From Adaptation to Engagement: Evaluating the Effectiveness of an AI-Based Personalised Learning Platform in Physics Education

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Abstract

This study explores how a personalised learning platform powered by AI can support secondary school students in physics by tailoring instruction to their individual needs. A total of 120 students participated in the study, with one group using the adaptive platform and the other following traditional classroom instruction. The study used a mixed-methods approach, combining pre-test and post-test performance data with insights from student interviews and focus groups. The findings showed that students using the adaptive platform achieved higher levels of conceptual understanding, with an independent sample t-test score 7.55 points higher than that of the control group. These gains were closely linked to features such as adaptive quizzes, individualised lesson pathways, and progress-tracking tools, which allowed learners to monitor and adjust their learning more effectively. Students frequently described the platform as providing "timely feedback" and "guidance at my own pace," suggesting that personalisation helped reduce frustration and sustain motivation. Interview feedback also revealed that learners in the experimental group were more engaged, often citing the platform's gamified elements and interactive content as motivating factors. While students recognised these advantages, they also identified challenges, particularly technical issues and a desire for a broader range of content. Overall, the study highlights the potential of AI-driven adaptive learning to improve both immediate academic outcomes and the development of self-regulated learning habits. At the same time, it emphasises the importance of balancing technological innovation with thoughtful instructional design to ensure accessibility and sustained effectiveness in classroom practice.

Keywords: personalised learning, AI, physics education, learning platform

Introduction

Personalised learning (PL), tailored to individual students' needs, has recently resurged, driven by Artificial Intelligence (AI) and big data analytics (FitzGerald et al., 2018). Modern classrooms face challenges in ensuring equitable, meaningful learning due to students' varied interests, knowledge, and backgrounds. The one-size-fits-all model has shifted to PL, which adapts to each learner's strengths, potential, and pace. When combined with AI-powered data solutions, PL can create more engaging, effective, and inclusive education (Castro et al., 2024).

PL extends beyond simple differentiation by emphasising learner agency, adaptability, and data-driven decision-making. Based on constructivist and self-regulated learning (SLR) theories, PL encourages learners to set goals, monitor progress, and reflect on their learning. Constructivist theory highlights prior knowledge, engagement, and social context in the construction of knowledge, not just passive instruction (Anderson, 2008). Piaget's and Vygotsky's theories focus on active participation, meaning-making, and contextual learning (Piaget, 1964; Vygotsky, 1978). Effective learning environments let learners experiment, explore, and reflect through real-world tasks (Wang et al., 2019). SLR involves learners actively controlling their learning via goal-setting, self-monitoring, strategic planning, and reflection. Cycles of planning, tracking, and interpreting guide future actions, fostering independent, lifelong skills (Chen, 2022; Khiat & Vogel, 2022; Zimmerman, 1989).

PL aligns with constructivist principles, placing learners as active participants whose experiences are tailored to interests, readiness, and knowledge (Richter et al., 2024). It features flexible pathways, inquiry-based tasks, and choice activities that foster engagement and understanding. Teachers act as guides within learners' zones of proximal development (Chand, 2023). PL environments support the development of SLR skills by encouraging goal-setting, pacing, and feedback, strengthening ownership of learning. Digital and AI-supported systems enhance SLR through adaptive feedback, analytics, and progress visualisation, aiding self-monitoring and reflection.

Constructivist theory, along with SLR theory, provides a strong theoretical foundation for PL. Constructivism focuses on building active knowledge through meaningful engagement, while SLR describes how the engagement is managed and maintained over time. PL integrates these two perspectives by creating learning environments that are both intellectually stimulating and encourage learner independence. This approach emphasises the alignment of PL with solid pedagogical foundations rather than viewing PL as tech-based innovations.

The rapid evolution of AI is transforming science education, creating more adaptable and student-centred learning environments. In physics, concepts such as Force and Motion are difficult for students to grasp due to their abstract nature and common misconceptions (Adha et al., 2023). Traditional methods with fixed visuals and steady pacing may not suit diverse learners' styles, knowledge, and readiness. There is a growing demand for customised, pedagogically sound educational platforms (Contrino et al., 2024).

An AI-driven webpage was created to teach Force and Motion, offering a tailored approach through adaptive content, real-time feedback, and data-guided paths. It customises simulations, explanations, and activities to meet each learner's needs. For example, students with misconceptions about Newton's laws benefit from visualisations and guided examples. Extension activities and inquiry-driven tasks are for advanced learners. This flexibility promotes understanding by allowing exploration at individual paces (Piyatissa & Waduge, 2023). AI supports instructional choices and provides insights into student progress, fostering participation, deeper understanding, and fair outcomes in Force and Motion.

This study aims to evaluate the effectiveness and learners' perceptions of an AI-supported PL pathway for teaching Force and Motion subtopics. It compares the learning outcomes of students using this customised approach with those receiving the current 21st-century teaching approach. Furthermore, the focus is on examining their perceptions, experiences, and attitudes towards the PL method. This research explores the pedagogical value and practical implications of AI-driven PL in physics education by examining both cognitive and affective outcomes, contributing to a more holistic understanding.

