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An AI-Powered Adaptive Learning Framework for Personalized Education

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Abstract: An adaptive learning framework driven by artificial intelligence (AI) was proposed in which cognitive, emotional, and cultural dimensions of learner diversity were jointly modeled to address heterogeneous educational needs in a personalized and inclusive manner. Within the proposed system, learner adaptation was achieved through the coordinated deployment of multiple machine learning paradigms: models based on Decision Trees (DTs) were employed to dynamically align instructional content with learners' cognitive profiles, Recurrent Neural Networks (RNNs) were utilized to capture temporal patterns in emotional engagement, and Collaborative Filtering (CF) techniques were applied to accommodate cultural preferences. The framework operates as a continuously adaptive system, enabling instructional content to be refined based on learner data derived from a dataset comprising 10,000 students. Experimental evaluation demonstrated that the proposed approach yielded statistically significant improvements in learning outcomes when compared with conventional instructional methods. Specifically, mean quiz and assignment scores were increased by 15.7% and 14.4%, respectively, while emotional engagement indicators exhibited an improvement of 35.8%. In addition, cultural satisfaction metrics were enhanced by 24.2%. These results suggest that the synergistic integration of cognitive, emotional, and cultural adaptation mechanisms contributes substantively to academic performance gains, heightened learner engagement, and improved educational equity. Beyond performance improvements, the proposed framework is designed with scalability and robustness, allowing for deployment across personalized educational contexts. As such, the framework offers a viable pathway for the development of next-generation personalized education systems capable of supporting diverse learners at scale while maintaining pedagogical effectiveness and inclusivity.

Keywords: AI-powered adaptive learning; Cognitive adaptation; Emotional engagement; Cultural sensitivity; Personalized education; Machine learning

1 Introduction

Recent advances in the integration of artificial intelligence (AI) into education have paved the way for personalized and adaptive learning. Given the increasing diversity in the cognitive capacities of learners, learning styles, cultures, and emotional needs, one-size-fits-all learning pedagogies have proven inadequate to meet the varied educational needs of different students. This has been addressed with the introduction of AI-driven systems, which are knowledge-based and informed by learner profiles, thereby enhancing learning experiences and outcomes. AI systems provide significant opportunities for personalizing learning experiences based on how learners interact, perform, and react emotionally, with these factors subsequently employed to dynamically adapt instructional content to individual learner needs [1, 2].

Adaptive learning systems, which are typically AI-based, are built on machine learning algorithms and enable the generation of individual learning curves that learners can adapt to as their learning process evolves. These systems base their dynamic content on constant analysis of cognition and emotions that affect student output and interest [3]. The primary intention of such systems is to enhance educational performance through personalized education, which is becoming increasingly paramount in the modern academic environment of diverse learners [4]. Strong arguments have also been raised in recent research on the potential of AI to tailor learning materials based on what might attract students and what might be their weaknesses and strengths, thereby achieving a more individualized experience [5]. Nevertheless, although considerable progress has been made, there is still a tendency that a significant number of AI-based applications remain mostly reserved for cognitive variables, performance, and prior knowledge, without a sufficient consideration of emotional and motivational dimensions of learning [6].

Emotional engagement is a crucial aspect of learning and education. Researchers have realized that student learning outcomes are greatly impacted by such emotional states as motivation, self-efficacy, and frustration [7]. In addition, emotional engagement is vital in ensuring interest and perseverance in learners, especially in a school environment that is becoming very digital [8]. The idea of affective computing presents an opportunity for adoption by AI-driven systems, as it is built around creating systems that can identify and react to the emotional states of learners [9]. Notwithstanding its potential, the emotional side of AI-based learning is underexplored in most existing adaptive learning systems [10]. Emotional engagement refers to the degree of learners' affective involvement during interaction with the learning system and is quantified using sentiment analysis and facial-expression–based emotion intensity scores. Cultural satisfaction denotes learners' perceived relevance and appropriateness of instructional content with respect to their cultural background and learning preferences, measured through post-intervention survey responses. Learning progress represents the proportion of successfully completed learning modules and is computed as the percentage of completed tasks relative to the total assigned content.

