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AI- based Personalised Learning

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Abstract

Learning being personalised has become an important step in today's education, which aims to modify today's content, instruction speed, pacing of the content being presented and an individual's preferred method. E-learning has been a staple for many years now but traditional e-learning fails because it follows a ‘one shoe fits all’ method. We all know that one method can't be applied for children with varied learning abilities, especially when a lot of children struggle with learning disabilities. So, taking into account a child's cognitive and behavioural health to improve the learning system has become an important part of the whole education scenario. The system proposed in this research paper takes into account the following parameters - a child's psychological abilities and their preferences of learning paths. Learners are classified into three levels - beginner, intermediate and advanced based on their initial knowledge about a given subject and according to their level, content is displayed. An LLM using GPT 4 is also employed to make the system adaptive and responsive to a child's learning patterns, which can be ever-changing, making the system adapt with the student's changing habits. This ensures a dynamic personalised system of learning and strategies are deployed according to an individual's needs.

Keywords: Personalised Learning; Artificial Intelligence in Education; Education System; Adaptive Learning Systems; Learning Analytics; Large Language Models; Machine Learning

How to Cite This Article

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Introduction

The increasing growth in digital education or e-learning has greatly increased one's access to a lot of learning resources, but it has also failed to properly regulate the learning system or the education system as a whole [1],[2]. Even though e-learning has been around for a long time now, traditional learning systems still exist in most institutions [1]. The problem with the current education system is that it follows one strict method for every student but because each student has different learning patterns and capabilities, the system fails them [2],[4]. The benefit of employing personalised systems is that they can adapt to a particular student's learning abilities and create a learning path according to the student's needs and preferences [1],[7]. As learners also differ greatly in their knowledge capability, cognitive ability, emotional state, motivation or anxiety levels, an adaptive system can take into account all these factors and help the student learn more efficiently by giving them a personalised experience.

This research proposes a system based on the above mentioned points using artificial intelligence and machine learning concepts, taking into consideration a student's IQ levels, their psychological and cognitive skills and their academic capability and performance. It also integrates an LLM into the architecture, which makes the system more adaptive and delivers an interactive user experience. The main objectives of this research are:

- To design a learner profiling mechanism that combines academic, cognitive, and psychological parameters.
- To develop a weighted scoring model for accurate learner classification.
- To implement adaptive learning paths based on learner level and behavioural analytics.
- To evaluate the effectiveness of LLM-based personalisation.

Related Work

Traditional Personalised Learning Systems

Early personalised learning systems were mostly developed within the domains of intelligent tutoring systems (ITS) and adaptive hypermedia systems. These systems relied on rule-based learner models, where instructional content was adapted using predefined conditions based on previously studied learner responses [4]. Although they were good enough for basic adaptation, such systems lacked flexibility and scalability when learner diversity increased [1].

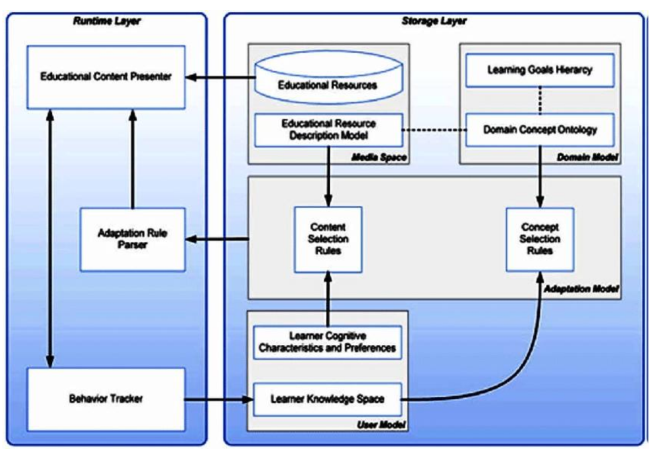


Fig. 1. *A block diagram demonstrating traditional learning system*

Key limitation**:** Personalization was limited to performance scores and did not consider emotional or cognitive differences. They also didn’t continuously adapt to a student’s changing learning habits or patterns [2].

