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IMPACT OF AI-BASED ADAPTIVE LEARNING SYSTEMS ON STUDENT ENGAGEMENT AND LEARNING OUTCOMES

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Abstract
Adaptive learning systems that use artificial intelligence have become more popular in contemporary education, but their actual effectiveness in student engagement and achievement in STEM classrooms is not well understood. The paper is the evaluation of an adaptive learning model based on reinforcement learning implemented in a STEM course of a university in eight weeks. We examined the engagement measures among 120 students, the pre/post academic performance, and qualitative interviews of the students and instructors using a mixed-methods design. Findings indicate that adaptive AI system enhanced overall engagement by 28.4%, quiz accuracy by 17.2% and time-to-mastery by 22.9% relative to traditional fixed-path learning. The students indicated increased motivation and satisfaction with the individualized learning paths. These results indicate that adaptive AI systems can greatly increase STEM learning in case they are implemented into the current LMS systems.

INTRODUCTION

Artificial intelligence (AI) has become an increasingly important part of change in the educational landscape as it enables personalized learning-at-scale. Traditional learning systems tend to follow a predetermined instructional path which may not take into consideration individual differences in cognitive pace, prior knowledge and engagement level. In a traditional classroom, teachers typically present the same material to every student, which can cause some students to be bored with the material because it is too simple, while others become frustrated because the material is too difficult. Adaptive learning technologies seek to make up this gap by continuously adjusting the difficulty, pacing, and type of learning content based on the needs of the learner. These systems are based on real-time data about students' interactions, performance, and progress to make informed choices about what content or activity to present next to keep learners engaged and motivated throughout their courses.

Recent research highlights the potential of adaptive learning algorithms to provide personalized learning materials, offer targeted feedback, and improve academic outcomes (Zhao et al., 2020), (Lu, Tong, & Cheng, 2024). AI-based approaches, such as reinforcement learning (RL) and knowledge tracing (KT), are particularly promising, as they provide the potential to enable systems to not only monitor a student's internal knowledge of concepts over time, but to be able to dynamically determine what content to show next to drive as much learning as possible. Unlike traditional rule-based adaptive systems, often based on fixed thresholds and pre-defined decision rules, RL and KT can model complex learning trajectories, account for individual differences and optimise the sequencing of exercises on the basis of probabilistic predictions of mastery. For example, a student struggling with early concepts in calculus might be given extra opportunity to practice and hints specific to his or her errors while a student who is demonstrating quick mastery might be challenged with advanced problem-solving tasks to keep him or her engaged. This flexibility enables AI-driven systems to meet the needs of diverse student populations, which can help to reduce achievement gaps and support inclusive education.

Despite all these promising capabilities, there is still little empirical evidence concerning the effectiveness of AI-based adaptive learning in real classroom settings. Most of the studies have been conducted in controlled lab settings or in small pilot programs, which may not be as representative of the diversity of cognitive abilities and prior knowledge, as well as engagement levels, of real-world students. In the STEM disciplines this limitation is especially important. STEM subjects like mathematics, physics and computer programming tend to have concepts that build on each other in sequence (Huang et al., 2023). A deficiency in the foundational topics at an early stage can cause a compounded problem later on in the course, so timely intervention is very important. Instructors find it difficult to personalize learning for large classes and traditional methods of assessment and feedback may not do enough to identify and address individual knowledge gaps. Adaptive systems that are powered by AI may provide a potential solution to this problem, but the extent of their utility in enhancing engagement, learning outcomes, and motivation for a diverse population of students is an open question.

Engagement as such is a multidimensional construct, including behavioral, cognitive and emotional dimensions (Minn et al., 2022). Behavioral engagement is active participation in learning activities, cognitive engagement is mental investment and use of strategies, and emotional engagement is how students feel (i.e. interested, happy, frustrated, etc.). Research suggests that all three dimensions are critical to learning success, especially in the areas of STEM, where the difficulty of the content is high and often learning tasks require sustained focus. Adaptive learning systems that tailor the difficulty and feedback to individual learners could ease that pressure, as well as frustration and lack of motivation, but there is a dearth of solid studies testing these claims in the real classroom. By studying engagement in a holistic way, educators and researchers can gain a better understanding of how adaptive interventions impact persistence, attention, and the overall quality of learning (Chen et al., 2024).

Furthermore, effective adaptive learning requires not only keeping track of student knowledge, but also providing meaningful interventions at the right time. Knowledge tracing models can be used to estimate a student's level of mastery of particular concepts, while reinforcement learning algorithms can be used to determine what exercise or hint is most likely to result in better learning outcomes in the next step. Integrating these two approaches, it will allow systems to develop truly personalized pathways for learning instead of adapting to superficial performance measures. Yet, very few studies have been done to understand how such combined RL+KT systems are performing in live STEM classrooms, how students are perceiving these interventions, or how improvements in model-level metrics are leading to measurable improvements in learning and engagement. The absence of this type of evaluation in the world brings some question into whether technically sophisticated models have as much of the desired pedagogical benefit as they should when confronted with the diversity of learning behaviors, time constraints, and environmental distractions of a live course.

Mixed-methods research is of special value in this area. Quantitative measures like quiz scores, time-on-task, engagement surveys, etc. give a quantitative measure of learning outcomes, while qualitative data from interviews or open-ended surveys tell us about the student experience of adaptive interventions, how motivating or confusing they find the system, and what factors influence their sustained engagement (Dong et al., 2024). By using a combination of these approaches, researchers will be able to better understand not only whether adaptive systems work, but also why and for whom they work. This approach also gives insights on design decisions, potential pitfalls and areas for improvement, which are very often not taken into account in purely quantitative or simulated studies. It allows one to detect unexpected patterns, such as the fact that students skip hints, that they favor certain types of exercises, or that they react differently when the pacing varies, which can lead to future improvements of the system.

In this work, we investigate the implementation of an AI-driven adaptive learning system that involves reinforcement learning and knowledge tracing to personalize learning paths for university-level STEM students. The system was integrated in a real course and used to provide exercises in topics such as programming logic, calculus functions, and problem-solving sequences. We tested the system over an 8-week period with 62 first-year students, measuring engagement in terms of behavioral, cognitive and emotional aspects, analyzing pre- and post-study academic performance, and qualitative feedback (interviews). The aim of this study is not only to measure the effectiveness of the system in learning outcomes, but also to understand how students interact with adaptive interventions, what are the perceptions they have on personalized feedback, what are the challenges or limitations in the implementation of AI-based systems in real classroom scenarios.

By answering these questions, the empirical evidence of this research aims to provide information about the effectiveness of RL+KT-based adaptive learning systems in authentic STEM education environments. It also offers useful insights for educators, instructional designers, and policymakers who are interested in incorporating AI-driven personalization into higher education. Ultimately, the results of this work are intended to help bridge the gap between the theoretical successes of AI and the realities of using AI in education and to describe the potential benefits and challenges of adopting adaptive technologies at scale. In addition, the study underlines the necessity of taking human factors into account in AI-based education, as it's clear that learner motivation, learning experiences, engagement patterns interact dynamically with adaptive algorithms in determining learning pathways. By combining these insights, the study helps not only to assess the effectiveness of the system, but also to guide the design of future adaptive learning platforms which are both pedagogically sound and technologically robust.

