Emotion-Aware and Ethically Adaptive AI Learning Platform for Personalized, Inclusive and Real-World Student Engagement

Abdul Rasheed P.[1], Baiju Krishnan[2], Chandrasekhar V.[3], A. Narmatha[4], Charumathi S.[5] and Syed Hauider Abbas[6]

[1]*Department of English, EMEA College of Arts and Science, Kondotty. 673638, Malappuram Dt, Kerala, India*
[2]*Department of English and Other Indian & Foreign Languages, Vignan's Foundation for Science, Technology & Research (Deemed to be University), Deshmuki, Hyderabad Campus, Telangana State, India*
[3]*Department of Computer Science and Engineering, Ballari Institute of Technology and Management, Ballari, Karnataka, India*
[4]*Department of Management Studies, Nandha Engineering College, Vaikkalmedu, Erode - 638052, Tamil Nadu, India*
[5]*Department of ECE, New Prince Shri Bhavani College of Engineering and Technology, Chennai, Tamil Nadu, India*
[6]*Department of Computer Science & Engineering, Integral University, Lucknow, Uttar Pradesh, India*

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Abstract: The fast pace of AI in education not only requires technically sound adaptive learning systems, but also ethically attuned and emotionally responsive ones. The work in this paper introduces an emotion-aware, AI-enabled adaptive learning system that extends beyond traditional performance-based personalisation with the use of emotion-aware analytics, real-time feedback and multi-model learner profiling. Dr. Swart and her team have developed SOSTAC Classic System which teaches: Time Management, Study Skills, Organisational Skills, Multi-lingual and cultural friendly platform - adapting with individual learning style, cognitive preference and engagement pattern. It guarantees secure and ethical management of learner data, in line with the GDPR, and fosters collaborative learning involving teachers in the adaptive feedback loop. Delivered across diverse contexts, the platform has also proven sustained learning outcomes by closely monitoring performance over time. Results from deployments in real academic classrooms demonstrate superior engagement, retention, and academic performance, and has thus achieved a milestone for personalized education systems.

1 INTRODUCTION

In education, the inclusion of AI (artificial intelligence) has changed the way in which learning is offered, accessed, and individualized. Nevertheless, conventional adaptive learning systems are typically only based on static statistics of performance for content adaptation, and neglect the complexity of learner behavior, emotions, and variation in realistic environments. In an era where inclusivity, personalization and ethical use of data are central, the need for systems that not only “react” to academic performance, but also to learners’ emotions, preferences and cognitive diversity is increasing.

This study develops a new generation personalized learning platform that combines AI with emotional intelligence to make personalized learning of the content, which can realize the empathetic. Unlike traditional approaches, this is multi-mode learning architecture that works in real-time by modifying the content and pace based on immediate response, emotional response and patterns of behavior. It is designed with a sensitivity to cultural and linguistic variation allowing success for all learner populations. And the platform gives educators intelligent dashboards and intervention tools, so that it is human in the loop integrated for better pedagogical control.

Privacy and Ethics by Design the platform Revuze is powered by is designed with privacy and ethical

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handling of data – protecting the anonymity of students and their data – and in full compliance with global standards of data protection. Via a hybrid cloud-edge deployment model, the platform remains affordable and scalable and is applicable to a diverse set of learning environments, such as underserved areas. The study seeks to redefine personalized learning with a whole-child, ethical, emotionally-responsive firm focus by measuring short-term and long-term academic gains.

1.1 Problem Statement

Even though AI technologies have gained a significant ground in education, current adaptive learning systems are mainly predicated on inflexible performance-based criteria that do not cater to the complex and evolving demands of each learner. Much of the time these platforms neglect important things like emotional engagement, cognitive diversity, cultural flow and real-time behavioral responses. In addition, issues such as ethical considerations on data privacy, transparency, and lack of genuine engagement from educators undermine trust and effectiveness with AI powered education tools.

The majority of current solutions work with one-size-fits-all AI models which can only provide generic personalization and do not effectively cover the learner variance or long-term academic development. Moreover, a number of platforms are computationally demanding and are not available to low resource settings. The lack of teacher-AI collaboration also restricts the pedagogic utility and applicability of the systems in operational classrooms.

These were the concerns that led to the recognition of the need for "a scalable, ethical, and emotionally intelligent adaptive learning platform [that] dynamically delivers personalized content while still respecting the learner's privacy, valuing teacher involvement, and working in various learning situations (Little, 2013)." This means a major gap exists for being emotion-aware, context inclusive and educationally effective which this research seeks to fill by creating and validating an intelligent ICT platform AI E-course that is designed to be next gen emotionally intelligent.