Machine Learning–Based Adaptive Learning

With the evolution of machine learning, adaptive learning systems began using predictive models that use machine learning concepts to estimate learner knowledge levels and recommend suitable content according to their level of need [1],[3]. These systems improved personalization by learning from historical learner data and interaction patterns with the students [2].

Table 1. *Comparison of Traditional and ML-Based Systems*

Aspect	Rule-Based Systems	ML-Based Systems
Adaptability	Static	Dynamic
Scalability	Low	High

Learner Modelling	Manual	Automated
Emotional Factors	Not considered	Rarely considered, and therefore a top priority in our research

Affective, Cognitive and Psychological Factors in Learning

Role of Affective Factors (Confidence & Anxiety)

Educational psychology studies confirm that emotional states strongly influence learning outcomes. High anxiety affects concentration by decreasing it and also leads to lower test performance, whereas a good level of confidence enhances the engagement and retention by the student. However, most learning systems treat affective factors as secondary inputs rather than core evaluation parameters.

Cognitive Ability and Psychological Profiling

Cognitive assessments such as IQ tests help estimate reasoning ability and learning speed of a student as every student doesn't possess the same mark of intellect. Psychological traits like—motivation, stress tolerance, persistence—play an important role in deciding how learners interact with content. Existing systems rarely integrate these dimensions into a unified learner model

Proposed System

System Architecture Overview

The proposed framework integrates academic, affective, cognitive, and psychological assessments to generate highly personalised learning paths. The system follows a structured architecture that has regular feedback and adaptation by the model.

Main modules include:

- Learner data collection
- Affective assessment of psychological factors
- Subject knowledge test
- Weighted scoring model
- Learner classification
- Personalized path generator
- LLM-based adaptation engine

Weighted Scoring and Learner Classification

A self-designed weighted scoring model constructed by us combines:

- Subject test score
- Confidence level
- Anxiety level (inverse weight)

The model was trained on data collected from 30 test students to determine optimal weights. The final weighted score (W) is expressed as:

$$W = \alpha(Test\ Score) + \beta(Confidence\ Level) - \gamma(Anxiety\ Level)$$

$$W = \alpha T + \beta C - \gamma A$$

Learning Path Personalization

On the basis of a learner's level (that is assigned to the student using the diagnostic quiz), their IQ score and psychological profile (based on various psychological tests that they are asked to take from time to time) the system generates a customized learning path for each learner that is registered.

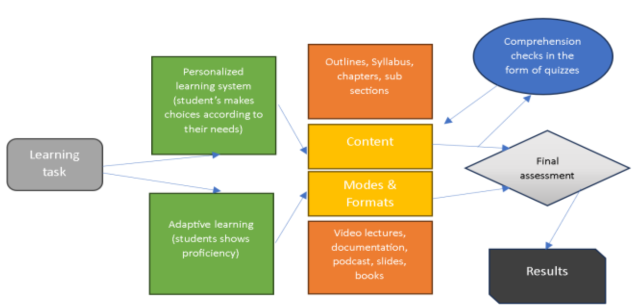


Fig. 2. *Systematic flow of the proposed AI-based personalised adaptive learning system*

Beginners receive basic concepts, intermediates receive revision and some difficult topics and advanced students get advanced level problems that ensure a greater understanding of any subject while keeping in mind the student's learning pace. Data is regularly collected from the interaction of LLM with the student and fed back to the system which in turn adapts and improves the whole personalized experience accordingly.

Continuous Adaptation Using LLM

A GPT-based Large Language Model is integrated to continuously personalize the whole learning experience of students by regular feedback and data collection. The LLM maintains long-term learner memory, including:

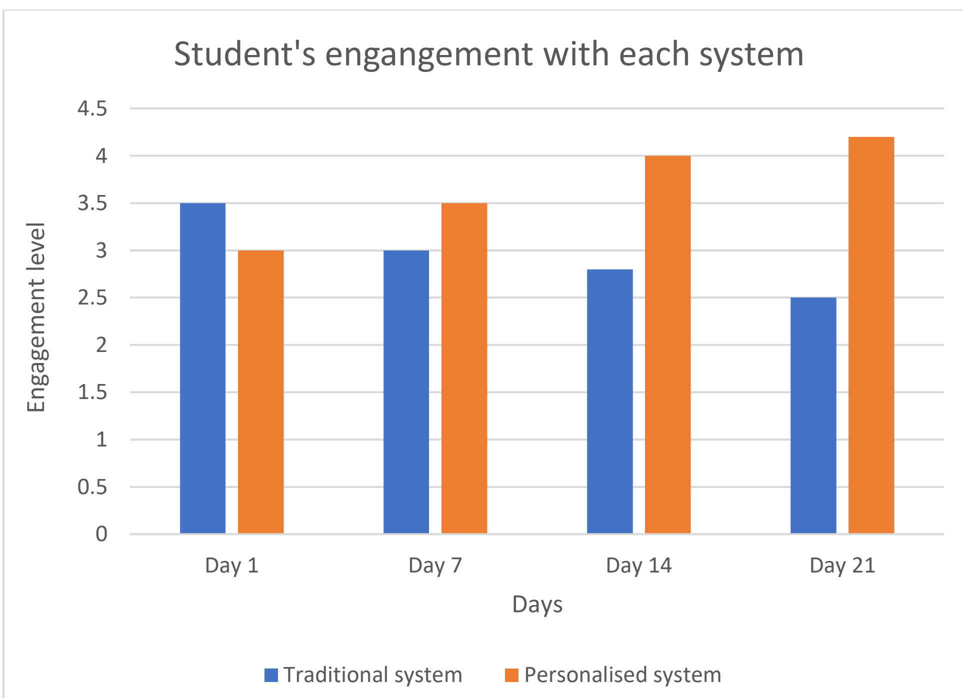
- Test scores
- Time spent on topics
- Attention span
- Memory retention
- Preferred learning style (text/video)

Results And Discussion

The proposed AI-based personalised learning system was evaluated using experimental data collected from a group of 30 students having varied academic backgrounds and learning habits. The evaluation focused on learner engagement, anxiety reduction, motivation upgradation, concept mastery, retention performance and classification accuracy.

Learner Engagement and Affective Impact

The results indicate a noticeable improvement in learner engagement when compared to traditional static learning systems. Learners interacting with the proposed system showed increased time-on-task and more consistent participation in learning activities. The inclusion of affective parameters like confidence and anxiety levels forces the system to adapt content difficulty and presentation style more appropriately. As a result, learners with higher anxiety levels felt reduced cognitive overload, leading to improved comfort and engagement maintained throughout the learning process. We studied the engagement level on a scale of 0-5 for 30 students for both traditional systems and personalised systems. We found that initially, people engaged more with traditional systems due to familiarity but with time, they were more inclined to study and preferred our personalised models over traditional systems.



Graph 1. *shows engagement level of students with each system*

Learning Performance and Concept Mastery

Faster concept mastery was seen among learners using the proposed framework. Adaptive content sequencing and personalized pacing enabled learners to progress according to their individual readiness levels rather than a fixed curriculum structure. Beginner-level learners benefited from structured explanations and frequent reinforcement, while advanced learners were able to move quickly through foundational material and focus on higher-level concepts. This adaptive strategy resulted in improved assessment scores over successive learning sessions. Students reported that due to personalised learning, they were able to grasp concepts on their own pace in their own way.

Knowledge Retention

The system also demonstrated higher knowledge retention rates compared to non-adaptive learning approaches, as it took student's history into account. Periodic recall-based evaluations and adaptive reinforcement mechanisms ensured that learners revisited concepts based on their retention performance. The LLM-driven personalization enhanced retention by modifying explanations and examples in response to learner behaviour and historical performance data, basically factoring in the student's cognitive behaviour into the answers. Also, multiple quizzes tailored to the student's capability helped them learn better.

Classification Accuracy and System Effectiveness

Integrating affective and psychological parameters enhanced learner classification accuracy majorly. The self-designed weighted scoring model, trained on data from 30 test students, provided a more comprehensive evaluation by including academic performance with emotional and cognitive indicators. This learner modelling approach reduced wrong classification and enabled more effective personalization of learning paths for each student.