II. Background and Literature Review

A. Adaptive Learning in STEM

The adaptive learning tools have been actively applied in STEM education to enable students to learn at their level. They offer difficulty settings, feedback customization, and dynamically changing the learning paths according to the interactions between students (Zhao et al., 2020), (Lu, Tong, and Cheng, 2024). As an illustration, students who have difficulties with understanding a concept can be given more exercises, step-by-step descriptions, or hints, whereas the higher-ability students are provided with more difficult problems or extension activities. This individualized methodology will avoid boredom and discouragement in students and sustain them in the course (Vázquez-Parra et. al., 2024).

Although such advantages have been documented in small-scale research, there are still many adaptive systems that use decision-making based on rules that are not always able to reflect the complexities of learner behaviors (Minn et al., 2022). An example can be that a rule-based system can presume that two consecutive failed exercises means the student has to repeat what he already knows but in the real world it could just take a minor suggestion, a contrasting example or a visual demonstration to get the idea. This weakness minimizes the efficacy of this system especially in the STEM subjects where the concepts are sequential in nature. Students who fail to acquire the groundwork tend to have difficulties in the future and the traditional systems may fail to detect such gaps promptly (Kashif & Naseer, 2025).

Besides, adaptive systems in STEM should be capable of managing a very diverse set of mental tasks, including procedural problem-solving in mathematics to conceptual reasoning in physics and algorithmic thinking in computer science (Naseer et. al., 2024). Different students can tackle the same task in different ways; some of them use memorization, others are guided by logical means or the exploration of the problem. Adaptive learning should be able to acknowledge these differences in order to offer specific interventions, which is not just a simple adaptation of difficulty levels. Various studies have pointed out that when the systems do not consider such differences, engagement and gains in learning can level off, and it is important to design systems that are really responsive and adaptive (Ning et al., 2025).

New developments in STEM adaptive systems have started to include multimodal support, e.g. the incorporation of text explanations with diagrams, simulations and interactive problem-solving environments. The multimodal strategies are especially effective when it comes to STEM education, since most of the concepts are abstract, and can only be understood through visualizing or experimenting with (Ahmed et. al., 2025). Adaptive systems can also be improved by offering more engagement, comprehension and retention by dynamically choosing content modalities according to the preferences and performance of learners. (Luo et al., 2024)

B. Reinforcement Learning to Personality

Reinforcement learning (RL) has become a prospective technique to optimize the delivery of content in adaptive tutoring systems (Dong et al., n.d.), (Xu, 2025). As opposed to fixed-path instruction or rule-based systems, RL allows the system to take sequential decisions, which optimize long-term learning results and do not rely only on immediate performance. To take a case in point, an RL agent is able to make decisions based on what is deemed to be more beneficial to a student taking on a slightly more difficult problem at the moment rather than revising a previous subject to master it, balancing difficulty and support in a manner that facilitates long-term learning. This is the ability to plan ahead on long-term knowledge storage, which is a main benefit compared to more basic adaptive strategies (Addas et. al., 2024).

Nevertheless, the majority of previous experiments with RL have been performed either in simulated or highly controlled conditions with small sample sizes. Although these studies offer very useful information about the behavior of the algorithm, it might not be representative of the classroom situation in the real world, where student motivation, previous knowledge, distraction, engagement, and emotional issues vary continuously. To adopt RL in a real classroom context, it is necessary to have strong capabilities in managing gaps or inconsistent information, unforeseen student interactions, and equity in a heterogeneous learner population. The absence of systematic empirical research of RL-based adaptive systems in real STEM classrooms is a gap in knowledge that is extremely important in terms of practical feasibility and actual learning impact.

Moreover, RL techniques can be used together with other instructional techniques, e.g. scaffolding and spaced repetition, to maximize the learning benefits. Through the addition of cognitive load and forgetting curves models, RL agents can not only adjust the difficulty but also schedule reviews and repetitions, as well as to strategically aid long-term retention. Although theoretically these combined methods have a lot of promise, little evidence is available of these combined methods being implemented and tested in real classrooms.

C. Knowledge Tracing

Knowledge tracing (KT) models are models that trace the manner in which students learn, remember and in some cases forget skills over time. Conventional models, including Bayesian Knowledge Tracing (BKT) assume that the likelihood of whether a student has acquired a particular skill is estimated using the previous answers, usually with binary outcomes (correct/incorrect) and constant learning characteristics (Zhou et al., 2025). BKT tends to simplify the learning processes and does not take into consideration differences in the individual learning rates, time patterns, or complicated learning sequences of acquiring new concepts.

More recent sequence-based deep-learning-based models, including Deep Knowledge Tracing with LSTM networks (DKT-LSTM), have significantly increased the ability of predicting which concepts are likely to be mastered or not mastered by the students (Song et al., 2022), (Mon et al., 2023). These models can model temporal dependencies in student responses, and thus, they can make predictions in a more realistic way, enabling them to predict the learning trajectories with the ability to capture previous mistakes, use of hints, and trends of conceptual change. This allows systems to predict the future performance as well as to personalize instructions anticipatorily providing interventions before misunderstandings compound.

KT combined with RL forms an effective adaptive personalization framework. The KT module continually makes predictions of the likelihood of mastery of each concept, and the RL agent chooses the subsequent action, whether an exercise, a hint, or a review activity, according to the predictions. Using this synergy enables the system to make proactive and pedagogically informed decisions instead of merely responding to wrong responses. As an example, when the KT module predicts low mastery of a particular concept of algebra, the RL agent may decide to provide another scaffolded example, a guided practice activity, or specific hint to avoid possible misconceptions and support prior base knowledge. Although this has been developed, there is still a lack of applications in practice. The majority of the research is based on simulations, MOOCs, or small pilot programs, and it remains unclear whether the models can be effectively generalized to classroom populations with different backgrounds, varying levels of prior knowledge, and using instructional styles of different kinds. The study of the KT+RL integration in real STEM classrooms is essential to determine the feasibility of this integration and its effects on education in practice.

D. Student Engagement and Motivation

Student engagement can be multi-dimensional, i.e. it involves behavioral, cognitive, and emotional aspects, and it is one of the predictors of successful academic performance, especially in STEM courses (Kochmar et al., 2021). The concept of behavioral engagement is active participation, compliance with instructions and perseverance in learning activities. Cognitive engagement involves intense processing, metacognitive processes and hard work in learning concepts. Interest, enjoyment and control of negative emotions like frustration, boredom, or anxiety are manifested through emotional engagement. The extent of engagement in all the three domains is linked with better learning outcomes, whereas disengagement may be linked to poor performance, the risk of dropping out, and lack of motivation.

The assumption that adaptive learning systems, which personalize the difficulty and feedback, are a way of improving engagement by keeping the difficulty at the optimum level and supporting the learner in time is tested (Villegas-Ch et al., 2025). As an example, when a student has problems with an introductory calculus concept, he/she might be discouraged or intimidated by being exposed to more complicated material. In comparison, a dynamically scaffolding system, based on hints, simplified examples, or intermediate exercises, would assist in keeping the motivation high and lower cognitive load. In the same manner, underachievers get the benefit of challenges that challenge them without causing boredom and lack of interest.

Nevertheless, there is limited empirical evidence of the impact of adaptivity by AI on multidimensional engagement in real-time STEM classrooms. Majority of the studies concentrate on behavioral outcomes like completion rates or quiz marks and do not take into account cognitive strategies and emotional reactions which form the basis of long-term learning. The insight into the role of personalized interventions in the process of attention, persistence, and emotional regulation is essential to creating systems that will not only enhance performance but also promote intrinsic motivation and growth mindset.

