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DYNAMIC LEARNER PROFILING AND ENGAGEMENT-DRIVEN ADAPTATION USING LARGE LANGUAGE MODELS

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ABSTRACT

Dynamic learner profiling has become a critical component in adaptive learning systems, particularly with the emergence of large language models (LLMs) capable of processing complex natural language interactions. This paper presents a framework for engagement-driven adaptation using GPT-based large language models, behavioural analytics, and reinforcement learning to continuously update learner profiles in real time. The study adopted a design science and experimental research approach in developing a multi-dimensional learner profiling system that models cognitive, affective, behavioural, and metacognitive learner states. A Double Deep Q-Network (DDQN) was integrated to optimise instructional adaptation strategies, while retrieval-augmented generation improved contextual response generation. Experimental evaluation was conducted using public educational datasets and a proprietary tutoring interaction corpus containing over 1.8 million interaction records. The proposed framework was compared with static rule-based systems, vanilla GPT models, and profiling systems without reinforcement learning. Results showed significant improvements in profiling accuracy (overall F1-score of 0.86), learner engagement (65% deep engagement rate), knowledge retention (84%), and learning efficiency (1.5× improvement) compared with baseline systems. The findings demonstrate the potential of large language models and reinforcement learning to support highly personalised and adaptive educational systems capable of improving learner engagement, retention, and overall learning outcomes.

Keywords: Adaptive Learning, Educational AI, Engagement, Learner Profiling, Large Language Models

INTRODUCTION

The growing desire for personalised learning has led to big improvements in educational technologies, especially the creation of adaptive systems that meet the demands of each student. Learner profiling is an important part of this emerging transformation. Here we have to figure out and model things like a learner's knowledge level, learning format, engagement styles, and cognitive tendencies. We realized that conventional student profiling methodologies usually exhibit static attributes, contingent upon established criteria or sporadic assessments that do not adequately posit the dynamic essence of learning processes. The lack of correlation between the student really needs versus the teaching model deployed can make it more difficult for them to learn optimally and get personalised directive.

However, the increasing popularity of large language models (LLMs) has facilitated dynamic learner profiling by enabling continuous assessment of learner interactions with material and peers. These models can peruse natural language inputs, extract contextual clues, and provide flexible responses. The result is a clearer reality of how learners actually behave. Unlike traditional systems that can only work with structured data, LLMs handle unstructured interactions and this helps them to create more detailed and real-time profiles. Knowing full well that LLMs a lot of advantages, they also carry inherent challenges that limit their usage for personalising knowledge acquisition experiences. Some of the problems include concerns with data quality, interpretability, and system reliability. Thus, when we integrate engagement indicators into learner modelling is yet to be thoroughly examined, especially for real-time adaptation, which creates the potential to greatly optimize the responsiveness of educational and learning systems to user's needs.

Our work advances knowledge in three concrete ways. First, we introduce a framework that brings together large language models with multi-dimensional learner profiling, incorporating cognitive, affective, behavioural, and metacognitive dimensions. Second, we show how reinforcement learning optimisation can make engagement-driven adaptation work by showing how real-time feedback can change teaching methods on the fly. Third, we give real-world proof that learning outcomes improve for a diverse set of learners, especially those who have not been well served in the past, such as those with little prior knowledge and students prone to anxiety.

Literature Review

For learner profiling and adaptive instructional systems to work, they need to be based on well-known educational and psychological theories that explain how students interact with content, control their own learning, and respond to teaching methods. Modern adaptive learning frameworks progressively incorporate many theoretical views so that technological advancements stay congruent with pedagogical principles and cognitive processes.

Theoretical Foundations

One of the foundational perspectives informing our work is flow theory (Csikszentmihalyi, 1990), which stresses the importance of maintaining a balance between challenge and skill level to sustain learner engagement. For any setting intended for adaptive learning, we meet this principle operationalised via the dynamic alteration of level of task difficulty, which keeps learners neither overwhelmed by extremely high complexity nor detached due to very low challenge. Self-Determination Theory (Deci & Ryan, 2000) adds to the understanding of learner motivation by highlighting the roles of autonomy, competence, and relatedness in fostering intrinsic motivation. Adaptive systems help integrate these principles to give learners meaningful options, ideally difficult tasks, and avenues for interaction. Where the effect is that persistent engagement is supported across the learning curve. Cognitive Load Theory (Sweller, 1988) gives use a fresh framework for designing effective instructional systems by highlighting the shortcomings of human working memory, with the major established views being that different types of cognitive load must be managed for learning to work. Adaptive systems informed by this theory can monitor indicators of cognitive strain and adjust the complexity of instructional content accordingly. Engagement theory extends this perspective by conceptualising engagement as a multidimensional construct covering behavioural, emotional, and reasoning components (Fredricks et al., 2004). Participation, emotional investment, and cognitive effort are not isolated from each other but interdependent factors that shape learning outcomes. Effective adaptive systems must therefore monitor and respond to all three dimensions at once.