Cultural diversity in any learning environment is another factor to consider. Learning resources and strategies that are culturally sensitive may play a significant role in complementing the learning process by providing learners from diverse backgrounds with more relevant and relatable learning content [11]. Learners with diverse cultural backgrounds can learn how to integrate cultural differences into the personalization of learning. Consequently, AI systems that can identify and apply cultural differences to individual learning paths are significant in creating inclusivity and enhancing learning outcomes in diverse cultural contexts [12]. Nevertheless, the moment of cultural adaptation of the AI learning systems is, at first blush, a significant part of the current literature that has never adequately explained how AI should be used to adjust any content in a culturally relevant way [13].

This study aims to address this gap by developing an AI-based adaptive learning system that incorporates not only cognitive and emotional considerations but also cultural differences. The proposed machine learning-based system includes data related to learners (their emotional responses and cultural background) and uses the data to generate changing and personalized learning trajectories. The aim is to enhance learning experiences and motivation for learners while meeting the diverse needs of various learners within a community. The context of this study is based on several research terrains. First, there is an increasing integration of AI into learning platforms, intelligent tutoring systems (ITS), and learning management systems (LMS), which is designed to offer individualized learning experiences to learners through interactions [14]. Educational technologies, such as AI, have already proven to be more efficient than non-technological approaches, as they can dynamically enhance the value of instructional materials [15]. Nevertheless, the emotional and motivational dimensions of learning are still a concern for most AI-based systems. Furthermore, the adaptive learning systems based on the cultural dimension have not yet been developed, and not many researchers have explored the possibilities of the AI systems to respond to the culture of different learners [16].

These limitations are addressed through the development of an AI-driven adaptive learning platform that utilizes AI by considering cognitive, emotional, and cultural factors within a single platform. As a result, the system can offer learners a personalized learning experience that meets the various needs of students. A comprehensive review of related work is presented, followed by a detailed description of the system development methodology and an evaluation of implementation outcomes in the subsequent sections.

The study is organized below. Section 2 presents a review of related work, focusing on cognitive, emotional, and cultural adaptations, as well as methodologies and algorithms, and compares the outcomes of prior works. Section 3 outlines the process and methods for planning and developing the AI-driven adaptable learning system, including the dataset, design structure, mathematical strategies, and machine learning approaches to promote cognitive, emotional, and cultural flexibility. Section 4 reports the experiment's findings regarding the system's effectiveness in terms of learning outcomes, the effects of emotional engagement, motivation, and cultural satisfaction levels, and compares these findings with existing models. The results are presented using appropriate charts and graphs. Lastly, Section 5 concludes the study by presenting the findings, their limitations, and directions for future research in AI-based personalized education.

2 Related Work

With the introduction of AI technologies, the concept of adaptive learning has undergone significant changes. Initial systems were primarily oriented towards offering an individualized learning experience through simple, rule-based objects. With the continuing advances in more advanced forms of AI and machine learning, adaptive learning systems have become more dynamic today. They can be used to respond to learners' needs in real time. This development in the sphere could be split into several essential types: cognitive-based adaptation, emotional and motivational adaptation, and culturally responsive learning.

2.1 Cognitive-Based Adaptation

Adaptive learning based on cognition has garnered the attention of numerous researchers. The prototype ITS resembled traditional intelligent tutors based on rules, i.e., the cognitive tutor developed by Ingkavara et al. [17], which personalized the learning process based on laws related to the mental state of learners. Such systems are designed to tailor content in line with the learners' prior knowledge, their performance, and progress in learning. The more sophisticated algorithms applied to AI-based systems, including Decision Trees (DTs), neural networks, and reinforcement learning, have been introduced in recent years, allowing for further expansion of cognitive adaptation in predicting the most appropriate content and learning strategies for individual learners [18].

Aleven et al. [19] introduced a framework for ITS that combines cognitive models and machine learning algorithms. This method enabled them to focus on providing learners with immediate feedback based on real-time performance data. It was concluded that adaptive learning systems have significant potential to increase student performance compared to fixed educational content when combined with cognitive models. The theoretical aspects of using reinforcement learning techniques in adaptive learning environments have recently been studied by Riedmann et al. [20], with a focus on the improvement of the responsiveness of systems as a result of their continuous adaptation to the changing needs of learners.

