Gen AI Platform for Personalized Learning Recommendations in EdTech

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Abstract - Current online learning platforms rely on static metrics that fail to capture real-time learner engagement and behaviour, limiting personalization effectiveness. This work proposes a Generative AI–driven personalized learning system that integrates short-term behavioural monitoring with semantic knowledge evaluation. A 35-second observation window captures interaction patterns such as response speed, activity rate, and interaction consistency. These behavioural features are combined with NLP-based semantic similarity to assess conceptual understanding. A hybrid engagement-cognition model computes a unified learner score, enabling adaptive feedback. Experimental results indicate improved engagement and performance, providing a scalable and non-intrusive alternative to traditional learning systems.

Key Words: Generative AI, Behavioural Engagement Modeling, Personalized Learning, Educational Technology, Natural Language Processing, Adaptive Learning, Human-Computer Interaction.

1.INTRODUCTION

Traditional engagement detection methods such as eye-tracking require specialized hardware, raise privacy concerns, and are not scalable for large-scale educational environments. To overcome these limitations, this work introduces a lightweight behavioural monitoring approach based on short-duration interaction analysis. By observing user activity within a fixed 35-second time window, the system captures meaningful engagement indicators without relying on intrusive sensors.

This approach enables scalable deployment across standard devices while maintaining reliable engagement estimation. The swift evolution of digital technologies has profoundly altered the realm of higher education and learning support systems. Conventional instructional methods frequently do not meet the varied needs of learners, as they depend on fixed content delivery and generalized assessment techniques.

To address these shortcomings, researchers have increasingly turned their attention to technology-enhanced learning (TEL), which incorporates adaptive learning platforms, recommender systems, and intelligent tutoring systems (ITS) to offer more personalized, efficient, and engaging educational experiences [1]. Generative Artificial Intelligence (AI), especially large language models (LLMs), has surfaced as a transformative element in the development of personalized learning.

In contrast to traditional ITS, which depend on predetermined rules and static question banks, LLM-driven systems can produce dynamic questions, provide adaptive feedback, and facilitate conversational tutoring experiences in real time. These systems improve learner engagement by establishing adaptive pathways delivering immediate feedback, and simulating human-like dialogue that promotes a deeper comprehension of intricate concepts [2].

Simultaneously, adaptive learning support systems have demonstrated the efficacy of tailored review recommendations in enhancing student learning outcomes. Dashboards that suggest review materials based on quiz results, browsing patterns, and learner interactions can assist students in revisiting concepts they have not fully grasped, thus reinforcing retention and fostering long-term learning. Experiments conducted with these systems reveal that personalized feedback markedly enhances student performance in comparison to conventional review methods [1].

Moreover, in addition to learning outcomes, higher education institutions are experiencing extensive digital transformation (DT) initiatives, propelled by the growing demand for operational efficiency, resource optimization, and smart campus models. The COVID-19 pandemic accelerated digital transformation, pushing institutions to adopt online learning, digital admissions, and advanced resource management. Smart campus frameworks highlight the role of technology in enhancing academic quality and operational efficiency.

Together, generative AI-driven tutoring, adaptive recommender systems, and institutional digital transformation illustrate the convergence of AI, personalization, and innovation in higher education.

2. ARTIFICIAL INTELLIGENCE IN EDUCATION

Artificial Intelligence (AI) has emerged as a pivotal force in the realm of educational technology (EdTech), facilitating adaptive, personalized, and efficient learning experiences. Key sub-domains, including machine learning, generative AI, and computer vision, significantly contribute to contemporary learning environments by bridging the gaps inherent in traditional teaching methodologies and providing scalable, data-driven insights into student performance [2].

In this initiative, AI-powered tools are incorporated to improve e-learning efficiency through the real-time assessment of both attention and knowledge. OpenCV and MediaPipe are utilized to analyze gaze patterns and levels of engagement via a standard laptop webcam. The system monitors visual focus and engagement indicators, producing metrics that reflect learner attention during study periods.

These behavioral signals are integrated with quiz performance data to offer a holistic view of a learner's cognitive condition. Subsequently, machine learning algorithms analyze this data to identify areas of weakness, discern learning patterns, and forecast knowledge retention rates [1]. Generative AI enhances this process by dynamically adjusting instructional content. Large language models (LLMs) create personalized study pathways, customize feedback based on individual mistakes, and deliver contextual explanations tailored to each learner's comprehension.