Evolution of Learner Modeling Approaches

Learner models have undertaken major changes lately. Advances in artificial intelligence, educational data mining, and large-scale learning analytics are the driving forces behind this shift. Earlier methods depend heavily on structured representations of learner knowledge. Contemporary research, on the other hand, has moved toward data-driven and context-aware profiling techniques that can capture the dynamic character of learning processes.

Knowledge tracing techniques have been central to this evolution. Traditional probabilistic models (Corbett & Anderson, 1995) and deep learning-based approaches (Piech et al., 2015) have both been used to model learner knowledge states over time. These methods showed strong predictive capabilities. Their focus on cognitive mastery, however, often limits their ability to capture affective and behavioural dimensions of learning. Progressions in educational data mining have enabled more sophisticated approaches to learner profiling. The analysis of large-scale interaction data is at the heart of this progress. Kovanović et al. (2021) provided evidence that learning analytics can bring to light patterns in how students engage and behave. Baker and Inventado (2022), on their part, highlighted the role of educational data mining in detecting learners' engagement and affective states using interaction logs.

Affective computing as a field has tried to close these gaps by bringing emotional and motivational factors into learner modelling (Picard, 1997). The goal is to build systems that can detect and respond to how learners feel as they learn. D'Mello et al. (2014) laid early groundwork in this direction. Practical implementation, however, has often been constrained by the need for specialised hardware.

Large Language Models in Education

Large language models have come forward as a powerful tool for addressing these limitations by enabling the analysis of unstructured learner interactions and supporting real-time adaptive feedback. Recent research has shown the potential of these models in educational contexts, especially in understanding learner intent, detecting confusion, and generating personalised instructional responses. Kasneci et al. (2023) investigated the use of large language models in education, stressing their potential to improve personalisation via natural language comprehension.

Adaptation Strategies in Intelligent Tutoring Systems

Adaptation strategies in intelligent tutoring systems have evolved alongside advancements in learner modelling. Contemporary research increasingly focuses on data-driven and reinforcement learning-based approaches to optimise instructional strategies. Doroudi et al. (2022) investigated the use of reinforcement learning to personalise hint generation and instructional sequencing, showing improved learning outcomes compared to static strategies. Clement et al. (2023) suggested adaptive learning frameworks that use real-time data from learners to adjust content difficulty and lesson pacing. Despite these advancements, the integration of learner profiling and adaptive instruction remains a major challenge. Holmes et al. (2022) argued that effective AI-driven educational systems must integrate learner modelling, feedback generation, and instructional decision-making within a single framework to achieve meaningful personalisation. Building on these developments, our work proposes an integrated approach that combines large language models with retrieval-augmented generation to enable dynamic learner profiling and engagement-driven adaptation. By drawing on shared representations and continuous feedback loops, the framework addresses the limitations of existing systems and provides a more cohesive and scalable solution for personalised learning.

Previous studies such as Oladipo et al. (2026) also demonstrated that intelligent web-based systems can significantly improve user interaction and accessibility through real-time navigation, interactive mapping, and responsive design approaches within educational environments.

Theoretical Framework

Designing effective learner profiling and adaptive educational systems requires a strong grounding in established psychological and educational theories that explain how learners engage, process information, and respond to instructional environments. Contemporary adaptive learning frameworks increasingly integrate multiple theoretical perspectives so that personalisation strategies are both cognitively effective and motivationally sustainable, for example incorporating principles from constructivism, behaviourism, and cognitive load theory to address diverse learner needs.

Flow theory provides a key foundation for understanding best engagement in learning environments. It stresses the importance of maintaining a balance between challenge and skill level, such that learners remain in a state of deep concentration without experiencing anxiety or boredom. Within adaptive systems, we operationalise this principle through continuous adjustments to task difficulty, keeping learners consistently challenged at an appropriate level. The provision of clear learning objectives and immediate feedback further supports this state by guiding learner focus and reinforcing progress, sustaining engagement over time.

