric data demand strict compliance with ethical standards, including obtaining approval and informed consent from participants. Users must be informed about how their data will be collected, processed, and stored to ensure transparency and maintain their privacy. Furthermore, concerns related to data security and potential misuse of personal information must be taken seriously. These ethical considerations represent a major limitation to the proposed framework. Additionally, the limited number of participants represents another constraint of the study, primarily due to the voluntary nature of participation.

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