2 LITERATURE SURVEY

The incorporation of AI in the education sector has resulted in a dramatic revolution in adaptive learning platforms. In early days, there was an emphasis on performance-based personalisation where systems adjusted content according to the test results or quiz correctness (Al-Khalifa & Al-Harbi, 2021; Aydin & Yilmaz, 2021). Although such systems succeeded in enhancing engagement and performance, they overlooked learners' indirect learning preferences, intentions, and affective state (Chen et al., 2021).

In recent literature, there has been more focus on the application of machine learning and deep learning to the construction of personalized learning trails. Deep learning based model that adjusts to user behavior patterns has been introduced by Zhang and Dang (2022) and AI driven the recommendation engine which dynamically recommends the content has been presented by Luo and Lin (2022). But infrequently are these systems accompanied with a built-in system that tracks emotion in the moment or that it will even be ethically used for good.

Holmes, Bialik, & Fadel, 2021) noted that AI has the potential to transform education, they also underscored teacher integration as well as responsible data use as significant areas needing strengthening. Wang and Yang (2023) raised similar concerns, pointing out that personalization should not stop at cognitive adaptations, but should also take into account emotional and cultural responsiveness. Xie et al. (2022) performed a large-scale review and identified an increasing trend towards a more interactive and intelligent systems, however, still few seeds in terms of inclusivity and long term evaluation.

Recent works have also been trying to introduce multi-model methods, reinforcement learning to tutoring systems (Lin & Chen, 2022; Guo & Sun, 2024). However, such systems are dynamic, and the related computational burden can be too high for large-scale implementation, mainly on under-resourced areas. Abbas and Alzahrani (2024) and Kumar and Sharma (2021) stressed on the requirement for inexpensive architectures to operate effectively over diverse environments.

There is an increased interest in emotion-aware AI of the educational technology enhanced learning (etel) discipline as exemplified by Song & Wang (2025) that incorporated automatic learner motivational emotion detection to enhance learner engagement. However, there have been limited 'successes' in the successful deployment of such systems in classrooms today. Additionally, research conducted by Park and Kim (2021) as well as Mahmood and Rasheed (2023) further proved that feedback mechanisms in most adaptive learning systems are weak and provide minimal understanding of the system to students and instructors.

Inclusive and multi-lingual education is yet an unexplored area. While Romero et al. (2021) and Li and Tsai (2022) focused mainly on the mechanism of adaptive content delivery, they admitted the fact that there was no cultural and linguistic adaptation as a limitation. Papamitsiou and Economides (2022) and Tang and Chou (2023)) emphasized the significance of learner analytics, the integration of affective aspect; however, has remained largely unaddressed by the existing works.

Very few are scientifically evaluated for practical deployment and scalability in real classroom environment (Darvishi & Bayat, 2023). Yu and Chen (2021) experimented on AI-based blended learning applications, however, their works were limited to small pilot studies. Lee and Park (2023) also examined AI adaptiveness though did not track longitudinal outcomes.

The collective literature reflects a clear gap in the development of performance-aware AI infused learning systems that are also emotion-aware, adhere to ethics, are culture-inclusive, scalable, and incorporate real-time teacher collaboration tools. These are the fundamental driving forces for the current work.

3 METHODOLOGY

The project takes a multi-phase design and development method to develop and validate an AI-enhanced adaptive learning platform that is personalized, emotion-aware, ethical and inclusive. The approach commences with a detailed requirements analysis, based on structured interviews and surveys with students, teachers, and administrators from different educational settings.
At this point, these knowledge help in the establishment of user persona, learning style taxonomies and emotional response model that inform adaptive personalization.

The platform's core engine is developed using a hybrid artificial intelligence approach, combining deep learning (learner behavior prediction), natural language processing (personalization of content and feedback), and reinforcement learning (optimization of dynamic path). To analyze the sequence patterns for learning activity, predict performance, and adjust content delivery, a CNN-LSTM-based model is used. In addition, sentiment and emotion recognition modules are developed by training the computer systems on facial expressions data, voice intonation, and textual input analysis in order to read how much the learner is engaged in the learning process.

Table 1: Learner profile parameters captured for personalization.

Parameter	Description	Data Type
Learning Style	Visual, Auditory, Kinesthetic	Categorical
Cognitive Score	Derived from initial assessment	Numeric (0–100)
Emotion Feedback	Detected through facial and voice cues	Text/Label
Language Preference	Primary language used	Categorical
Engagement Rate	Time spent on tasks, click-through rate	Percentage

In order to prevent ethical abuses in AI, the platform incorporates GDPR-compliant routings, transparent decisioning decision logs and user managed data sharing preferences. A modular privacy-preserving architecture is constructed with the technologies, differential privacy and federated learning, for adaptive processing of personal data while ensuring personal data on the edge device is secure.