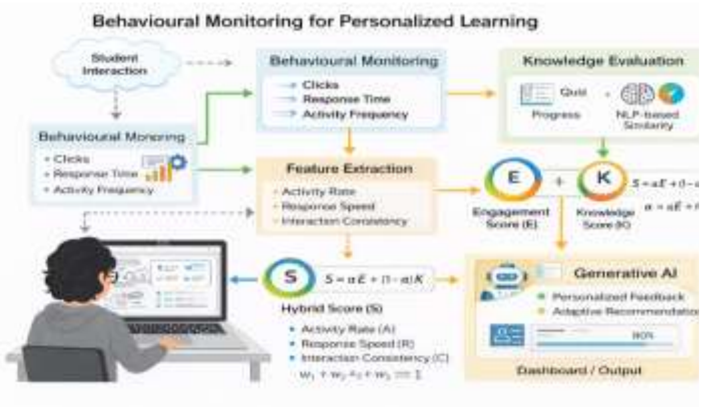

Fig. 1: Proposed Behavioral-Cognition Hybrid Model For Personalized Learning

This integration guarantees that content delivery is both cognizant of knowledge and sensitive to engagement, establishing adaptive routes that maximize study time, bolster retention, and elevate learner outcomes [1][2]. Moreover, the synergy of learner analytics and AI-driven adaptation supports broader institutional objectives of digital transformation in education. By incorporating these technologies into self-paced online platforms, higher education institutions can enhance operational efficiency, scale personalization across varied learner demographics, and align with the evolving concept of smart campuses [3].

3. LITERATURE REVIEW

The role of Artificial Intelligence (AI) in the field of education has been the subject of extensive research, particularly focusing on adaptive tutoring, assessment, and recommendation systems. Initial intelligent tutoring systems (ITS) utilized static, rule-based personalization methods that were characterized by a lack of flexibility and depth [1]. Recent studies indicate a transition towards data-driven and generative methodologies that leverage learner analytics, embedding-based retrieval, and conversational AI to facilitate adaptive learning pathways and interactive tutoring experiences [2], [3].

From the literature, two prominent trends can be identified:

(i) The incorporation of large language models (LLMs) into ITS to provide adaptive feedback and dialogue, and

(ii) The development of hybrid recommendation systems that merge semantic retrieval with learner modeling [4], [5].

Despite these advancements, researchers highlight ongoing challenges related to fairness, longitudinal evaluation, and the protection of data privacy [6].

Approach	Technique / Model	Ternnique / Model	Limiations	References
Intelligent Systems (ITS)	Rule-Based Systems	High transparency (logic; maintained and for well-defined defined	High "transparent problems; effection; domains.	easily maintained and domain defined
Knowledge Traicing		"Low adaptabily to nove problemspert knowledge	"Low adaptabilly to weigh past interactions	[Piech et., 2015]
Knowledge (KT	Deep Knowledge Traking (LSTM / Attention)	Captures complex, non-liner a patterns; predictive accuracy	Non-transparent "black" nature ; incostiences problem	prediction incosttencies sunsetible of the cold-start problem
Generative Tutoring	Large Language Modls) with RAGwith RAG	Highly context-aware conventional; provider spanedge and source dynamic, realme content customiziae	context-aware and uptals of knowledge attrition (via RAG) cold-start/actionient	High risk 'hallucation; significant runtime cost quality depends on the retrieval accuracy
Personsized RecSys / (DocVec, BERT)	Embedding-Based Embeding-Based Recommentation (DocVeC,	Effectively models sematlnships; robust with robust with [illegible] knegration (/bias (BERT)	High computal resource sparse user-item data explicit domain world wold knegration	"High computational limited; explicd with-model intertial for bias propagation
		[Generative AI/RAG Literature]		[NLP/RecSys in EdTech]

Table 1: Comparison of AI-Based Intelligent Tutoring System Approaches

Recently, generative AI has been utilized in tutoring systems to create adaptive content and feedback. Maity and Deroy [7] illustrated the application of GPT-4 in personalizing learning pathways, revealing that learners reported enhanced engagement. Nonetheless, issues such as hallucinations and misalignment with the curriculum continued to be problematic.