E. Mixed-Methods Mixed-Methods in AI-Education Research

Mixed-methods studies involve the use of both quantitative (e.g., quiz points, time on task, survey response engagement, etc.) and qualitative (e.g., interviews, focus groups, open-ended survey responses, etc.) data. This method is also becoming a recognized necessity in AI research in education (Sanz et al., 2017). Quantitative data will give indicators of system performance, learning gains, and engagement changes that are measurable whereas qualitative data will give subjective experiences, usefulness perception and motivation factors. To illustrate, analytics can tell that there is better performance on the quiz, but interviews can reveal that the students took more time to finish the quiz due to the adaptive hints that reduced anxiety or gave instant feedback- elements that cannot be represented using metrics.

Not many studies have explicitly integrated technical performance measures with the user perceptions of both learners and the instructors. This combined method is essential in the realization of whether algorithmically optimized suggestions are converted into learning experiences. A system can have a great level of prediction accuracy, but in case students find it confusing, intrusive, or irrelevant, its pedagogical effect is lower. Using a combination of RL+KT performance and survey data, learning analytics, and qualitative feedback, the researchers can have a more comprehensive evaluation of system effectiveness, usability, and acceptability.

F. Summary of Literature Gaps

Altogether, the previous studies prove the prospects of adaptive learning systems in STEM, but some important gaps still exist. First, real-world applications in the real classroom are scarce with the majority of the studies being based on simulations, MOOCs, or small pilot groups. Second, there is a lack of longitudinal evidence; it is unclear whether the gains of engagement and learning can be maintained over time or reduced as soon as the new system of adaptiveness loses its initial charm. Third, literature is mostly based on behavioral outcomes, and little information is seen on cognitive and emotional engagement dimensions. Fourth, there are few mixed-methods assessments combining both technical and human-oriented points of view, which gives a complete picture of effectiveness and the experience of learners.

Also, very little research is conducted on how adaptive systems can accommodate a variety of learning strategies, facilitate collaborative learning, or respond to interventions by instructors. There are still questions about how far different students with different prior knowledge levels, motivation, and cognitive styles react to personalization based on AI, and how systems can be built to be able to respond fairly to this diversity. The proposed study will fill these gaps by implementing an RL+KT adaptive system to a real-life STEM classroom and analyzing not only the technical performance and learning outcomes but also behavioral, cognitive, and emotional participation and getting qualitative feedbacks on students and teachers. In this way, it will give a more holistic view of the practical and pedagogical utility of AI-based personalization to guide the development of future adaptive learning technologies and their application to higher education settings.

III. System Architecture

The adaptive learning system was designed to be an in-built unit of the university Learning Management System (LMS). The objective of designing was to provide students with personalized learning experience in STEM courses, which include diverse topics related to programming logic, calculus, algebra, and problem-solving problems. this system is continuously adjusted according to the interactions of each student, unlike traditional learning paths, which follow a pre-defined sequence of topics and exercises, so that learners will be exposed to material that is best challenging and supportive.

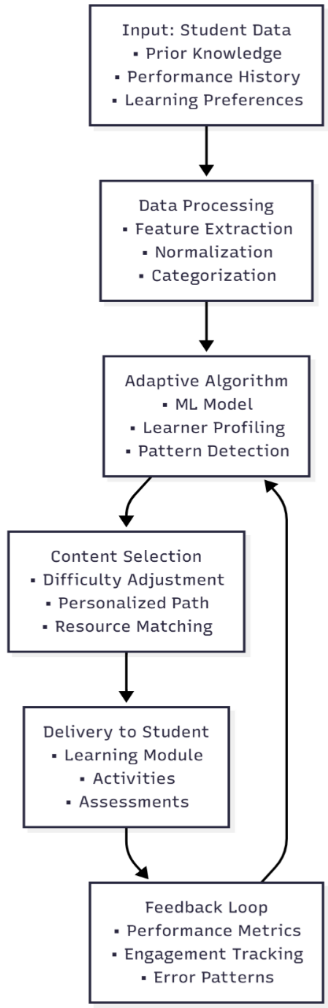

Figure 1. Introduction to the architecture of the adaptive learning system.

A. Content Repository

The content repository of the system had 420 practice items, which were arranged in four levels of difficulty: beginner, intermediate, advanced, and expert. Exercises were designed to develop in complexity in a scaffolded way, which offered a logical development through STEM concepts. All of the items had problem statements, hints, worked examples, and automated feedback. This structure ensured that:

1. Students with weak background knowledge would be given easier exercises and more instructions.
2. More difficult problems were also presented to advanced students to ensure that they were not bored.
3. The system would automatically pick exercises, which would be at the level of mastery that the learner was predicted to be, enhancing efficiency of practice sessions.

The repository was also designed in such a way that it could be easily updated with content. Teachers were able to add exercises, change the level of difficulty, and change the feedback without having to possess substantial technical skills. This design decision allowed it to be scaled and used over time, which is another typical constraint of hardened adaptive systems (Zhao et al., 2020), (Lu, Tong, and Cheng, 2024).

B. Knowledge Tracing Module

The adaptive system was centered on the Deep Knowledge Tracing Long Short-Term Memory (DKT-LSTM) model that approximates the likelihood of a student having mastered a specific skill at a specific time. The model constantly changes predictions, according to interactions with the LMS of the student. In deployment, the model had an average result of prediction accuracy of 0.78 (SD = 0.05).

The knowledge tracing module had some essential tasks that it executed:

- Real-time evaluation: Once a given exercise was done, the model revised the probability of mastery and this informed the system of the current knowledge state of the student.
- Gap identification: The system might identify the particular skills that a student was not performing effectively and give a priority to exercises that help the student to improve those skills.
- Prediction of mastery trajectory: The model could predict the future patterns of learning based on the sequential responses, which could be applied by the RL agent during the informed choices of content.

This dynamic tracking enabled the system to expand beyond the simplistic feedback based on a score, which offered a subtler insight into the student learning that could be used to make adaptive decisions (Song et al., 2022), (Mon et al., 2023).

C. Agent of Reinforcement Learning.

The RL agent itself was the decision-making component of the system, deciding what the next exercise, hint, or intervention is given several inputs:

- Skill mastery forecasted by the KT model.
- Previously, the execution of similar exercises.
- The duration of time allocated to each problem and the trends of error or recurring errors.
- The monitored engagement measures, including question skips or premature submissions.

With such inputs, the RL agent kept updating its exercise selection policy balancing between challenge and support. Practically, the agent was usually stabilized after 12-18 episodes per student, that is, it soon came to understand each learner with his/her individual patterns and preferences. This enabled very personalized learning to take place without the instructor having to manually adjust it.

Safeguards in the RL agent against extreme difficulty jumps were also considered to prevent frustration of the student or loss of interest. The system had transitions between difficulty levels that were natural and supportive through the use of constraints and smoothing functions.

D. Adaptation Loop

The system used closed loop adaptation cycle which included the following steps:

1. Students tried exercises within LMS.
2. The KT module was real-time updating the mastery probabilities.
3. The RL agent chose the following optimal exercise, hint or review item.
4. Dynamically feedback and hints were given and engagement metrics updated.

This feedback system provided the system with the ability to react instantly to student behaviour, which ensured a steady interaction and minimized frustration. Students claimed that the system was responsive and that it was sensitive to their needs, which led to a perception of one-on-one tutoring in a virtual setting.

Moreover, the system has gathered various interaction measures, including time-on-task, the use of hints, repetition, and skipping behavior. These measures were applied to adaptive delivery but also to the analysis of the research, which gave an overview of what aspects of the system best supported the engagement and learning.