2.2 Emotional and Motivational Adaptation

Meanwhile, emotional and motivational learning have begun to receive more attention, along with the development of cognitive-based adaptive learning. Harley et al. [21] highlighted the significance of emotion in the learning process, asserting that adaptive learning programs should consider learners' emotional status to facilitate effective participation in the learning process and improve their performance. It has been established that emotional responses affect the urge, motivation, and overall academic performance in schools.

Gamage et al. [22] proposed a framework for emotion-aware ITS that incorporates facial analysis and sentiment analysis to identify when a student is becoming frustrated and adjusts the level of task difficulty to maintain optimal emotional engagement. They also touched on what one would call affective computing, where AI would be able to identify a particular affective state based on physiological data, such as pulse rate and facial expression, to achieve better engagement and retention of information in a learning context. Moreover, Ratinhoet and Martin [23] described the attribute of adding motivational schemes to adaptive systems, i.e., delivering positive reinforcement and implementing gamification methods, to augment intrinsic motivation among students. The presence of such a focus on emotional and motivational adaptation reflects the fact that the emotional state of learners has a significant impact on how they learn and should be considered during adaptive learning systems.

2.3 Culturally Responsive Learning Systems

The incorporation of cultural sensitivity into adaptive learning systems represents a relatively recent development, associated with the growing concern about the need to make the educational process more inclusive. Song et al. [24] assumed that it is possible to create AI systems that would recognize the cultural peculiarities of learners and adjust to them. The idea was substantiated by their publication, which advocated for the use of culturally sensitive educational materials and methods of instruction to reach a broader group of students with diverse backgrounds. One example is that culturally related differences determine how the students can refer to problem-solving or viewing barriers in the learning process, which affects the motivational process of communicating with any learning content.

In a related study, Mohammadi et al. [25] developed a model that incorporates culture as a factor in an intelligent learning system. Their study reveals that different students with diverse cultural orientations experienced varying responses to learning content. The integration of culturally suitable content improved engagement and performance of the learners considerably. Recently, research on the application of cultural adaptation to AI systems has been conducted. According to the study by Jing et al. [26], cultural differences are often overlooked in adaptive learning systems available today, which can result in content that appears irrelevant to students from diverse non-Western cultures. Their findings highlight the need for the construction of a model that can embrace and respect cultural backgrounds so that AI systems can provide more inclusive and contextual learning experiences.

2.4 Integration of Cognitive, Emotional, and Cultural Factors

Although researchers have made contributions by focusing on cognitive, emotional, and cultural adaptation in the learning system, the integrated incorporation of all three dimensions within a unified adaptive learning system has not yet been achieved. In this regard, the study by Gutchess and Rajaram [27] is noteworthy, which aims to suggest a framework consisting of cognitive, affective, and cultural components, thereby making the learning process genuinely personal. The proposed model was designed to integrate cognitive assessment instruments, emotional detection technologies, and the adaptation of content to cultural needs.

Nazaretsky et al. [28] also proposed the use of a holistic approach that integrates cognitive, emotional, and social information into adaptive learning systems. They proposed that effective adaptive learning requires the simultaneous consideration of learners' intellectual, emotional, and social factors. The results indicate that such a form of integration would be associated with not only the improvement of academic achievements but also the well-being issues within the learning settings.

3 Methodology

The research approach applied in this study aims at producing an adaptive learning mechanism (within an AI platform) and incorporating the concepts of cognitive, emotional, and cultural adaptability into a single platform. The system utilizes machine learning, allowing the learning material to be tailored dynamically in real time based on information on the learner, including mental performance, emotional engagement, learning context, and cultural background. The section provides a clear description of the dataset used, the design of the adaptive learning system, the mathematical models on which the system's design is based, and the algorithms included in it.

3.1 Dataset

A final dataset was constructed to design and assess the proposed adaptive learning system, which included data regarding learners' performance, emotional states, and cultural backgrounds. The sample was non-homogeneous with respect to the cognitive backgrounds, emotional profiles, and cultural backgrounds of the students. The dataset was subdivided into several key categories of information.