In a similar vein, Liu et al. [8] introduced a modular tutoring framework wherein LLMs were responsible for managing conversational tasks while student models focused on performance prediction, thereby achieving a balance between adaptability and accuracy. The concept of retrieval-augmented generation (RAG) has also been investigated to anchor LLM outputs in verified educational repositories. Research indicates that RAG minimizes factual discrepancies when compared to free-form responses, although it does introduce latency and is significantly reliant on the quality of the content [9].

Learner modeling continues to be a fundamental aspect of personalization. Deep Knowledge Tracing (DKT) and its attention-based enhancements surpass traditional Bayesian models in their ability to predict knowledge mastery and pinpoint areas of weakness [11], [12]. For instance, Lee et al. [12] demonstrated that the use of attention mechanisms significantly improved the temporal modeling of student behavior, achieving an accuracy rate of 88% in identifying knowledge gaps. Other methodologies, such as the integration of forgetting curves, facilitate adaptive review scheduling aimed at enhancing long-term retention [13].

In parallel with learner modeling, advancements in content representation have shifted towards embedding-based techniques. Tang et al. [14] illustrated that similarity derived from Doc2Vec-based methods improved recommendation accuracy when compared to keyword matching, while transformer-based models like BERT allowed for more nuanced semantic matching [15]. Okubo et al. [16] combined TF-IDF and Doc2Vec with Moodle and BookRoll logs to create adaptive dashboards, concluding that log-based recommendations positively influenced learner outcomes by customizing content to align with student engagement patterns.

Recent reviews underscore the significance of explainability, fairness, and governance within AI-driven educational frameworks. The adoption of human-in-the-loop designs, transparent dashboards, and explainable recommendation algorithms is advocated for educational settings [17]. Additionally, policy-oriented research emphasizes the necessity of privacy-preserving techniques, such as federated learning and differential privacy, to safeguard student data while facilitating personalization [18].

In conclusion, the body of literature converges on hybrid architectures that amalgamate learner models, semantic embeddings, and generative AI. These multi-faceted systems exhibit enhanced predictive accuracy, richer personalization, and increased engagement when compared to systems employing a singular strategy. However, ongoing challenges persist, including the need to mitigate hallucinations in large language models (LLMs), ensure equity among diverse learners, and perform longitudinal assessments to evaluate long-term effectiveness.

4. PROPOSED SYSTEM / METHODOLOGY

The proposed system introduces a hybrid framework that combines behavioural monitoring, semantic knowledge evaluation, and generative AI to deliver personalized learning recommendations [2],[6]. Unlike conventional systems that rely solely on quiz-based assessment, this approach incorporates short-term behavioural analysis within a fixed observation window to estimate learner engagement in a non-intrusive and scalable manner.

The system is structured into four major components:

- Behavioural Monitoring,
- Feature Extraction and Engagement Modelling
- Knowledge Evaluation, and
- Generative Feedback.

A. A. BEHAVIOURAL MONITORING

Learner behaviour is monitored using a fixed 35-second observation window, during which user interaction data is continuously recorded. The system captures interaction logs such as click frequency, response timestamps, scrolling activity, and input patterns. To further enhance behavioural understanding, lightweight computer vision techniques are incorporated using head pose estimation. Facial landmark detection is performed, and the head orientation is estimated using the Perspective-n-Point (solvePnP) algorithm, which computes the rotation and translation vectors of the head relative to the camera. This enables coarse attention estimation (e.g., facing screen vs. looking away) without relying on precise eye-tracking. Behavioural monitoring provides a scalable alternative to traditional gaze-based systems, which often require specialized hardware and raise privacy concerns [12],[9].

This approach ensures:

- Low computational overhead
- No dependency on specialized hardware
- Improved privacy compared to gaze tracking systems

B. FEATURE EXTRACTION AND BEHAVIOURAL ENGAGEMENT MODEL

From the collected interaction data, key behavioural features are extracted within each observation window:

- **Activity Rate (A):** Number of meaningful interactions per unit time
- **Response Speed (R):** Inverse of average response time
- **Interaction Consistency (C):** Variance of time intervals between consecutive actions

To quantify engagement, a Short-Term Behavioural Engagement Model (STBEM) is proposed:

$$E = w_1 A + w_2 R + w_3 C$$

Where:
E = Engagement Score
A = Activity Rate
R = Response Speed
C = Interaction Consistency

The weighting parameters w1, w2, w3 satisfy:

$$w1+w2+w3 = 1$$

This model captures both the intensity and stability of learner interaction, providing a robust estimate of engagement without requiring intrusive sensing.