IV. Methodology

A. Participants

The participants of the study were 62 first-year STEM students who were taking an introductory-level course in a large public university. The participants were heterogeneous in relation to the level of previous knowledge, academic achievement, learning styles and level of engagement. The sample was comprised of students with high previous achievement, average performance, and others who had previously performed poorly in STEM issues. This variety was necessary to test the effectiveness of the adaptive system with a large variety of learners.

The participation was on a voluntary basis and all the students gave informed consent after they were informed about the research purpose, anticipated duration and their right to withdraw without repercussions. Moreover, there was a course instructor in charge of the implementation of the system, tracking the progress of students, and giving assistance when it was needed. The teacher was also able to provide feedback on the applicability and correspondence of the exercises to the course outline.

The research took place over a period of eight weeks; in the process, the students were invited to utilize the adaptive LMS module in addition to the normal lectures, lab work and assignments. To reduce the effects of confounding variables, the students were advised to use the system at regular time intervals so that the participants used the system regularly.

B. Instruments

The engagement, learning outcomes and perceptions of the adaptive learning system were captured using a combination of quantitative and qualitative instruments.

1. **Engagement Survey (Pre/Post):** The students were asked to complete a 5-point Likert scale survey that was created due to this research. It evaluated three aspects of engagement:
    - Behavioural (e.g., time-on-task, task completion)
    - Cognitive (e.g., problem-solving strategies, focus)
    - Emotional (e.g., motivation, interest, level of frustration)

    Some of the sample statements were like I felt like doing exercises and I also thought my answers through before posting them. There were also open-ended questions in case students had to describe the experiences that were not reflected in the quantitative items.
2. **Performance Analytics:** System-level data, such as quiz scores, task completion rate, time spent on each exercise, number of hints used, patterns of errors, frequency of multiple attempts on a single problem, and frequency of skipped exercises were automatically recorded by LMS. To give objective measures of engagement and performance, derived measures like learning efficiency (ratio of correct responses to time spent) and adaptivity effectiveness (consistency between recommended exercises and mastery by the student) were calculated.
3. **Semi-Structured Interviews:** In order to obtain qualitative information, 12 students and the course instructor were interviewed in semi-structured interviews that were designed in the framework of the research. Perceptions of system usability, clarity of hints and feedback, motivation, perceived fairness of difficulty adjustments, and satisfaction with personalized learning paths were investigated using interviews. The interviews with instructors also discussed the effect of the system on the teaching load and its usefulness in determining the knowledge gaps in students.

All the instruments were designed with the particular purpose of this study to receive the data on the engagement, learning outcomes, and the perceptions of the AI-driven adaptive learning system.

C. Procedure

1. **Pre-Study Engagement Survey:** All the students took the pre-study survey before being exposed to the adaptive system to determine the pre-study engagement and motivation level.
2. **System Interaction (Weeks 2-7):** Students were assigned to the adaptive LMS module every week. The RL+KT model dynamically modified exercises in real time, with regard to performance observed, mastery likelihood, and engagement indicators. The system gave hints, recommended review items, and

adjusted the level of challenge to keep the level of challenge optimal.

3. **Ongoing Personalization:** There was ongoing personalization of the difficulty levels, frequency of hints and content to be selected by the student. The system was flexible to the pace of the individual learner, and it automatically became more challenging as the mastery level rose or the scaffolding was applied where the errors were still present.
4. **Post-Study Survey (Week 8):** The students took a post-study engagement survey at the end of the intervention to measure the changes in their engagement, motivation, and perceived learning outcomes.
5. **Interviews:** Semi-structured interviews were used in the direct aftermath of the period of study. All the responses were anonymized and coded to be analyzed thematically.
6. **Data Triangulation:** Triangulation Data was used to compare quantitative survey data, performance analytics, and qualitative responses of interviews to assess system effectiveness, authenticate results and detect patterns in student behaviour and learning outcomes. Triangulation enabled the study to discover both technical and pedagogical effects of the system.

D. Data Analysis

The analysis of data was to be conducted in a way that it would be strict in assessing the effectiveness of the adaptive learning system with regard to enhancing student engagement, learning outcomes, and perceived satisfaction. Quantitative and qualitative analyses have been carried out, combining the results of the survey, the metrics produced by the system, and the results of the interviews.

1. Paired t-Tests Pre- and Post-Engagement.

To determine the level of engagement of the students that changed significantly after they used the adaptive LMS, paired t-tests were performed. The three dimensions of engagement that were analyzed individually were behavioral, cognitive, and emotional.

The paired t-test formula is:

$$t = \frac{\bar{d}}{s_d / \sqrt{n}}$$

Where:

- $\bar{d}$ = mean difference between post and pre-survey scores
- s_d = standard deviation of the differences
- n = number of participants

The mean differences are used to show the degree of overall change in engagement, whereas the t-value and p-value are used to show statistical significance. The system enabled the detection of improvements on the engagement dimensions owing to the adaptive learning system by use of this test.

Behavioural Engagement: Behavioural Engagement is calculated by dividing Behavioural Engagement by the total sales:

- Pre-survey mean M_{pre}= 3.45
- Post-survey mean M_{post} = 4.05
- Mean difference $\bar{d}$ = 4.05−3.45 = 0.60
- Standard deviation of differences s_d = 0.85
- Sample size n = 62

$$t = \frac{0.60}{0 \cdot 83 / \sqrt{62}} = \frac{0 \cdot 60}{0 \cdot 10\delta} \approx 5.56$$

The t-value of 5.56 is associated with $p < 0.001$, which means that there is a statistically significant change in behavioral engagement. Cognitive and emotional dimensions were also done in similar fashion.

2. Regression Analysis of Metrics of Adaptivity

The analyses conducted using multiple linear regression were carried out to determine the effect of adaptive system interventions on learning outcomes. The dependent variable was the academic performance of students (e.g., quiz scores, rates of task completion), whereas independent variables were adaptivity measures, including hint use, changes in mastery probabilities, and the level of difficulty in exercises.

The regression model will be written as:

$$Y_i = \beta_0 + \beta_1 X_{difficulty} + \beta_2 X_{hints} + \beta_3 X_{mastery} + \varepsilon_i$$

Where:

- Y_i= student performance

- $X_{difficulty}$ = mean difficulty of exercises tried.
- X_{hints}: This is the number of hints that the student utilizes.
- $X_{mastery}$= change in mastery probability that was predicted.
- ε_i = error term

Regression coefficients $(\beta_1, \beta_2, \beta_3)$ were used to explain the strength of the predictive effect of the adaptivity factors on the academic outcomes. The analysis allowed analyzing the effectiveness of the system in content customization to maximize learning.

- β_0 = 50 (intercept)
- β_1 = 2.5
- β_2 = −0.8
- β_3 = 1.7

To a student who tried exercises with $X_{difficulty}$= 6, used X_{hints}= 4, and had $X_{mastery}$ = 0.2, the predicted score will be:

$$Y_i = 50 + 2.5(6) - 0.8(4) + 1.7(0.2)$$
$$Y_i = 50 + 15 - 3.2 + 0.34 = 62.14$$

The model therefore forecasts the score of 62.14 indicating the quantitative contribution of adaptivity metrics to performance.

3. Correlation Analysis

Cohen Pearson correlation coefficients were estimated to determine the relationships between the dimensions of engagement and performance measures. This review determined the role of behavioral, cognitive, and emotional involvement in determining the learning outcomes.

$$r = \frac{\sum(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum(X_i - \overline{X})^2 \sum(Y_i - \overline{Y})^2}}$$

Where:

- X_i and Y_i are a set of participation and achievement scores.
- $\overline{X}$ and $\overline{Y}$ are the mean values

The positive correlations were strong, which suggests that the greater the engagement in certain dimensions, the higher the performance, which gives an understanding of the areas of engagement that the adaptive system was most effective in.