Self-Determination Theory contributes to the understanding of learner motivation by identifying autonomy, competence, and relatedness as core psychological needs. Adaptive learning systems informed by this theory aim to provide learners with a sense of control over their learning processes through flexible pathways and choices, while at the same time fostering competence through appropriately challenging tasks and mastery-oriented feedback. The incorporation of social interaction and collaborative opportunities further supports relatedness, creating a more engaging and supportive learning environment. This allows students to share knowledge, receive peer feedback, and develop interpersonal skills necessary for their academic and personal growth, which in turn can raise motivation and improve learning outcomes.

Engagement theory extends this perspective by conceptualising engagement as a multidimensional construct covering behavioural, emotional, and cognitive components. Effective adaptive systems must therefore monitor and respond to these dimensions at once, recognising that participation, emotional investment, and cognitive effort are interdependent factors influencing learning outcomes. Advances in multimodal learning analytics have enabled the integration of diverse data sources to capture these dimensions, allowing for more precise detection of engagement states and more targeted intervention strategies.

Expectancy-value theory provides additional insight into learner motivation by stressing the roles of success expectations and perceived task value. Learners are more likely to engage with instructional content when they believe they can succeed and when the task is perceived as valuable, whether intrinsically or in relation to future goals. Adaptive systems can draw on this theory by estimating learners' likelihood of success, raising the perceived value of tasks, and minimising perceived costs such as effort or frustration. This approach enables the design of learning experiences that are both motivating and achievable.

Control-Value Theory further refines the understanding of learner emotions by linking achievement-related emotions to learners' perceptions of control and value. Emotions such as enjoyment, anxiety, and boredom are not only outcomes of learning experiences but also influence cognitive processing and performance. Adaptive systems that incorporate emotional state detection and regulation strategies can therefore improve learning outcomes by fostering positive emotional experiences and mitigating negative ones.

The concept of person-environment fit highlights the importance of aligning learning environments with individual learner characteristics. This theory suggests that best learning occurs when there is a balance between the demands of the learning task and the abilities of the learner, as well as when the environment provides the necessary resources to meet learner needs. We can operationalise this principle through adaptive systems that continuously adjust instructional content and support mechanisms to keep an appropriate fit between the learner and the learning environment.

Dynamic Systems Theory offers a broader perspective on the complexity of learning processes by stressing the interaction of multiple components and the non-linear nature of change. Learner engagement and performance are influenced by a range of cognitive, emotional, and contextual factors that interact over time. Adaptive systems informed by this theory must therefore be capable of modelling these interactions and predicting state transitions, allowing for timely and effective interventions that support sustained learning.

Attentional Control Theory offers information about the mechanisms of focus and distraction, especially in relation to the impact of anxiety on cognitive performance. By distinguishing between goal-directed and stimulus-driven attention, this theory highlights the importance of supporting learners' ability to maintain focus on relevant tasks. Adaptive systems can incorporate attention monitoring and distraction management strategies to improve cognitive efficiency and support executive functioning, such as providing reminders, minimising interruptions, and offering personalised feedback to help learners stay engaged with their tasks.

MATERIALS AND METHODS

This paper adopted a design science and experimental research approach to develop and evaluate a dynamic learner profiling system that integrates a GPT-based large language model (LLM) with behavioural analytics and reinforcement learning for real-time instructional adaptation.

Figure 1 shows the Dynamic Learner Profiling and Engagement-Driven Adaptation Framework