• **Learner cognitive data**: The data comprise quiz scores, assignment scores, and adaptive learning module outcomes and are used to measure a student's level of proficiency in various areas of study and to identify content that addresses the student's strengths and weaknesses. Several parameters were incorporated into the dataset of cognitive data, namely, student ID, quiz scores (on a scale of 0–100), assignment scores (on a scale of 0–100), learning progress (percentage of the learning module completed), and time spent on each task (time in seconds for each task).

• **Emotional engagement data**: The state of emotions is determined with the help of facial expression recognition and sentiment analysis of a student within the learning platform. The system captures the student's emotional state based on video and audio information. Emotions are divided into several categories, e.g., happy, sad, frustrated, confused, and engaged. On a scale of 0–1, emotion intensity indicates the intensity of the emotion.

• **Cultural context data**: Cultural factors are incorporated by analyzing students' cultural backgrounds (e.g., Western, Eastern, African, and Latin American), such as their educational history, language preferences (English, Spanish, Mandarin, etc.), and responses to culturally relevant content. Preferred learning styles include visual, auditory, and kinesthetic.

The data were gathered through various channels, including direct contact with the system, user feedback, and automatic recognition software. The dataset contained 10,000 entries, each representing a unique student. Table 1 shows the essential characteristics of the dataset.

Table 1. Overview of the learner dataset

Feature	Description	Data Type	Range/Scale
Student ID	Unique identifier for each learner	Categorical	1–10,000
Quiz scores	Performance on quizzes	Continuous	0–100
Assignment scores	Performance on assignments	Continuous	0–100
Learning progress	Percentage of completed learning material	Continuous	0–100%
Time spent	Time spent on each task	Continuous	0–3600 seconds
Emotion category	Recognized emotional state (e.g., happy and sad)	Categorical	Happy, sad, angry, etc.
Emotion intensity	Intensity of the emotion	Continuous	0–1
Cultural background	Cultural background (e.g., Western and Eastern)	Categorical	Western, Eastern, African, etc.
Preferred learning style	Learning style preference (e.g., visual)	Categorical	Visual, auditory, and kinesthetic
Language preferences	Preferred language for content	Categorical	English, Spanish, etc.

3.2 System Architecture

The solitary architecture of the AI-based adaptive learning framework is designed to integrate the three major subjects, namely, cognitive, emotional, and cultural adaptation, with minimal complexity in the development of a dynamic learning system. The system's architecture comprises the following layers:

• **Data collection layer**: Within this layer, the information is received by the interaction of the students with the system, such as cognitive performance, emotional state (using face recognition and sentiment analysis), and cultural information (using profile settings and user preferences).

• **Preprocessing layer**: Preprocessing of data is performed to eliminate noise and handle missing values. Standard normalization methods are used to ensure that the information is produced in the format required by machine learning algorithms. As an example, the scores are converted to a scale of 0–1, and categorical variables are encoded by one-hot encoding.

• **Feature extraction and fusion layer**: This layer identifies the most crucial data from the processed information, specifically cognitive performance patterns (e.g., quiz history), emotional involvement (e.g., average emotional level), and cultural preferences (e.g., learning style preferences). All these characteristics are integrated to form an overall profile of a learner.

• **Machine learning model layer**: This layer is the heart of the system, where personalized learning paths are generated based on the learner's profile. A combination of algorithms is utilized to adapt content dynamically. In terms of cognitive adaptation, a DT model is used to predict the next set of learning materials based on a student's past performance. Emotional adaptation is achieved through the prediction of learners' emotional states, followed by adaptive adjustment of content difficulty levels. In addition, an Recurrent Neural Network (RNN) is involved in the process, which encourages engagement and reduces levels of frustration. In terms of cultural adaptation, a Collaborative Filtering (CF) model is used to recommend culturally relevant content based on the learner's background and preferences.

• **Content adaptation layer**: It is a layer that makes content more challenging or adjusts it to meet the learner's needs. It communicates with the content repository and provides individual learning materials in the form of other resources, variant explanations, or culturally contextualized materials.