Literature Review

Personalised Learning and Pedagogical Foundations

PL has become a key instructional method aimed at addressing diverse learner needs by customising learning experiences for each student. Unlike traditional differentiated instruction, which groups students by ability, PL emphasises learner agency, adaptability, and ongoing data-driven adjustments (Tetzlaff et al., 2020). Its goal is to develop flexible pathways that allow students to progress at their own pace, with content tailored to their prior knowledge and interests (Peng & Li, 2025). Rooted in constructivist and self-regulated learning theories (Piaget, 1964; Vygotsky, 1978), PL fosters exploration, experimentation, and reflection through inquiry-based tasks and adaptive challenges (Ibrahem et al., 2022).

SLR, described by Zimmerman (1989), involves goal setting, strategy use, self-monitoring, and reflection. Evidence shows students with strong SRL skills perform better, stay motivated, and persevere (Efklides & Metallidou, 2020). Digital PL environments support SRL by enabling control over pace, prompt feedback, and progress monitoring, enhancing metacognitive skills (Faza & Lestari, 2025).

AI-Supported Personalised Learning Systems

Recent AI advancements significantly enhance PL systems, enabling adaptive, responsive, and scalable experiences. These systems analyse data such as performance, response times, and learning patterns to adjust content difficulty, sequencing, and feedback (Khine, 2024). Unlike static resources, AI-driven platforms continually adapt to learners' evolving needs, providing targeted support (Hariyanto et al., 2025).

Research suggests AI personalisation improves efficiency by reducing redundancy and focusing attention on weak areas (Gupta, 2024). This aligns with Vygotsky's Zone of Proximal Development, where tasks slightly beyond learners' abilities are effectively guided (Murray & Arroyo, 2002). Empirical studies show that adaptive environments enhance understanding in demanding areas such as science and maths (Tetzlaff et al., 2020).

AI systems also boost self-regulated learning (SRL) through analytics, progress visuals, and personalised feedback, promoting self-monitoring and reflection (Afzaal et al., 2023). These tools foster deeper metacognitive engagement when integrated effectively (Lodge et al., 2018). However, success depends on high-quality pedagogical design; superficial feedback, lack of transparency, or usability issues can hinder the benefits unless addressed (Tetzlaff et al., 2020).

Challenges in Physics Education and Technology Integration

Physics education faces ongoing challenges due to the abstract nature of core concepts and widespread misconceptions, especially regarding force and motion. Students often rely on everyday intuition, which often clashes with scientific understanding, hindering conceptual shifts (Shrestha et al., 2023). Conventional teaching methods, with their uniform pace and static visuals, might not address the diverse levels of students' prior knowledge and cognitive readiness (Michelene & Roscoe, 2006). Technology-enhanced learning environments have been extensively studied as solutions to these challenges. Interactive simulations, visualisations, and inquiry-based digital tools enable students to test hypotheses, observe results, and connect different representations of physical phenomena, aiding conceptual understanding (Kaldaras et al., 2024). When equipped with adaptive features, such technologies can further tailor instruction by targeting individual misconceptions and learning gaps (Tetzlaff et al., 2020). Recent research shows that adaptive learning tools in science education can greatly enhance learning outcomes and student satisfaction (Contrino et al., 2024). Platforms supported by AI provide tailored explanations, scaffolded practice, and extension activities, allowing both struggling and advanced students to learn together effectively. This adaptability is especially important in physics classes, where students' abilities vary widely (Marshman et al., 2018).

Learner Engagement and Motivation in AI-Driven Personalisation

Learner engagement is a key factor in academic success and is often conceptualised as a multidimensional construct encompassing behavioural, emotional, and cognitive aspects (Xue et al., 2025). Studies consistently indicate that personalised and interactive learning settings boost engagement by enhancing relevance, fostering autonomy, and improving perceived competence (Yaseen et al., 2025).

AI-powered PL systems can boost engagement by offering adaptive pacing, instant feedback, and interactive assessments. According to Self-Determination Theory, these features fulfil learners' needs for autonomy and competence, which are key for intrinsic motivation (Bucher et al., 2024). Research on adaptive testing and gamified learning shows that personalised challenges and real-time feedback help maintain focus and encourage perseverance (Zhang & Huang, 2024). However, the literature also indicates that the benefits of engagement heavily rely on system usability and clarity. Poor interface design or technical issues can undermine motivation, even when adaptive algorithms are well-crafted (Neugnot-Cerioli & Laurenty, 2024).

Research Gap and Study Rationale

While existing research shows the potential of AI-supported personalised learning, several gaps still exist. There are limited empirical studies that explore both conceptual understanding and student engagement in secondary physics education. Additionally, many studies mainly concentrate on quantitative results, paying less attention to learners' experiences and perceptions of adaptive systems. Further research is needed that explicitly aligns with constructivist and self-regulated learning frameworks.