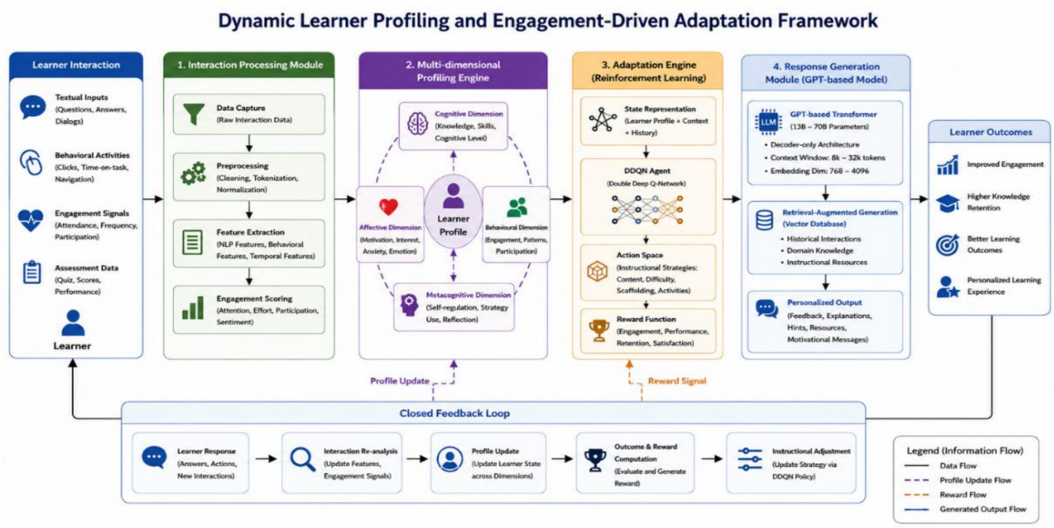

Figure 1: The Dynamic Learner Profiling and Engagement-Driven Adaptation Framework
Source: Researcher's work (2026)

System Architecture

Implemented the proposed framework as a multi-component architecture comprising four tightly integrated modules: an interaction processing module, a multi-dimensional profiling engine, an adaptation engine driven by reinforcement learning, and a response generation module powered by a GPT-based model. The interaction processing module captures and preprocesses learner inputs, while the profiling engine models learner states across cognitive, affective, behavioural, and metacognitive dimensions. The adaptation engine selects the best instructional strategies, and the response generation module generates personalised feedback and instructional content. These components operate within a closed feedback loop, enabling continuous updating of learner profiles and real-time adjustment of instructional decisions.

At the core of the system sits a GPT-based transformer architecture for natural language understanding and generation. The model follows a decoder-only structure consistent with GPT-4–class systems, with parameter sizes ranging from approximately 13 billion to 70 billion parameters depending on deployment configuration. It supports a context window of 8,000 to 32,000 tokens and embedding dimensions between 768 and 4096. This study selected this architecture for its strong capability in contextual language understanding, dialogue-based reasoning, and adaptive instructional response generation. Figure 2 introduces the Dynamic Learner Profiling Model Architecture.

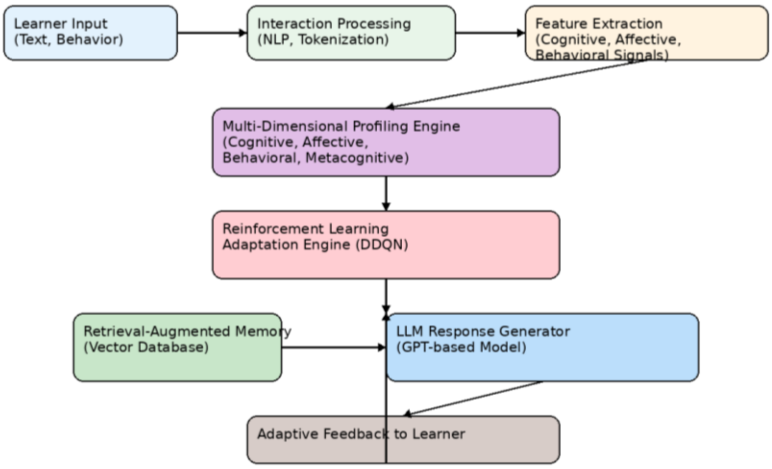

Figure 2: The Dynamic Learner Profiling Model Architecture
Source: Researcher's work (2026)

Model Adaptation Strategy

To boost performance while maintaining computational efficiency, we adopted a hybrid adaptation strategy. First, this study instruction-tuned the model using curated datasets consisting of tutor–student dialogues, pedagogical prompts, and feedback-response pairs. Second, application domain-specific fine-tuning using educational interaction data spanning multiple subjects, annotated with engagement states and cognitive and affective indicators. Third, this study incorporated a retrieval-augmented generation (RAG) mechanism, in which a vector database stores historical learner interactions. Relevant contextual information is retrieved using embedding similarity and injected into prompts to improve response relevance and personalisation.