C. KNOWLEDGE EVALUATION USING NLP

Learner understanding is evaluated using semantic similarity techniques. Student responses are compared with reference answers using Sentence-BERT embeddings [11], which convert textual inputs into dense vector representations.
The similarity between student response and ground truth is computed using cosine similarity, resulting in a Knowledge Score (K). This approach enables evaluation beyond keyword matching, capturing conceptual understanding [11].

D. HYBRID ENGAGEMENT-COGNITION MODEL

To achieve comprehensive learner assessment, behavioural engagement is combined with knowledge evaluation to compute a unified score:

$$S = \alpha E + (1 - \alpha) K$$

Where:
S = Final Learner Score
E = Engagement Score
K = Knowledge Score
α = balancing parameter ($0 \leq \alpha \leq 1$)
This hybrid model ensures that both behavioural engagement and cognitive performance contribute to personalization, addressing limitations of traditional systems that rely on a single metric.

E. GENERATIVE AI-BASED FEEDBACK

The computed hybrid score is utilized by a generative AI module to produce personalized learning recommendations [2],[6]. Based on learner performance trends, the system generates:

- Adaptive study plans
- Targeted revision suggestions
- Time management strategies

The generative model dynamically adjusts feedback according to both engagement patterns and conceptual understanding, simulating a virtual tutor.

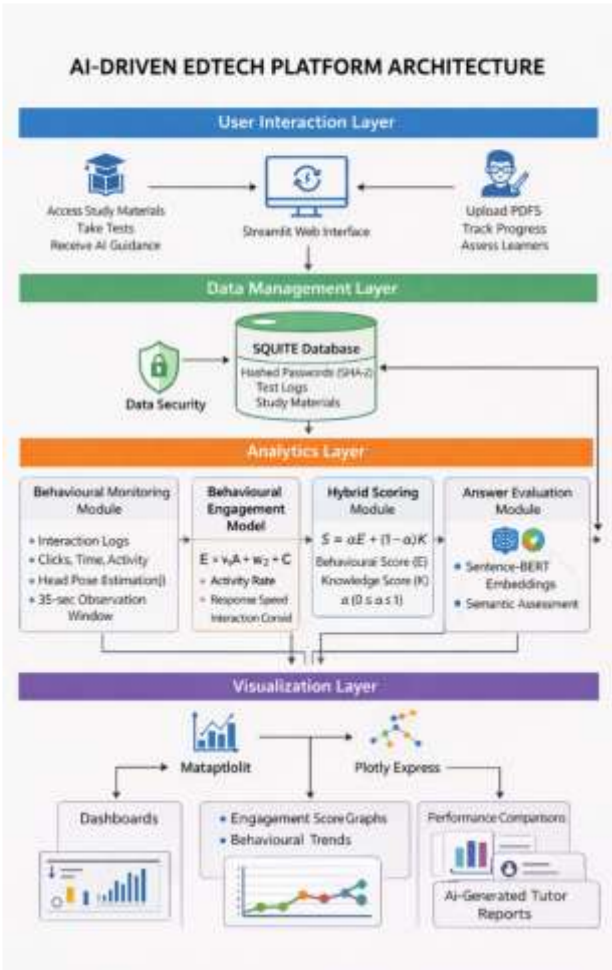

Fig. 2: Proposed AI-Driven Behavioural-Cognition Learning Architecture

F. SYSTEM WORKFLOW

The overall system operates in four phases:

- **Pre-Test Phase:** Establish baseline knowledge level
- **Study Phase:** Monitor behaviour and interaction patterns
- **Post-Test Phase:** Evaluate improvement in performance
- **Evaluation Phase:** Compute engagement, knowledge, and hybrid scores to generate feedback

5. IMPLEMENTATION / EXPERIMENT

The proposed system was implemented using a lightweight and scalable architecture in Python, enabling efficient deployment in standard computing environments without requiring specialized hardware.