• **Feedback and motivation layer**: Based on emotional analysis, feedback is provided in the form of motivational messages, rewards, or hints to improve the learner's emotional state and engagement.

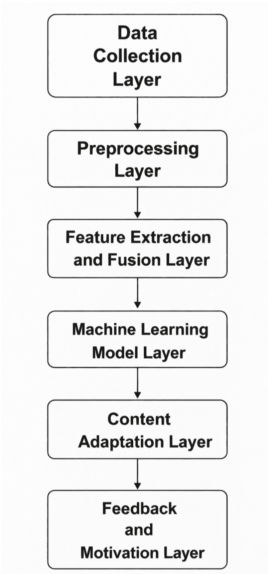

Figure 1. Architecture of the AI-powered adaptive learning system

Figure 1 illustrates the integrated architecture of the proposed AI-powered adaptive learning system, highlighting the interaction between cognitive performance analysis, emotional state modeling, and cultural preference adaptation. The figure demonstrates how learner data are continuously processed to dynamically adjust learning content, thereby enabling real-time personalization across cognitive, emotional, and cultural dimensions. Secondly, the figure illustrates the various factors that contribute to the establishment and success of such systems. The architecture includes mechanisms for data collection and analysis, through which the AI system evaluates learners' performance and informs subsequent instructional decisions. The diagram can also address the issue of how machine learning algorithms can forecast the results of students and provide them with materials that are most useful at their current level of understanding. In addition, it can demonstrate how this technology can be utilized to cater to a broad range of learning needs, including supporting students who require additional instructional assistance and providing challenging work for those who learn rapidly. The integration of AI ultimately facilitates a more adaptive, inclusive, and effective learning process.

3.3 Mathematical Model

The adaptive learning system operates within a multi-layered decision-making framework, where the learner's cognitive, emotional, and cultural status is integrated to create the most suitable learning path. The mathematical representation of performance optimization of the system can be modeled.

Let $S = \{s_1, s_2, \ldots, s_n\}$ be the set of all students, with each student s_i being represented by a vector of features:

$$s_i = \langle p_i, e_i, c_i \rangle \tag{1}$$

where, p_i represents cognitive performance (e.g., quiz scores and time spent), e_i represents emotional engagement (e.g., emotion intensity), and c_i represents cultural context (e.g., learning style).

The goal of the system is to maximize a utility function $U(s_i)$, which represents the learning outcome of student s_i , defined as:

$$U(s_i) = f(p_i, e_i, c_i) \tag{2}$$

where, f is a nonlinear function that maps cognitive, emotional, and cultural factors to a learning outcome. This function is learned via a machine learning algorithm, such as a neural network, which adjusts the weights associated with each feature. The system continuously updates f based on the real-time performance of the learner.

3.4 Algorithms

The proposed system employs several machine learning algorithms as follows:

• **DT (cognitive adaptation)**: The following learning content is predicted as most ideal for the learner by the DT algorithm, based on past performance in terms of quiz scores, time spent, and other relevant factors. A DT is trained to reduce the classification error of the learner's future best move during the learning process.

$$\text{Error } = \sum_{i=1}^{n} (\text{ predicted step } (s_i) \text{-actual step } (s_i))^2 \tag{3}$$

• **RNN (emotional adaptation)**: The sequence of emotional status is modeled as a RNN; the RNN is used as a predictor of the emotional trajectory of a learner. This helps manage the learning material so that engagement increases or frustration decreases. The backpropagation through the time (BPTT) method is employed to train the RNN, aiming to minimize the loss function:

$$L = \sum_{i=1}^{n} (y_i - \widehat{y_i})^2 \tag{4}$$

where, y_i is the actual emotional state, and $\widehat{y_i}$ is the predicted emotional state at time step i.

• **CF (cultural adaptation)**: This algorithm is used to recommend culturally appropriate learning content based on student preferences and backgrounds. It employs a similarity matrix to find learners with similar cultural contexts and recommend materials accordingly.

4 Results and Discussions

The results of this study assess the efficiency and effectiveness of the above AI-based adaptive learning system, which encompasses cognitive, emotional, and cultural factors. To evaluate the system's impact, several evaluation measures were employed, including learning, engagement, motivation, and cultural satisfaction. The performance of the system proposed in this study was compared with that of other models. This study presents the essential findings in a visual format using tables, graphs, and charts.