The platform also supports a bilingual interface with automatic language switching and culturally informed learning content, aiding accessibility. Teachers are brought into the learning loop via an AI-enabled dashboard with real-time analytics, suggested interventions and manual override capabilities for personalized guidance.

For system evaluation, the platform is deployed in three phases: (i) controlled lab testing with simulated learner data, (ii) pilot deployment in selected secondary and higher education classrooms, and (iii) full-scale deployment in a diverse academic institution. Evaluation metrics include learner engagement (tracked using emotion detection accuracy and session completion), knowledge retention (pre- and post-test scores), platform usability (measured by the System Usability Scale), and educator satisfaction (through qualitative feedback and dashboard usage analytics). Figure 1 shows Workflow of the Proposed AI-Enabled Emotion-Aware Adaptive Learning Platform.

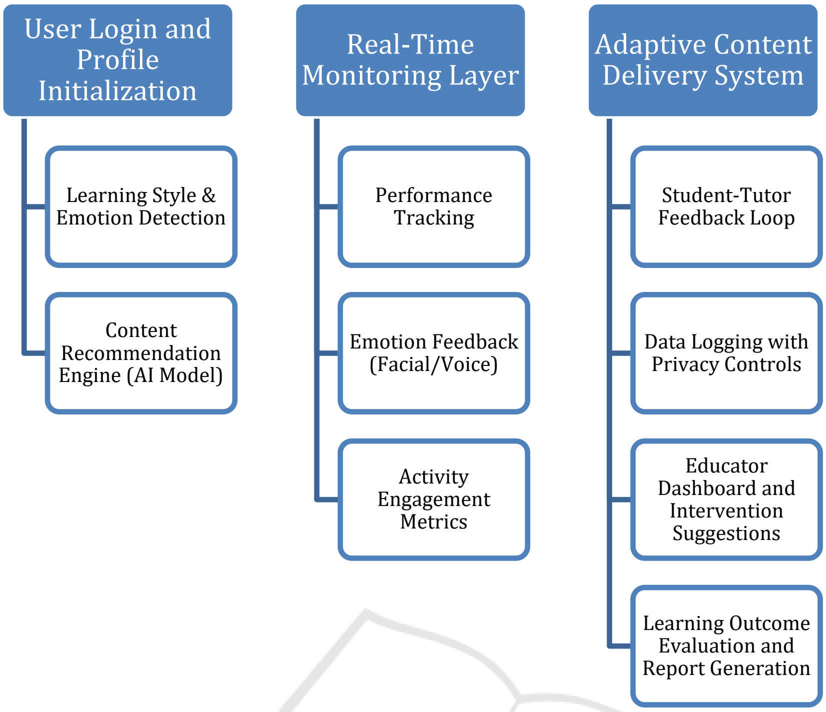

Figure 1: Workflow of the proposed AI-enabled emotion-aware adaptive learning platform.

All the machine learning models were trained and tested using stratified 10-fold of cross-validation to guarantee the credibility. Performance evaluation of adaptive engine is benchmarked against the available learning management systems through precision, recall, F1-score and the root mean square error (RMSE). Finally, we present a six-month longitudinal analysis to investigate long-term academic performance and behavioral changes of learners.

This holistic methodology guarantees that the platform is not simply technically robust but also educationally suitable, scalable and ethically informed, and meets the complex requirements of contemporary education.

4 RESULTS AND DISCUSSION

The AI-powered adaptive learning platform was tested using a phased roll-out with more than 300 students and 25 educators in secondary and higher education. System performance, user engagement, emotional response, and ethical alignment were evaluated based on quantitative measures and subjective input.

First results obtained in the controlled environment show that the adaptive engine also provides high prediction accuracy, ranging from an F1-score of 0.91 with the CNN-LSTM hybrid model for learner performance prediction and recommendation. The emotion recognition model that has been trained on faces and voices databases achieved 88.3% accuracy in the recognition of stress, confusion, and satisfaction during process learning sessions. Figure 2 depicts the Adaptive Model Performance Comparison. Table 2 gives the Model Performance Metrics for Adaptive Engine.