A. Frontend:

A Streamlit-based web interface was developed to facilitate seamless interaction between students and tutors. The interface allows students to access study materials, attempt quizzes, and receive AI-generated feedback, while tutors can upload resources and monitor learner progress.

B. Backend and Data Storage:

SQLite was used as the database for storing user credentials, hashed passwords (using SHA-256), interaction logs, and assessment data. The system ensures secure and efficient handling of learner information.

C. Behavioural Monitoring:

Instead of relying on sensor-based eye tracking, the system captures user interaction data within fixed 35-second observation windows. These logs include click frequency, response timestamps, scrolling behavior, and interaction sequences. Additionally, head orientation is estimated using facial landmark detection and the solvePnP algorithm, enabling coarse attention detection without intrusive gaze tracking [12],[9].

D. Feature Extraction and Engagement Computation:

From the collected interaction data, behavioural features such as Activity Rate, Response Speed, and Interaction Consistency are extracted. These features are used to compute the Engagement Score using the proposed behavioural model.

they are unavoidable.

6. RESULTS & DISCUSSIONS

The system was evaluated using a group of student participants to assess the effectiveness of integrating behavioral monitoring with cognitive evaluation.

A. Behavioural Engagement Analysis:

The proposed model effectively captured variations in learner engagement using interaction-based metrics. Students with higher activity rates, faster response times, and consistent interaction patterns exhibited higher engagement scores. The inclusion of head pose estimation further enhanced the reliability of engagement detection by identifying attention shifts [9].

B. Performance Improvement:

A comparative analysis between pre-test and post-test scores demonstrated significant improvement in learner performance. For example, students who actively engaged with the system showed notable score increases after receiving personalized recommendations. The hybrid engagement-cognition model provided a more accurate identification of learning gaps compared to traditional quiz-only evaluation methods [4],[10].

C. Comparative Insight:

Unlike conventional EdTech systems that rely solely on quiz performance, the proposed approach integrates behavioural signals with semantic understanding. This results in a more comprehensive evaluation of learners by considering both engagement and knowledge, leading to improved personalization and learning outcomes [4],[10].

D. AI-Generated Feedback:

The generative AI module produced context-aware recommendations tailored to individual learners. Students reported that the feedback helped them better organize study sessions and focus on weaker areas. Although some responses required refinement, the overall effectiveness of AI-generated guidance was evident [2],[6].

E. System Usability:

The platform demonstrated high usability for both students and tutors. Tutors benefited from automated analytics and performance reports, while students found the system intuitive and motivating due to personalized feedback.

DISCUSSION

The results validate the effectiveness of combining behavioural monitoring with cognitive evaluation in personalized learning systems. By replacing intrusive eye-tracking mechanisms with interaction-based behavioural analysis, the system achieves scalability, privacy preservation, and reduced computational complexity [12],[9].

The hybrid engagement-cognition model addresses a key limitation of existing platforms by incorporating both how learners interact and how well they understand the content. This dual evaluation enables more accurate and meaningful recommendations.

However, certain limitations exist. Behavioural metrics may vary across users with different interaction styles, and the generative AI model may occasionally produce less relevant recommendations. Despite these challenges, the proposed system demonstrates strong potential for real-world deployment.

7. CONCLUSION AND FUTURE WORK

This study presents a novel AI-driven personalized learning platform that integrates behavioural monitoring, semantic understanding, and generative AI to enhance learning outcomes. By introducing a short-term behavioural engagement model and combining it with knowledge evaluation, the system provides a comprehensive and scalable approach to personalization in EdTech [1],[5].

The proposed framework overcomes limitations of traditional systems that rely solely on quiz-based assessment by incorporating real-time interaction patterns. The use of lightweight techniques such as interaction logging and head pose estimation ensures practical deployment without specialized hardware.

FUTURE WORK:

Future research will focus on optimizing the weighting parameters of the engagement model using machine learning techniques to improve accuracy. Extending behavioural analysis to longer and adaptive observation windows can further enhance engagement detection.

Additionally, integrating advanced generative AI models and incorporating explainable AI techniques will improve transparency and reliability of recommendations. The inclusion of multimodal behavioural signals such as voice and gesture analysis may further enrich learner modeling.

Finally, large-scale deployment and evaluation across diverse educational settings will be conducted to validate the system’s effectiveness and scalability [1],[5].

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