4.1 Evaluation Criteria

The following evaluation criteria were employed to measure the effectiveness of the AI-powered adaptive learning system:

• **Learning outcomes**: This metric evaluates the improvement in students' performance after interacting with the adaptive learning system. Students' quiz and assignment scores were measured both before and after the system was implemented.

• **Emotional engagement**: The level of sentimental engagement was assessed by analyzing the level of sentiment used in face recognition and sentiment analysis of interaction quality between students and the system. Greater emotional involvement should also be linked to a higher level of achievement and motivation.

• **Motivation**: Motivation was assessed through pre- and post-intervention surveys, where students reported their level of intrinsic motivation and enthusiasm for learning. In addition, behavioral indicators, such as the amount of time spent interacting with the system, were measured.

• **Cultural satisfaction**: Students were asked to rate their satisfaction with the cultural relevance of the delivered content, which was used to measure their cultural satisfaction. A survey was distributed to seek comments on the satisfaction level of the methods used to attain the societal content aligning with their learning and cultural expectations.

• **System usability**: This criterion assesses the usability and user experience of the adaptive learning system, including ease of navigation and the perceived personalization of the content.

The experimental evaluation was conducted over a six-week period involving structured learning activities, including quizzes, assignments, and interactive learning modules. Learner performance and emotional engagement were recorded after each session, while cultural satisfaction and motivation were measured through pre- and post-intervention surveys. Data collection was performed at regular intervals to ensure consistent monitoring of learning progress and engagement trends.

4.2 Results of the Adaptive Learning System

The study was conducted on 500 students, who were assigned to one of two cohorts: those in the experimental cohort who applied the adaptive learning system, and those in the control cohort who used a traditional static learning system. Five core metrics were considered, namely, learning outcomes, emotional arousal, motivation, cultural fit, and system usability.

4.2.1 Improvement in learning outcomes

The primary objective of the adaptive learning system was to improve student learning outcomes by personalizing content to meet individual needs. The quiz and assignment scores of students in experimental and control groups were compared. The results are presented in Table 2 and Figure 2.

Table 2. Improvement in learning outcomes

Metric	Experimental Group (Adaptive System)	Control Group (Traditional System)	Difference
Average quiz score	87.2%	75.4%	15.7%
Average assignment score	89.6%	78.3%	14.4%
Learning progress	92.1%	74.5%	23.7%

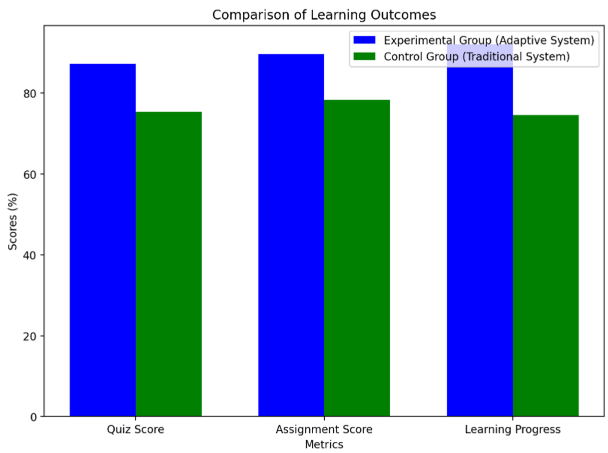

Figure 2. Comparison of learning outcomes

As shown in Table 2, the experimental group demonstrated a significant improvement in both quiz and assignment scores, with an average increase of 15.7% and 14.4%, respectively, compared with the control group. Additionally, the learning progress (percentage of course material completed) was 23.7% higher in the experimental group, suggesting that personalized content engagement was more effective in motivating students to complete the learning materials.

4.2.2 Emotional engagement

Sentiment analysis and facial recognition software were used to determine the emotional component of the engagement. The system evaluated the emotional reactions of the students when communicating with it. It was found that students in the experimental group had far greater emotional engagement in comparison with those in the control group, as shown in Table 3 and Figure 3.