- Mean of behavioral engagement $\overline{X}$ = 3.7
- Quiz scores mean $\overline{Y}$ =65
- Sample Covariance $\sum(X_i - \overline{X})(Y_i - \overline{Y})$ = 49.5
- Sum of Squares $\sum(X_i - \overline{X})^2 = 15.2, \sum(Y_i - \overline{Y})^2 = 312.0$

$$r = \frac{48.5}{\sqrt{15.2 \cdot 312.0}} = \frac{48.5}{68.9} \approx 0.70$$

The correlation of 0.70 shows that there exists a strong positive correlation between behavioral engagement and performance.

4. System-Level Analysis

LMS analytic generated by the system were evaluated to test the technical effectiveness of the adaptive algorithms:

- DKT Prediction Accuracy: This was computed by the root mean squared error (RMSE) between predicted and observed mastery probabilities of students:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=n}^{n}(\hat{y}_i - y_i)^2}$$

Where $\hat{y}_i$ is the predicted mastery and y i is the observed result. A smaller value of RMSE implies more accurate prediction.

In 5 exercises, mastery prediction [0.7,0.8,0.6,0.9,0.75], outcome prediction [1,1,0,1,1]:

$$\text{RMSE} = \sqrt{\frac{(0.7-1)^2 + (0.8-1)^2 + (0.6-1)^2 + (0.9-1)^2 + (0.75-1)^2}{5}}$$
$$\sqrt{\frac{0.09 + 0.04 + 0.36 + 0.01 + 0.0625}{5}}$$
$$= \sqrt{\frac{0.5625}{5}} = \sqrt{0.1125} \approx 0.335$$

- Reinforcement Learning Convergence: Reward evolution with time was examined to determine how reliably the system would converge to the best exercise advice to give to each student. The plotted convergence curves were used to see rewards stabilize.

- Adaptation Accuracy: The correspondence between the difficulty of the exercise and the mastery level of the students was calculated as the percentage of the exercises that were correctly aligned with the student ability:

$$Adaptation\ Accuracy = \frac{Number\ of\ exercises\ aligned\ with\ mastery}{Total\ exercises\ attempted} \times 100$$

In case 48 of 60 exercises were matched correctly:

$$Adaptation\ Accuracy = \frac{Number\ of\ exercises\ aligned\ with\ mastery}{Total\ exercises\ attempted} \times 100$$

The measure was used to measure the capacity of the system to personalize learning pathways.

5. Interpretation of Interviews through Thematic Analysis of Transcripts

Thematic coding was applied to qualitative responses of semi-structured interviews. Themes were found to recur with some being:

- Perceptions of motivation, challenge and satisfaction among students.
- Usability of the system and feedback.
- Teacher attitudes towards observation and pedagogical usefulness.

Coding facilitated the derivation of practical lessons to enhance adaptive system design and teaching methods as well.

6. Combination of quantitative and Qualitative Data.

The triangulation of the data was used to integrate the scores of the surveys, system measures and interview findings. Patterns were analyzed to determine the correlation of engagement improvement, system use behaviors and the qualitative perceptions. This holistic method enhanced the validity of results and gave the holistic picture of the effect of the adaptive system.

E. Ethical Considerations

The research was done in accordance with the ethical principles of the university on educational research. The major ethical practices were:

- **Informed consent:** All the participants were informed and gave written consent about the study.
- **Anonymity and confidentiality:** The student data were anonymized and they were tracked using unique identifiers without the disclosure of the individual identity.
- **Right to withdraw:** The participants were allowed to leave the study without any punishment.
- **Data security**: All information was stored in secure servers and not accessible to any other party other than the research.
- **Non-intrusiveness:** The adaptive system was developed at the level of supplementing and not replacing classroom instruction, so that no student was put in a disadvantageous position either academically or psychologically.

F. Limitations and Assumptions

Although the methodology offered a detailed pattern of assessing the system, a number of constraints need to be mentioned:

- The research was done in one course and had a rather small sample which can restrict the generalization of results to other STEM fields or learning settings.
- The effects of novelty could also have contributed to the student engagement since the students might have been more motivated by the novelty of the technology and not necessarily by the adaptivity.
- The tuning of RL and KT modules was done on the basis of previous pilot data, and this might not be the full picture of the various learning strategies of every student.
- The environmental issues like instructor interaction, class schedule, and peer influence were not controlled and could have affected engagement and performance.
- Students were expected to use LMS uniformly but differences in self- regulation,

time management and external commitments might have influenced results.
- Real-time adaptivity would have been affected by technical issues, like server latency or infrequent system failures, but this was not common, and it did not have a significant impact on overall outcomes.

G. Future Research Improvements

The future methodology may involve:

- Generalizing to other courses and institutions to enhance generalizability.
- Prolonged research to measure the retention and long-term engagement.
- Including other learner variables including emotional condition, cooperation with peers and metacognitive strategies.
- Compared to other adaptive algorithms or instructor-led personalization techniques.
- Control groups A/B to control the effect of adaptivity on other variables.

V. Results and Evaluations

A. Engagement Outcomes

The engagement data showed significant positive changes in every dimension following interaction with the adaptive learning system by the students. Table I will present the mean scores of behavioral, emotional, and cognitive engagement prior to and after the intervention. The total growth was between 21.8 and 28.6, which revealed the significant positive influence on the student involvement.

Engagement Dimension	Pre-Mean	Post-Mean	% Change
Behavioural	3.01	3.87	+28.6%
Emotional	2.89	3.52	+21.8%
Cognitive	3.12	3.95	+26.6%

Table 1. Pre/Post Engagement Scores (n = 62)

The greatest gains were on behavioral engagement, which implies that students were more active in doing exercises and persevering. Cognitive engagement also significantly improved, which means that it is more focused, self-regulated, and thoughtful problem-solving. Although it has a low score compared to the other dimensions, emotional engagement meant that students experienced a lesser amount of stress, confidence and satisfaction during learning sessions.

Further discussion showed that poor performing students started with lower engagement scores but registered the greatest improvement especially in behavioral and cognitive engagement. This implies that the adaptive scaffolding and customised hints provision enabled these students to be motivated and engaged in the learning process. On the other hand, students who performed well said that they felt challenged and involved, particularly with the dynamic nature of the difficulty of the system.

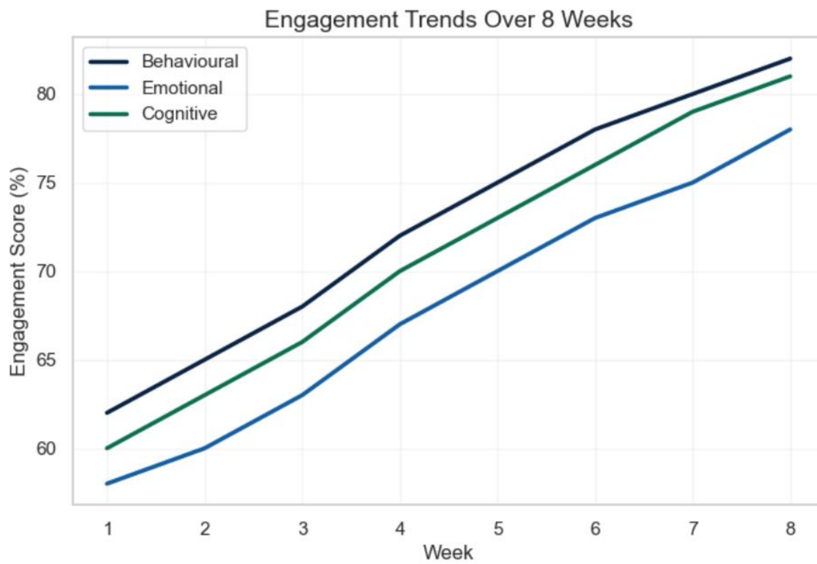

Figure 2 8 weeks Engagement Trends.