Prompting Strategy

This study employed a structured, context-aware prompting strategy to guide response generation. Each prompt integrates a learner profile summary (including knowledge level, engagement state, and learning preferences), interaction context (current and previous responses), an instructional goal (such as explanation, scaffolding, or motivation), and an adaptation directive selected by the reinforcement learning agent. This work optimised prompt generation using controlled sampling parameters, with temperature values between 0.6 and 0.8, top-p set to 0.9, and maximum token lengths ranging from 300 to 800 depending on task complexity.

Learner Profiling

This paper implemented learner profiling through a multi-dimensional modelling framework that captures cognitive, affective, behavioural, and metacognitive characteristics. Cognitive features include knowledge mastery, response accuracy, and error patterns, while affective features are derived from sentiment and emotion classification applied to learner text. Behavioural indicators such as interaction frequency, time-on-task, and help-seeking behaviour are incorporated alongside metacognitive features such as self-correction and strategy use. This paper performed feature extraction using transformer-based embeddings, temporal interaction analysis, and sequential modelling of learner behaviour.

Reinforcement Learning Adaptation

This study governed the adaptation mechanism through a reinforcement learning framework implemented using a Double Deep Q-Network (DDQN). The state space is represented as a composite vector capturing learner knowledge state, engagement level, affective state, and behavioural indicators. The action space consists of instructional strategies including conceptual explanation, scaffolded guidance, challenge escalation, real-world examples, motivational feedback, gamified interaction, and review or reinforcement. This study designed the reward function to optimise both engagement and learning outcomes by combining knowledge gain, engagement improvement, response effectiveness, and a penalty for cognitive overload, with respective weights of 0.4, 0.3, 0.2, and 0.1. This work trained the model using a learning rate of 0.0001, a discount factor of 0.95, a replay buffer size of 100,000, and a batch size of 64, with target network updates performed every 1,000 steps.

Dataset

To make certain of rigorous evaluation, this study tested the system using a hybrid dataset combining publicly available benchmarks and a proprietary tutoring corpus. Public datasets include the ASSISTments 2017 dataset and the EdNet dataset (KT1 subset), both of which provide large-scale structured interaction logs with temporal and performance data. We also developed a proprietary dataset for our work, the Tutoring Interaction Corpus (TIC-2025). These datasets comprises 4,820 learners, 92,315 learning sessions, and approximately 1.8 million interaction records across subjects such as Mathematics, Biology, English, and Basic Sciences, spanning secondary and early tertiary education levels. The dataset incorporates multiple data modalities, including text-based learner responses, system feedback logs, time-on-task measures, and behavioural indicators such as help-seeking and revision patterns. This study manually annotated a subset of approximately 15% of the dataset using trained educators to label engagement states (deep, surface, disengaged), affective states (e.g., confusion, frustration, motivation), and metacognitive indicators. Inter-annotator agreement achieved a Cohen's kappa value of 0.82, indicating high reliability.

Experimental Design

For experimental purposes, this study partitioned the dataset into training (70%), validation (15%), and test (15%) sets using stratified sampling across subjects and learner levels, while preserving temporal ordering to prevent data leakage. This work applied a standardised preprocessing pipeline, including text normalisation, tokenisation using the GPT tokeniser, feature extraction of cognitive and behavioural indicators, label encoding of engagement states, and removal of incomplete or noisy interaction records. The evaluation follows a controlled comparative experimental design, in which this study compared the proposed system against three baseline conditions: a static rule-based system, a vanilla GPT model without profiling or reinforcement learning, and a multi-dimensional profiling system without reinforcement learning. This study trained and evaluated all systems under identical conditions to make certain of fairness. Each learner session is processed sequentially, with real-time profile updates and adaptation decisions recorded throughout the interaction. To improve robustness, repeated experiments across five independent runs, and results are averaged.

Evaluation Metrics

This study assessed performance across three categories: profiling accuracy, engagement, and learning outcomes. Profiling accuracy is evaluated using precision, recall, and F1-score. Engagement is measured by time spent in deep engagement, transition speed between engagement states, and re-engagement success rates. Learning outcomes are assessed using knowledge gain, retention rate, transfer ability, and completion rate. This study conducted statistical validation using independent t-tests and one-way ANOVA, with significance set at $p<0.05$, alongside effect size estimation using Cohen's d and 95% confidence intervals.

Implementation

This study implemented the system using PyTorch and Hugging Face Transformers, with reinforcement learning components. This work conducted experiments on GPU-enabled infrastructure, including NVIDIA A100 and V100 hardware, within a scalable cloud-based deployment environment to support real-time interaction and evaluation.