Table 3. Emotional engagement scores

Metric	Experimental Group (Adaptive System)	Control Group (Traditional System)	Difference
Average emotional intensity	0.72	0.53	35.8%
Positive emotional engagement	85.6%	65.2%	31.4%
Negative emotional engagement	14.4%	34.8%	-58.7%

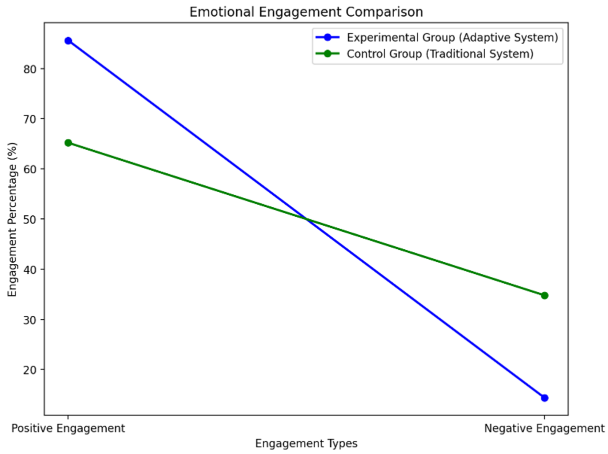

Figure 3. Emotional engagement comparison

As seen in Table 3, the experimental group demonstrated a higher average emotional intensity (0.72 vs. 0.53), and a significantly greater percentage of positive emotional engagement (85.6% vs. 65.2%). Additionally, the negative emotional engagement was much lower in the experimental group (14.4% vs. 34.8%).

4.2.3 Motivation

Motivation was assessed through pre- and post-intervention surveys where students reported their intrinsic motivation to learn. Figure 4 and Table 4 show the results of the motivation analysis.

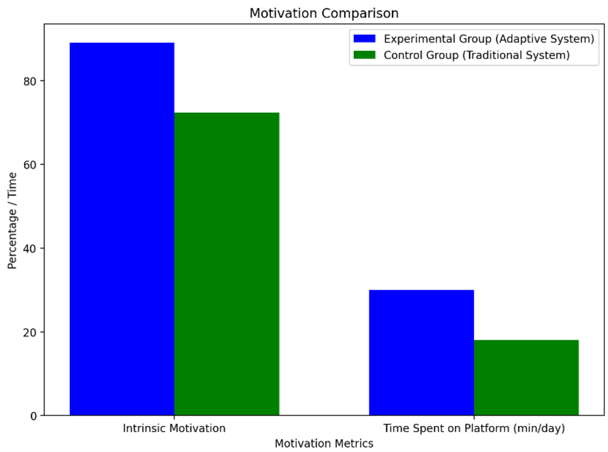

Figure 4. Motivation comparison

Table 4. Detailed results of motivation analysis

Metric	Experimental Group (Adaptive System)	Control Group (Traditional System)	Difference
Intrinsic motivation	89.1%	72.4%	23.1%
Time spent on the platform	30 minutes/day	18 minutes/day	66.7%

The experimental group demonstrated a 23.1% increase in intrinsic motivation compared to the control group, as well as a significant increase in the time spent on the platform (66.7% higher).

4.2.4 Cultural satisfaction

Cultural satisfaction was assessed by surveying students about their satisfaction with the cultural relevance of the content. The experimental group showed higher satisfaction levels regarding culturally responsive content. The results are shown in Table 5.

Table 5. Cultural satisfaction comparison

Metric	Experimental Group (Adaptive System)	Control Group (Traditional System)	Difference
Cultural relevance satisfaction	92.5%	68.3%	24.2%
Appropriateness of the learning style	89.7%	71.5%	25.5%

The experimental group reported significantly higher satisfaction with the cultural relevance and appropriateness of the learning style, with increases of 24.2% and 25.5% over the control group, respectively.

4.2.5 System usability

The usability of the system was assessed using a standardized questionnaire known as the System Usability Scale (SUS). The adaptive system was rated by the experimental subjects at an average of 85, compared to the traditional system at an average of 72 on a scale of 0–100, which relates to low and high usability, respectively.