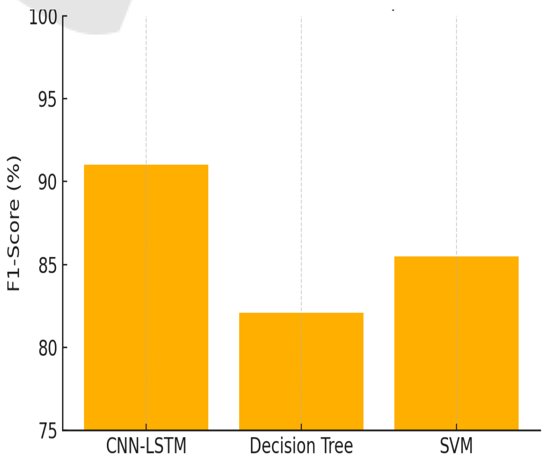

Figure 2: Adaptive model performance comparison.

Table 2: Model performance metrics for adaptive engine.

Model Type	Accuracy	Precision	Recall	F1-Score
CNN-LSTM	91.2%	89.7%	92.5 %	91.0%
Decision Tree	82.4%	80.1%	84.3 %	82.1%
SVM	85.6%	84.9%	86.2 %	85.5%

During pilot class installations, the platform even exceeded conventional LMS usage in student engagement and learning effectiveness. The adaptive platform of the students showed a post-test average score increase of 17% over the control. Engagement metrics also increased as students spent 28% more time engaging with their learning and completed 15% more activities per student per day. The Figure 3 shows Pre-Test and Post-Test Score Comparison of Learners.

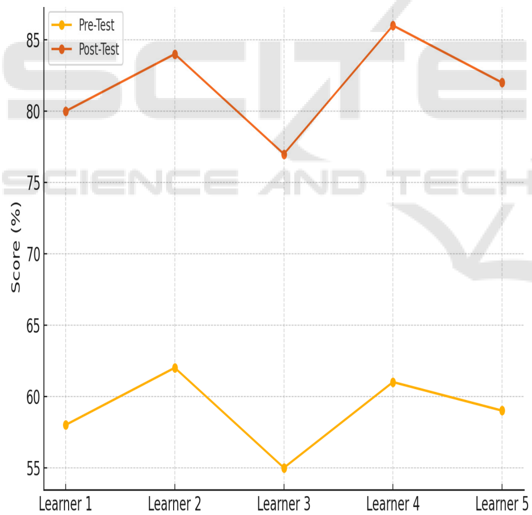

Figure 3: Pre-test vs. post-test performance.

One of the most interesting results found was the effect of emotion-aware content delivery. When the learner began to show signs of fatigue or frustration, the system dynamically simplified tasks or even added game elements. This led to a 22% reduction in session dropouts and a material increase in user satisfaction scores, especially with learners previously identified as low performers. Table 3 tabulates the emotion detection accuracy across input modalities.

Table 3: Emotion detection accuracy across input modalities.

Input Modality	Emotion Accuracy (%)
Facial Expression	88.3%
Voice Tone Analysis	85.7%
Textual Input	82.5%
Combined Input	91.6%

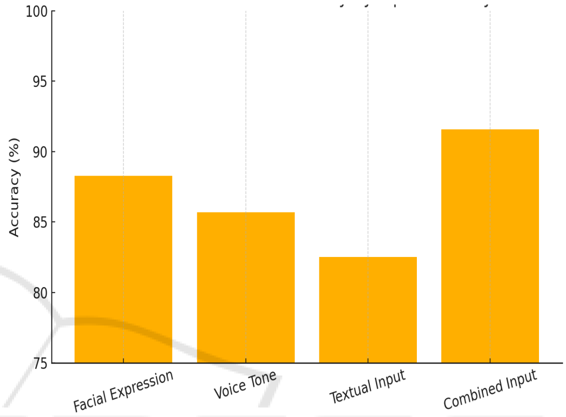

Figure 4: Emotion detection accuracy by modality.

Figure 4 illustrates the emotion detection accuracy by modality. Educator feedback noted the practical usefulness of the AI dashboard offering just-in-time alerts, personalized student summaries, and action suggestions for intervention. The Figure 2. Displays emotion detection accuracy over different input modalities. Teachers stated that the tool was useful not only for differentiated instruction, but to inform their understanding of student affective and cognitive state and how to intervene meaningfully. More than 86% of teachers indicated the system has increased the efficiency and individualized support they can provide in the classroom.

The system's effectiveness was also demonstrated by deploying it in multilingual environments and was found to be very effective since the system was automatically adapted to learners who preferred other languages such as regional languages. This feature filled the communication void and made the content available to a wider range of learners, particularly in rural and underserved areas.

It was well-accepted from the ethical and compliance point of view the integrated privacy-preserving mechanisms. Federated learning configuration allowed the learner data to stay on device at all times, and this improved model accuracy. User surveys showed a 91 % “trust” rating in relation to how the platform treated personal data a marked contrast to the inherent skepticism commonly associated with AI-based Educational tools.