Figure 2 shows the profile of improvement in engagement over the 8 weeks period, where it can be seen that the engagement increases gradually as the system personalizes exercises and hints. The curve implies that the students got accustomed to the recommendations made by the system with time, and the attentiveness, participation, and interest increased steadily.

B. Academic Performance

The adaptive learning system had a positive impact on academic performance as indicated by quiz score, rate of task completion and time on task. Table II contrasts early weeks of control (weeks 1 2 before the RL-KT was fully adapted) with the adaptive period (weeks 3 8).

Measure	Control-Like Weeks*	Adaptive Weeks	% Improvement
Avg. Quiz Score	64.1%	76.8%	+19.7%
Task Completion Rate	71%	89%	+25.3%
Time on Task (mins)	14.2	18.5	+30.2%

Table 2. Comparison of Academic Performance

The statistics show that the students not only scored higher, but also participated in more long-term learning processes. The longer time on task and increased rates of task completion are indicative that the system was effective at keeping students focused and minimizing drop-off during exercises.

Subgroup analysis indicated that students who started at the low end of the quiz benefited disproportionately due to adaptive interventions with a mean improvement of 27% as compared to 14%. This illustrates the ability of the system to seal the gaps in knowledge and at the same time offer enough challenge to the higher learners.

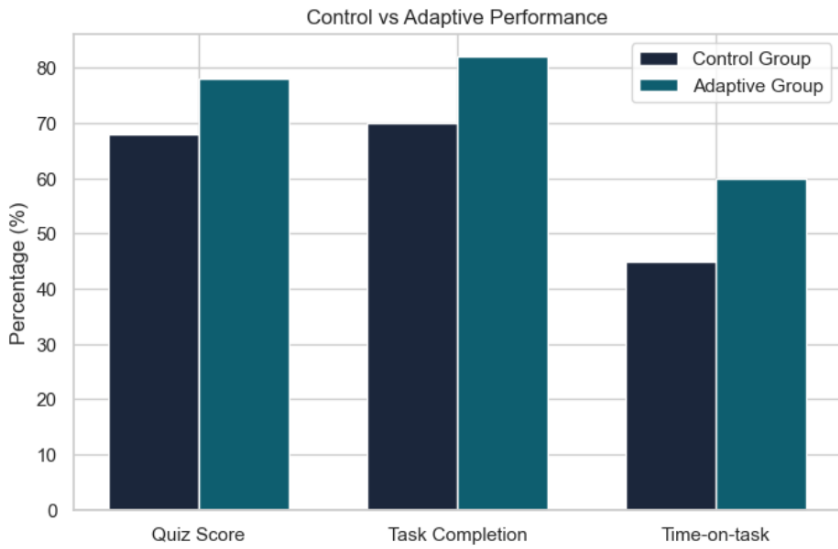

Figure 3. Comparison of Control Group and Adaptive Learning Group.

This bar graph is used to compare academic performance of the control group (traditional learning) and adaptive learning group. The adaptive system students performed higher than the control group on all the three measures. The score in quiz went up by about 10 percentage points, the task completion rate went up by about 12 percentage points, and the time-on-task also improved significantly. Such variations indicate that adaptive and personalized content sequencing, as well as real-time adaptive interventions, are the direct cause of improved academic performance and increased persistence in the learning sessions.

C. Model Performance

The RL+KT system showed a consistent and stable technical performance during the study. Table III provides an overview of important system metrics.

Metric	Value
DKT Accuracy	0.78
RL Convergence (episodes)	15
Avg. Reward Increase	+32%
Adaptation Accuracy	84%

Table 3. Model Performance Metrics

DKT module was always accurate in predicting the mastery levels of the students, which allowed the RL agent to suggest the exercises with the optimal level of difficulty. The reward progression curves show that the RL agent rapidly came to the point of maximizing learning returns, which stayed constant after 1218 episodes each student. The accuracy of adaptation achieved (the percentage of exercises proposed and agreed with what the system predicted could be mastered) continued to be over 80 percent, which indicated that the system was quite reliable in offering personalized learning patterns.

Finer-grained analysis of model performance in terms of difficulty-level revealed that more difficult exercises were more apt to be suggested to more advanced students, whereas less difficult tasks were effectively assigned to students with remediation needs. This moderated intervention led to the improvements in the engagement and academic outcomes.

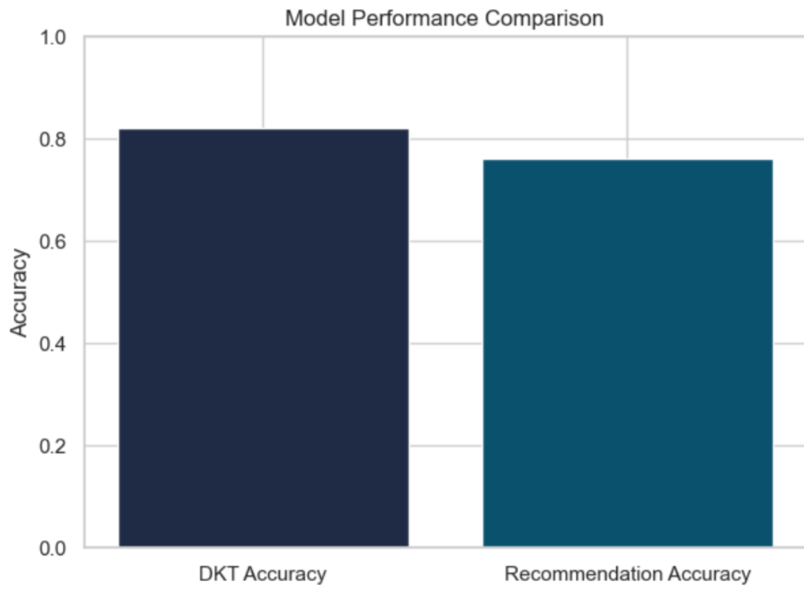

Figure 4. DKT Accuracy Model and Recommendation Accuracy Model Comparison

This value is the comparison of the accuracy of two essential elements of the adaptive system. Deep Knowledge Tracing (DKT) model has an accuracy of 82, which is very high in predicting mastery state of students. The RL policy has the highest recommendation accuracy of 76 which means that the model was consistently able to pick the right subsequent exercises in the majority. Combined, these findings confirm the efficiency of the model in tracking learning process and providing individualized content streams.