Overall, the experimental results confirm the effectiveness of the proposed system in delivering improved learning outcomes. By integrating academic, affective, cognitive, and behavioural data with continuous LLM-based adaptation, the system performs better than traditional score-based personalized learning frameworks and shows strong potential for scalable, learner-centred education. It maintains engagement and better academic development of student body as a whole.

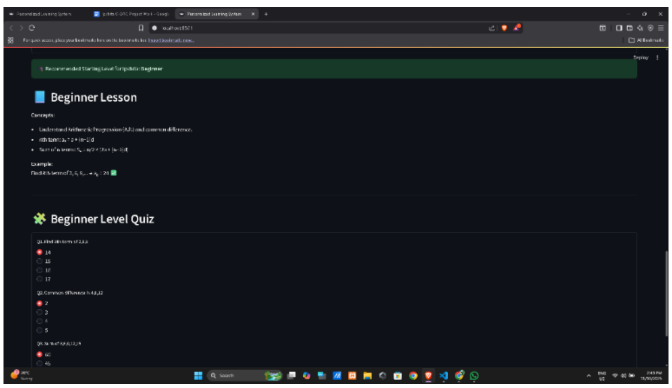


Fig. 3. *Recommending level with diagnostic quiz*

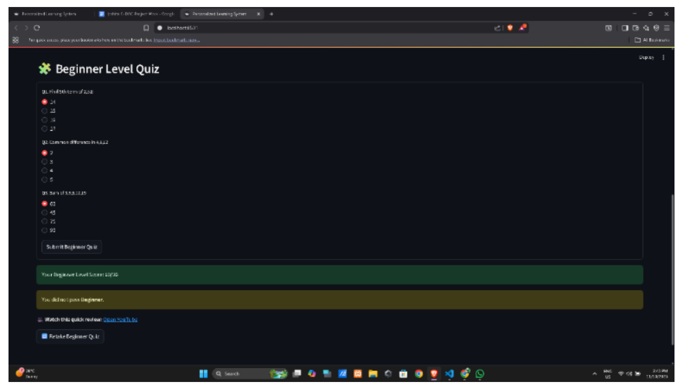


Fig. 4. *Video recommendation and student asked to re take quiz if it fails a level*

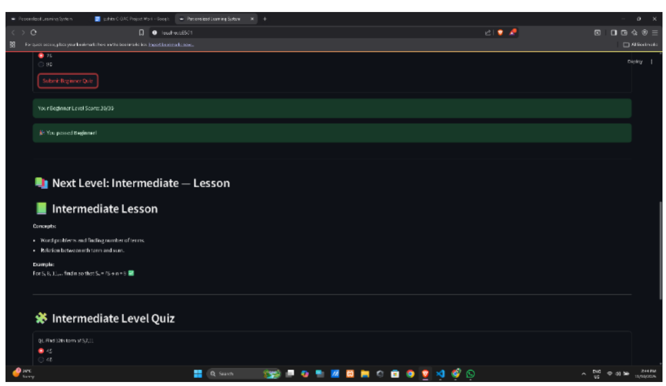


Fig. 5. *Moves on to new level as soon as a level is completed*

Conclusion And Future Work

This research presented an AI-based personalized learning framework that integrated academic assessment with affective, cognitive, and psychological profiling to deliver adaptive and learner-centred education. By combining a self-designed weighted scoring model by us with continuous LLM-driven personalization using GPT-4, the system effectively classifies learners and generates customized learning paths that adapt to individual needs and learning behaviours.

Experimental results show improved learner engagement; faster mastery of concepts and higher retention rates compared to traditional static learning systems.

Future work will focus on expanding the dataset to improve model generalization, incorporating real-time behavioural and physiological signals for deeper affective analysis, and conducting long-term studies to evaluate learning outcomes that are sustained through a period of time. Also, more optimization of LLM memory mechanisms and explainability of adaptive decisions will be explored to enhance transparency and scalability of the whole approach.

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