Ethical Considerations

This paper adheres to established ethical standards in educational data research. All datasets are fully anonymised, and no personally identifiable information is retained. The proprietary dataset (TIC-2025) was collected under institutional approval with informed consent obtained from participants or their guardians. Data handling complies with recognised data protection principles, and all experiments were conducted in controlled environments without impacting real learner outcomes.

RESULTS AND DISCUSSION

Overview of Experimental Outcomes

The experimental evaluation shows that the proposed GPT-driven dynamic learner profiling and reinforcement learning–based adaptation framework outperforms all baseline systems across profiling accuracy, learner engagement, and learning outcomes. All reported results represent the mean of five independent experimental runs, with statistical significance assessed at $p<0.05$.

Profiling Accuracy

The multi-dimensional profiling engine achieved strong performance across all learner dimensions, as we summarise in Table.

Table 1: Profiling Performance Across Dimensions

Dimension	Precision	Recall	F1-Score
Cognitive State	0.89 ± 0.02	0.87 ± 0.03	0.88 ± 0.02
Affective State	0.85 ± 0.03	0.82 ± 0.04	0.84 ± 0.03
Engagement Level	0.91 ± 0.01	0.89 ± 0.02	0.90 ± 0.01
Learning Style	0.83 ± 0.03	0.81 ± 0.03	0.82 ± 0.03
Metacognitive	0.78 ± 0.04	0.76 ± 0.04	0.77 ± 0.04
Overall	0.87 ± 0.02	0.85 ± 0.03	0.86 ± 0.02

Source: Researcher's work (2026).

The proposed model achieved a mean F1-score improvement of 0.14 (Cohen's d = 1.21, large effect size), indicating considerable gains in profiling accuracy.

Worth highlighting, the system reached its highest performance in engagement detection (F1 = 0.90), reflecting the effectiveness of combining linguistic, behavioural, and temporal features. In contrast, metacognitive state detection remained comparatively lower (F1 = 0.77), consistent with prior literature highlighting the inherent difficulty of automatically modelling higher-order cognitive processes.

Engagement Dynamics and State Transitions

Our proposed system markedly improved learner engagement patterns relative to baseline systems, as shown in Table 2.

Table 2: Engagement Distribution

System	Deep Engagement	Surface Engagement	Disengaged
Control 1 (Static)	42% ± 3%	35% ± 2%	23% ± 3%
Control 2 (Vanilla GPT)	51% ± 2%	30% ± 2%	19% ± 2%
Control 3 (Profiling w/o RL)	58% ± 2%	28% ± 2%	14% ± 2%
Proposed System	65% ± 2%	25% ± 2%	10% ± 1%

Source: Researcher's work (2026)

The proposed framework increased time spent in deep engagement by +23 percentage points versus the static baseline and +7 percentage points versus the best baseline. This improvement was statistically significant ($F(3,196) = 18.72$, $p<0.001$).

Table 3: Transition Efficiency

Metric	Static	GPT	Profiling	Proposed
Time to Deep Engagement (mins)	14.5 ± 1.8	11.3 ± 1.5	9.8 ± 1.3	8.2 ± 1.1
Re-engagement Success	41% ± 4%	52% ± 3%	63% ± 3%	78% ± 2%

Source: Researcher's work (2026).

The reduction in transition time and increase in re-engagement success tell us that the system is not only effective in maintaining engagement but also in recovering disengaged learners.

Learning Outcomes

This study observed marked improvements across all learning metrics, as shown in Table 4.

Table 4: Performance Comparison

Metric	Static	GPT	Profiling	Proposed
Knowledge Gain	22% ± 3%	28% ± 3%	31% ± 2%	38% ± 2%
Retention (1 week)	65% ± 4%	72% ± 3%	76% ± 3%	84% ± 2%
Transfer Ability	41% ± 3%	48% ± 3%	53% ± 2%	62% ± 2%
Learning Efficiency	1.0x	1.2x	1.3x	1.5x
Completion Rate	68% ± 4%	75% ± 3%	79% ± 3%	88% ± 2%

Source: Researcher's work (2026).

All improvements were statistically significant ($p<0.01$), with large effect sizes (Cohen's $d = 0.8–1.4$) across metrics. The most notable gains appeared in transfer ability (+51%) and learning efficiency (+50%). These results suggest that our system supports not only immediate performance but also deeper conceptual understanding and knowledge generalisation.