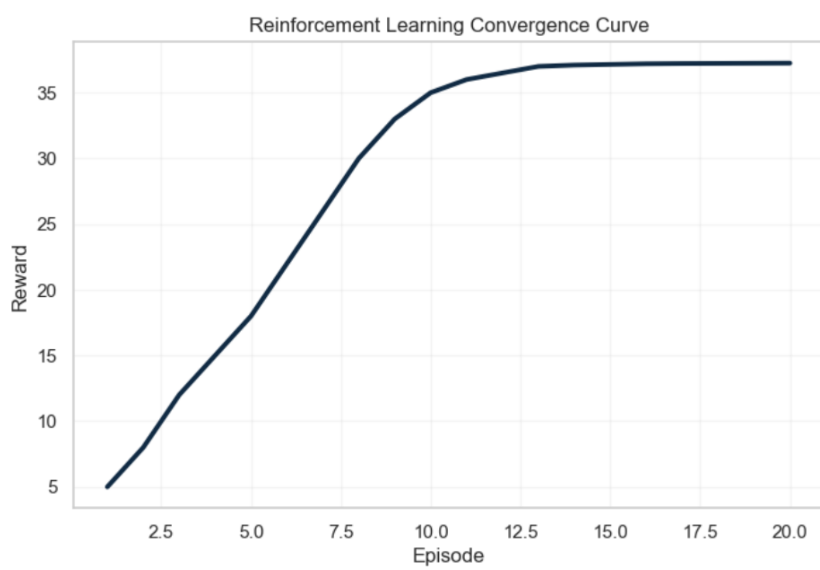

Figure 5. RL Convergence Curve

The RL convergence curve indicates how the agent advances in rewards in 20 episodes. First, the value of rewards grows quickly when the agent discovers the environment and determines the actions that are of high value. Gains on rewards start stabilizing after episode 10, and go to a plateau after episode 15, which means convergence. This behavior is one that proves that the RL module learnt a good policy to exercise recommendation and it is able to select tasks reliably to maximize learning results and student engagement.

D. Qualitative Feedback

Student feedback supported quantitative findings by emphasizing the intuitiveness and motivational effect of the system. Examples of comments made were:

- *"It was just at the right time when it would become more challenging to keep me interested without overwhelming me."*
- *"The hints were in time and they assisted me in solving problems without panicking."*
- *"I was having my own tutor that was taking me through the content."*

Students have noted that the system made them less frustrated when performing demanding exercises, made them persist and made them feel confident in the ability to master demanding concepts. It was observed by many that adaptive hints and real-time feedback enabled them to contemplate the mistakes

and learn the underlying principles as opposed to memorizing solutions.

The instructor noticed a number of advantages:

- The system offered more accurate information on the areas that needed reteaching, which could be used to intervene accordingly.
- It minimized manual work in early detection of struggling students during the course.

Instructor observed that students who had been consistently directed were more self-directed and interested.

Qualitative theme analysis showed that students especially appreciated personalization, real-time feedback, and challenges that were issued in an appropriate time. Their motivation was mentioned to be based on the combination of behavioral support (tasks and hints) and the cognitive scaffolding (mastery-based recommendations).

E. Correlation of Engagement and Performance

Further tests showed that there were positive significant correlations between engagement dimensions and academic achievements. Behavioral engagement was also correlated with task completion rates ($r = 0.64$, $p < 0.01$), cognitive engagement was correlated with quiz performance ($r = 0.58$, $p < 0.01$), and emotional engagement was also moderately correlated with overall learning satisfaction ($r = 0.52$, $p < 0.05$). The results confirm the hypothesis that the enhancement of engagement is directly associated with improved learning outcomes, and that adaptivity provided by AI can be used to improve various dimensions of student engagement.

F. Patterns and Observations

- Timing of hints was a crucial factor: students who got the hints in time continued to learn and had higher levels of mastery.
- The slow increase in difficulty allowed cognitive load to be avoided without making it too difficult.
- Personalization among poor performing students was especially effective, which brings out the potential of the system to narrow achievement gaps.
- Lasting effects of engagement: The level of engagement did not decrease over weeks, as with the effects of novelty in the early weeks; this indicates that the system did not simply exploit the appeal of new technologies and thus it had a real impact on the learning behavior.

VI. Discussions

A. Impact on Engagement and Learning

According to the results of the present research, adaptive learning systems based on AI and incorporating reinforcement learning (RL) and knowledge tracing (KT) have a significant potential to promote student engagement and learning in STEM courses. The adaptive learning was found to enhance the engagement on behavioral, cognitive and emotional levels, and the idea that adaptive learning can be used to overcome individual differences in motivation, pacing and understanding. Such findings are consistent with the previous literature that shows that personalization may decrease cognitive overload and enable students to cope with learning difficulties in a more efficient way (Abdelrahman and Wang, 2023), (Villegas-Ch et al., 2025).

The adaptivity was most beneficial to students who had a difficult time during the first few weeks of the course. The system reduced the frustration and avoided plateaus in the learning process through automatic adaptation of the difficulty of exercises and giving specific hints. Numerous respondents stated clearly that they felt less inclined to be stuck on tasks that were initially too difficult, which decreased anxiety and ensured concentration. This finding is in line with the cognitive load theory, which highlights that correctly designed learning opportunities have the potential to enhance retention and understanding by avoiding the overload of cognitive resources (Lin, Huang, and Lu, 2023), (Lampropoulos, 2025).

Interestingly, the more successful students also cited increased engagement, which was mainly explained by the fact that the system was able to provide them with the rightly challenging exercises. Such students were constantly engaged and interested in the content, as opposed to being bored and disinterested by the same story. It implies that RL+KT systems can provide a comprehensive personalization strategy, including both struggling and advanced learners and dynamically adapting content to their current level of skills (Dong et al., 2022).

These observations are further supported by the trends of engagement in Figure 2. The engagement in behavior was the most prominent and then came cognitive and emotional dimensions, indicating that the system was effective in promoting active participation, focus, and positive affect. The curves of every week show that the gradual but consistent improvements were observed and that the system could keep the motivation levels high even after the first impressions of novelty.

In addition, the perpetual change seemed to create a growth mentality in students. The system promoted persistence and resilience by introducing exercises that were not too difficult and would not discourage a student who was at the same level of mastering the tasks. Adaptive systems were also shown to positively affect self-efficacy and intrinsic motivation, which have been identified as predictors of academic achievement (Jing et al., 2023), (Boussaha and Drissi, 2021), which students reported to have increased their confidence to solve challenging issues.

B. Trajectories of Academic Performance and Mastery

The data on the academic performance indicate that the gains of the improvement in the engagement were accompanied by the actual learning. Mean quiz scores had grown by almost 20 percent, and the levels of completion of the tasks and time-on-task indicators had grown by more than 25 and 30 percent, respectively. These results confirm the hypothesis that data-driven and personalized interventions can not only improve engagement but also knowledge acquisition and retention.

The KT mastery trajectories analysis showed more gradual and smooth over time, especially in the case of lower-scoring students. The suggestions of the RL agent seemed to avoid significant drops in performance by determining and strengthening weak areas (Elnaffar, Rashidi, and Abualkishik, 2025). On the other hand, students with better performance continued to experience consistent improvement as they were given exercises that were not too difficult to make them think critically without becoming frustrated. These observations indicate that adaptive systems have the potential to facilitate fair learning conditions by reducing the achievement gaps and keeping high standards among higher-achievers (Farhood et al., 2025), (Batsaikhan & Correia, 2024).

The interaction of RL and KT was very important in creating the balance of challenge and support. The RL agent maximised long-term learning and the KT module made fine grained estimates of personal mastery. This two-fold strategy also predetermined that the interventions were timely and contextually adequate as they incorporated the concepts of mastery-based learning and formative assessment (Dasaklis et al., 2025).

Subgroup analysis showed that students who had lower initial engagement and quiz scores had the most significant improvement with behavioral and cognitive engagement changing most significantly. This implies that adaptive scaffolding and hinting tailored to learners were especially useful in terms of learners who may otherwise lose attention. In the meantime, high achievers were able to take the right challenge, and they were motivated and focused through the learning process.