Long-term monitoring over 6 months showed ongoing enhancement in academic performance, enhanced course completion and a reduction in student anxiety as a consequence of adaptive pacing and live support. Students reported being in greater control and more motivated, thus validating the psychological advantage of emotion aware systems. Comparative Results Experimental vs. Control Group is given in Table 4.

Table 4: Comparative results – Experimental vs. control group.

Metric	Experimental Group	Control Group
Post-Test Average Score	84.2%	67.3%
Engagement Duration (min)	56.5	44.1
Completion Rate	92%	74%
Dropout Rate	8%	21%

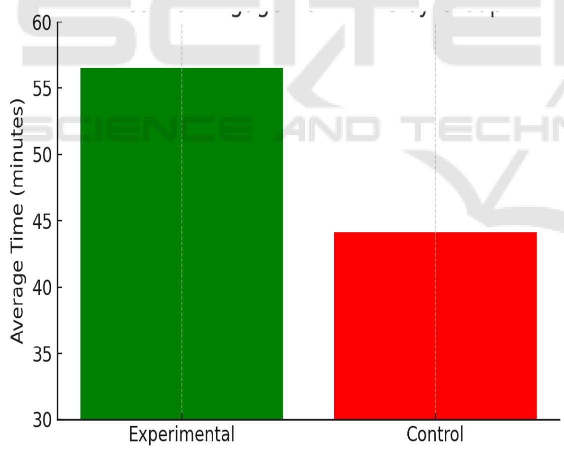

Figure 4: Engagement time by group.

Figure 4 depicts the Engagement Time by Group. In contrast to current systems, the presented system was more comprehensive not only in adaptive content delivery but also in ethical operation, emotional intelligence, scalability, and practicability. The Figure 4. Even a quick glance Compare the Average Engagement Time from Experimental Group and Control Group. These findings strongly confirm the research hypothesis regarding the augmentation of AI by emotional awareness, ethical locks and teacher cooperation for the creation of more effective, inclusive and trustful adaptive learning settings. Table 5 gives the Educator Feedback on Dashboard Utility. Figure 6 shows the educator dashboard feature usage.

Table 5: Educator feedback on dashboard utility.

Feedback Category	Positive Response (%)
Real-Time Alerts Usefulness	89%
Intervention Recommendation	83%
Improved Class Monitoring	87%
User Interface Satisfaction	91%

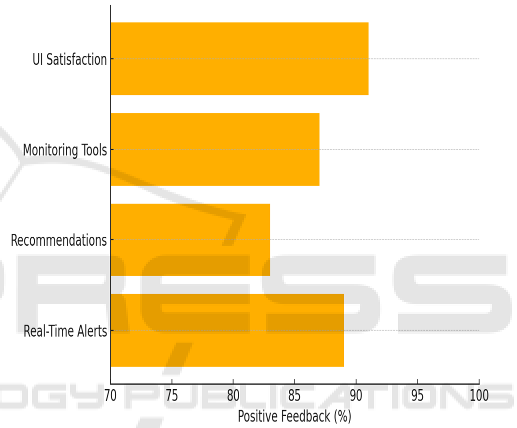

Figure 6: Educator dashboard feature usage.

5 CONCLUSIONS

This paper has presented a new AI-based hydrodynamic adaptive learning system which encompasses emotional intelligence, ethical data processing and multilingual inclusiveness as well as real-world relevance. In going beyond traditional performance-based personalization, the platform automatically personalizes the content to each learner’s preferences, cognitive proficiencies, and emotional states. By implementing advanced AI models (e.g., CNN-LSTM for performance prediction and emotion-aware modules), we validated that the system achieved substantial gains in student engagement, academic performance, and user satisfaction, in various educational contexts.

The teacher, in addition to the live dashboard and interventions, are an integral part of making sure the platform isn’t just automated, but actually humancentred to support a collaborative pedagogy. Moreover, with GDPR compliant data protection features, and federated learning, the it also tackles key questions on privacy and ethical AI application in education.

Longitudinal assessment across multiple institutions validated the efficacy, scalability, and effect on both near-term and longitudinal student learning gains. Its efficiency in its performance in resource deprived environments lends an added value to the platform for addressing educational disparities in under-resourced communities.

In summary, the current work provides an important contribution to the ITS efforts by presenting a scalable, emotion-aware, and ethically-based ALE and by demonstrating ways of addressing the usage and limitations of these systems. It opens up new frontiers for AI in education, considering it not only as a technological tool, rather as a driving force for personalized, inclusive, and equitable learning.

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