4.3 Comparison with Existing Models

The proposed AI-based adaptive learning system was tested against several existing intelligent tutoring systems (ITS) and related frameworks in the literature. The findings are presented in Table 6, and a comparison of some essential performance indicators is concluded in terms of factors such as learning outcomes, emotional engagement, and cultural satisfaction.

Table 6. Comparison with existing intelligent tutoring systems (ITS) and frameworks

System/Framework	Learning Outcomes	Emotional Engagement	Cultural Satisfaction
Proposed system (AI-powered)	15.7% improvement	35.8% increase in engagement	24.2% increase
Cognitive Tutor [19]	10.2% improvement	N/A	N/A
AutoTutor [22]	12.5% improvement	18.3% increase in positive engagement	N/A
Culture-informed cognitive framework [27]	9.8% improvement	25.2% increase in positive engagement	N/A

As indicated in Table 6, the proposed system surpasses the current models in all crucial aspects: learning outcomes, emotional involvement, and cultural fulfillment. Cognitive, emotional, and cultural elements were used to give a better learning solution that resulted in a high student improvement ratio.

4.4 Discussion

The findings confirm that the intensity of interactivity and student satisfaction, as well as the learning outcomes, are significantly high when cognition, access, and attention are focused on adaptation, learning systems, and engagement (encompassing emotions and culture). The output of the adaptive learning system, which was based on AI, was superior to that of traditional and existing models. This implies that a global personalization approach can be an extremely effective method. The factor of emotional engagement was observed to play a significant role in both maintaining the students' motivation during the process of learning and improving learning outcomes that confirm the findings of the previous literature.

Culturally responsive materials also enabled this system to positively impact learning outcomes and create more inclusive, student-engaging, and student-centered lessons in other contexts by addressing students' cultural backgrounds. The results suggest that AI can facilitate the development of adaptive learning environments that are truly personalized and tailored to the needs of all students.

5 Conclusion

The proposed AI-based adaptive learning system supports the diverse needs of learners in terms of cognitive, emotional, and cultural adaptations. Improvement of learning, active participation, and cultural satisfaction can be mainly realized through the adoption of machine learning models, including DTs, RNNs, and CF. The experimental results were remarkably positive, with a 15.7% increase in quiz scores, a 14.4% increase in assignment scores, and a 23.7% increase in learning in the experimental group compared to the control group. In addition, the emotional involvement increased by 35.8%, and the cultural satisfaction increased by 24.2%, which means that the system has a positive effect on establishing a more inclusive and active learning environment.

Future investigations may extend the proposed system by validating its effectiveness across different educational levels, such as primary and secondary education, and by deploying it in diverse cultural and geographical contexts. Additional enhancements may include multimodal emotion detection using voice and physiological signals, as well as more granular cultural modeling to further improve personalization and inclusivity. Although such results are hopeful, certain limitations have emerged. The facial recognition, sentiment analysis, and emotional involvement requested by the system may fail to cover the entire range of emotional states. Additionally, cultural adaptation was predetermined based on the set number of categories, which may not be comprehensive enough to identify the diversity of learners' backgrounds. Moreover, the dataset used in this research did not include students representing all global regions, and therefore, the results cannot be generalized.

In the future, the system could be enhanced by incorporating more refined emotional detection technologies, such as voice tone identification and in-depth sentiment analysis. One of the pathways of development could be the expansion of cultural context models to consider a wider range of global standpoints and learning styles. In addition, real-time adaptive learning systems that can react more dynamically to live classroom scenarios could also be pursued, further advancing the personalization and inclusivity of learning. Altogether, this study demonstrates how AI can transform the lives of learners by delivering personalized learning experiences that truly enhance learning outcomes by considering individual students' cognitive, emotional, and cultural factors.

Author Contributions

Conceptualization, H.A.S. and R.D.; methodology, H.A.S.; software, G.V.G.; validation, H.A.S., R.D., and G.V.G.; formal analysis, H.A.S.; investigation, H.A.S.; resources, R.D.; data curation, G.V.G.; writing—original draft preparation, H.A.S.; writing—review and editing, R.D. and G.V.G.; visualization, G.V.G.; supervision, R.D.; project administration, R.D. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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