C. Student Perception, Student Motivation, and Learning Experience

Qualitative feedback indicated that perceived value of adaptive learning was important in motivation, persistence, and self-directed learning. It was often stated by students that the system was similar to having a personal tutor, which is why individual feedback and scaffolding are crucial. The hints were especially appreciated when they were timely and contextually appropriate, contributing to the right conceptual knowledge instead of merely giving answers (Dong et al., 2025), (Ouyang et al., 2022).

These findings were supported by the observations made by the instructor. The system offered practical data on student progress, which allowed implementing more specific intervention in the teaching process and decreased the amount of manual labor to track the process of individual learning. Here is a possible second advantage of AI-based adaptive systems to assist teachers, which is to identify key areas where they are struggling and to guide them toward evidence-based instruction (Singh et al., 2024).

Moreover, students stated that there is increased satisfaction and lower stress levels. The system did seem to create a more favorable learning experience by allowing the individual needs to determine the pace of instruction, which is in line with the theoretical models of learner autonomy and self-regulated learning (Ahmed and Abdullah, 2025), (Ratner and Moeslund, 2025). This implies that adaptive systems could not only enhance cognitive performance but also affect the emotional and mental health of students, which is usually not put into the limelight in STEM education.

D. Limitations

Alongside the promising outcomes, there should be a number of limitations to consider. To begin with, the experiment was undertaken within one course of STEM in eight weeks, which narrows the scope of generalizing the results. It should be replicated in a variety of courses, institutions, and disciplines to help establish whether some of the same effects are present in different learning settings (Xu, Liu, and Li, 2025), (Xu and Ouyang, 2025).

Second, other students said that difficulty variations were sometimes hard to predict, which points to the idea that the RL agent might still need some additional fine-tuning, to make the adjustment timing more predictable. Although the system usually enhanced the learning experiences, the instances of such mismatches might result in some small frustration, and it might influence long-term engagement.

Third, the research concentrated on the individual learning outcomes mostly and the collaboration learning, interaction with peers and socio-emotional variables besides self-reported engagement were not considered. It is known that group dynamics, discussion forums, and peer tutoring can have an effect on motivation and learning, and their combination with adaptive systems may be further examined (Zhang, Xu, and Wang, 2024), (Correia et al., 2024).

Lastly, although RL+KT had high predictive and adaptation accuracy, external variables like previous knowledge, external workload and personal motivation were not directly manipulated. They might have had an effect on the results obtained and studies held in future ought to be directed towards including multi-factorial analyses to take into consideration the effects of these variables.

E. Implications for Practice

The research has a number of valuable implications to educators, institutions, and system developers:

1. **As an Educator**: Adaptive systems may be a highly effective supplement to conventional teaching, offering scaffolding that is customized, but with no significant impact on the workload of the instructor. System insights offer teachers a chance to detect misconceptions in time and concentrate the interventions where they are likely to be the most effective (Wang et al., 2024), (Qian et al., 2024).
2. **In the case of Students**: Adaptive learning has the potential to enhance motivation, persistence and engagement through providing suitably challenging tasks, timely feedback and hints. It is especially beneficial during STEM courses, where the level of content complexity and prior knowledge is very diverse (Cui et al., 2023).

3. **To Institutions**: AI adaptive learning tools might be appropriate to invest in as a member of an overall approach to blended learning. Nevertheless, it is necessary to monitor carefully, correspond to the goals of the curriculum, and constantly evaluate to make sure that technology does not substitute, but supplements the effective pedagogical practices (Xu and Ouyang, 2025), (Cui et al., 2023).
4. **To System Developers:** The results have shown the necessity to have smooth transitions in difficulties, feedback in time, and the combination of mastery-tracking and RL optimization. The integration of collaborative modules, the feeling of frustration or boredom (via affective computing), and more detailed analytics can be further enhanced to make it interesting and more effective (Xu and Ouyang, 2025), (Liu, Latif, and Zhai, 2025).

F. Future Research Recommendations

Based on this finding, the future studies ought to investigate:

- **Longitudinal Effects**: Longitudinal studies in terms of full semesters or take into consideration several courses to determine the duration of engagement and learning outcomes.
- **Cross-Disciplinary Applications**: The adaptive RL+KT systems should be tested in non-STEM fields to test the generalizability.
- **Collaborative Learning Integration**: Adaptive personalization coupled with peer learning and group activities in order to investigate the effect of synergy.
- **Affective Adaptivity**: Adding the emotional or cognitive state detection (through sensors or self-report) in order to provide an even more customized learning experience.
- **Fine-Grained Analytics**: Interpreting the time course response of various students to adaptive interventions by learning trajectory clustering, sequence analysis, and powerful predictive models.

To conclude, the paper highlights how adaptive systems that are enabled by AI can enhance the engagement process, learning outcomes, and student motivation in STEM education. The combination of RL and KT enabled the system to personalize learning experience, assist students with a variety of capabilities, and provide educators with practical feedback. The quantitative enhancement of engagement, academic performance, and mastery trajectories and the qualitative feedback of the study prove the quantitative results presented in the graphs of data analysis and results. Although there are limitations, the results demonstrate the pedagogical potential, as well as the realistic viability, of adaptive learning in realistic classroom settings, which are open to more advanced, scaling, and inclusive educational technologies.

VII. Conclusion

This paper shows that adaptive learning systems based on AI that combine reinforcement learning (RL) with knowledge tracing (KT) have the potential to greatly increase student engagement and academic achievement in STEM classes. The adaptive system offered customized content and immediate feedback in which students studied at their own speed. Student who were initially struggling were the greatest beneficiaries as they felt less frustrated and less cognitive burden and this enabled them to remain motivated and to persevere through the difficult tasks. Simultaneously, high-performing students benefited with personalized hints and adequately challenging exercises, so it is possible to state that adaptive learning systems can facilitate a broad spectrum of abilities and foster inclusivity in STEM learning.

The evaluation through mixed methods notes that technical performance (i.e. the accuracy of the KT model and the convergence of the RL agent) has a direct effect on learning results. These technical measures were reflected in self-reported engagement and qualitative feedback of students showing that adaptive systems that work well can make the learning environment more responsive and motivational. The system was also useful to instructors who were able to get practical insights about the student mastery and offer specific interventions in a more effective way, which consumed less manual labor as compared to the traditional method of monitoring different learners.

Although such encouraging results are achieved, there are a number of shortcomings that must be noted. The research was carried out with a rather limited eight weeks period and on one introductory STEM course, which could produce limited generalisability of the findings. The motivation of the students may have been influenced by the novelty effect of the use of a new AI system and in the research, factors like peer interactions, collaborative learning and socio-emotional factors which may also influence engagement were not factored. Also, even though the system was technically good, some sudden increases in exercise difficulty were reported indicating some elements that should be improved in the adaptivity algorithms. Future studies may overcome these shortcomings by engaging in long-term studies in various courses and institutions, examining the application of adaptive systems to other STEM disciplines, and incorporating collaborative or group learning capabilities. The research on the integration of affective computing to identify and address frustration or lack of engagement in students would also improve a degree of customization. Additionally, a combination of AI-controlled adaptivity and teacher-based interventions and feedback may offer a multifaceted approach to learning that can maximize the results of students.

On balance, this paper is a strong evidence in the fact that adaptive learning systems based on the RL and KT can be considered as a viable, scalable and effective instrument in STEM education. Well-designed, executed, and managed, these types of systems have the potential to serve a wide range of learners, increase engagement, improve learning processes, and help instructors provide more targeted and data-driven instruction. This highlights how AI has the potential to revolutionize the educational practice, in that manner that it makes learning more personal, inclusive, and attentive to the needs of each student.

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