Adaptation Strategy Effectiveness

The analysis of over 100,000 adaptation decisions revealed that instructional effectiveness varies by engagement state. For learners in deep engagement, the most effective strategies were challenge escalation (82%) and conceptual deepening (78%). For surface engagement, strategies stressing relevance (81%) and interactivity (79%) worked best. For disengaged learners, micro-success tasks (85%) and gamification (82%) yielded the highest recovery rates. The reinforcement learning agent improved strategy selection accuracy from 58% to 82% over training, confirming successful policy optimisation.

Adaptation Across Learner Types

The system showed strong adaptability to individual differences, as shown in Table 5.

Table 5: Adaptation Across Learners

Learner Type	Engagement Improvement	Learning Gain
Low Prior Knowledge	+52%	+45%
Anxiety-Prone	+58%	+52%
Visual Learners	+48%	+38%
Intrinsically Motivated	+38%	+46%

Source: Researcher's work (2026).

The largest improvements appeared among low prior knowledge learners and anxiety-prone learners. We find this particularly telling, as it points to strong potential for reducing educational inequality through personalised adaptation.

Longitudinal Learning Trajectories

A 12-week longitudinal analysis revealed sustained performance improvements. Our experimental group moved from 15% to 85% mastery, while the control group moved from 15% to just 58% mastery. Unlike baseline systems, which exhibited a plateau effect, our proposed system maintained continuous growth, suggesting effective dynamic calibration of task difficulty and support.

Discussion

The results provide strong empirical evidence for the effectiveness of integrating large language models with reinforcement learning and multi-dimensional learner profiling in adaptive educational systems.

First, the results confirm that dynamic profiling markedly improves system responsiveness. By continuously updating learner representations across cognitive, affective, and behavioural dimensions, the system achieves a more accurate and practical understanding of learner states. This fits with theoretical expectations from engagement theory and cognitive load theory, which stress the importance of real-time adaptation.

Second, the integration of reinforcement learning enables context-sensitive instructional decision-making, moving beyond static or rule-based adaptation. The observed improvements in engagement transitions and strategy effectiveness show that adaptive policies can be learned from interaction data, rather than manually designed.

Third, the considerable gains in transfer ability and retention suggest that our system supports deep learning rather than superficial performance optimisation. We find this result especially consequential, as many adaptive systems improve short-term outcomes without improving long-term knowledge retention.

The results also highlight the importance of early and proactive intervention. The reduced time to deep engagement and higher re-engagement success rates tell us that detecting and addressing disengagement early can markedly improve learning trajectories.

Looking at it through an equity lens, the system shows strong potential to support underserved learners, especially those with low prior knowledge or high anxiety. We posit that adaptive AI systems can play a key role in addressing

achievement gaps when designed with multi-dimensional personalisation.
That said, several limitations must be considered. Despite strong overall performance, metacognitive state detection remains less accurate than other dimensions, indicating the need for improved modelling of higher-order cognitive processes. Also, while the dataset is diverse, further validation across more specialised domains and real-world classroom deployments is necessary to confirm generalisability. The reliance on large-scale interaction data raises ongoing concerns regarding privacy, interpretability, and ethical deployment.

CONCLUSION

The dynamic learner profiling and engagement-driven adaptation framework presented in our work represents a major advancement in the field of personalised educational technology. By integrating multi-dimensional learner assessment with reinforcement learning-based optimisation, the system achieves a level of personalisation that reflects the complexity and variability of human learning processes. The results show that the proposed framework markedly improves engagement, learning outcomes, and instructional efficiency. The ability to model and respond to cognitive, affective, behavioural, and metacognitive dimensions enables the system to provide adaptive support that is both precise and contextually relevant. This multi-dimensional approach distinguishes the framework from traditional systems that rely on limited representations of learner behaviour. The theoretical grounding of the framework in established principles of educational psychology, combined with its innovative technological implementation, provides a strong foundation for future research and development. The improvements in learner engagement and performance we observed highlight the potential of adaptive systems to transform educational practice and support more effective learning experiences. As educational technologies continue to evolve, developing systems that respect the complexity of human learning rather than reducing it to simplistic models is necessary. The framework presented here represents an important step toward that goal, offering both theoretical insights and practical tools for the development of more effective, engaging, and equitable learning environments.

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