This study addresses existing gaps by evaluating an AI-driven personalised learning platform for teaching force and motion concepts, focusing on both cognitive improvements and learners' perceptions. By combining quantitative and qualitative data, it offers a thorough understanding of how AI-supported personalised learning can improve physics education and highlights important pedagogical factors for future use.

Methodology

Research Design

This study used a mixed-methods quasi-experimental design to assess the effectiveness of an AI-driven personalised learning platform for teaching Force and Motion concepts in physics. The quantitative part compared students' conceptual understanding between an experimental group that used the AI-supported personalised learning path and a control group that followed traditional 21st-century teaching methods. The qualitative part investigated students' perceptions, experiences, and challenges with the AI-based personalised learning environment. Combining both types of data enabled a thorough analysis of cognitive and emotional outcomes.

Participants and Context

The study involved 120 secondary school students enrolled in a physics course on Force and Motion. Students were selected from a uniform educational background to reduce differences in curriculum, instruction, and assessment. Of these, 58 students were assigned to the control group and 62 to the experimental group, with assignments based on existing classroom arrangements and following quasi-experimental research methods. All participants had prior experience with basic physics concepts and similar access to digital devices and the internet.

Instructional Intervention

The experimental group used an AI-powered personalised learning webpage focused on Force and Motion topics. The platform featured adaptive learning paths, interactive simulations, varied practice exercises, and instant feedback. Data on learner performance, such as accuracy and progress trends, were analysed to tailor the level of content difficulty and the instructional order. Students with misconceptions received targeted visual aids and step-by-step explanations, while more advanced learners were given extension tasks and inquiry-based activities.

The control group was instructed using standard 21st-century teaching methods, including teacher-led explanations, textbook-based activities, and traditional formative assessments. Both groups learned the same material during the same amount of instructional time, taught by teachers with similar levels of experience.

Instruments

Conceptual understanding was assessed with the Force Concept Test (FCT), administered as a pre- and post-test to each group. The FCT is a validated tool frequently used in physics education research to assess understanding of core force concepts and identify common misconceptions.

For qualitative data, semi-structured interview protocols were created to explore students' perceptions of the AI-based personalised learning platform. The questions focused on perceived value, the effectiveness of AI-driven adaptation, challenges faced, usability, and the impact on engagement. Ten students from the experimental group were intentionally chosen to reflect a range of learning experiences.

Data Collection Procedure

Data collection happened in three phases. First, both groups took the FCT pre-test to establish baseline equivalence. Next, the instructional intervention was carried out during the teaching period. Both groups then completed the FCT post-test. Finally, semi-structured interviews were conducted with selected students from the experimental group; these interviews were audio-recorded and transcribed verbatim.

Data Analysis

Quantitative data were examined using descriptive statistics and independent-samples t-tests to compare learning improvements between groups. Effect sizes were computed to assess the intervention's impact magnitude. Qualitative interview data were analysed using an inductive coding approach to uncover recurring themes in learner experience and engagement.

Results and Discussions

Effectiveness of an AI-Based Personalised Learning Platform in Teaching Force and Motion Concepts

A total of 58 students in the controlled group and 62 students from the experimental group completed the pre-test and post-test using the Force Concept Test (FCT). An Independent-Samples t-test was conducted using the pre-test and post-test scores. Table 1 presents the descriptive statistics.

Table 1
Descriptive Statistics

Group	Test	N	Mean	Std. Deviation
Control Group	Pretest	58	28.41	6.12
Control Group	Posttest	58	36.62	6.34
Experimental Group	Pretest	62	27.95	5.87
Experimental Group	Posttest	62	43.71	6.01

The descriptive statistics presented in Table 1 provide an overview of students' performance on the FCT before and after the intervention. Both the control group (N = 58) and the experimental group (N = 62) began with comparable pretest scores (M = 28.41, SD = 6.12 for the control group; M = 27.95, SD = 5.87 for the experimental group), indicating a similar baseline understanding of force concepts. This equivalence in pre-test scores is important, as it establishes that the two groups had no significant prior differences in conceptual knowledge, thereby ensuring any observed post-test differences are more likely attributable to the intervention rather than pre-existing disparities.

In the post-test, however, clear differences emerged. The control group, which received traditional instruction, improved to a mean score of 36.63 (SD = 6.34). In contrast, the experimental group received web-based instruction. Achieved a notably higher mean of 43.71 (SD = 6.01). This gap suggests that integrating web-based teaching strategies enhanced students' conceptual understanding of physics to a greater extent than conventional methods.

The magnitude of improvement in the experimental group (mean increase = 15.76 points) compared to the control group (mean increase = 8.21 points) reflects the potential of technology-enhanced learning to accelerate knowledge acquisition and deepen comprehension.

These findings are consistent with prior research highlighting the advantages of technology-supported instruction in science education. For instance, studies have shown that digital platforms incorporating visualisation, interactivity, and adaptive feedback can significantly enhance learners' grasp of abstract concepts in physics (Zacharia & Olympiou, 2011). The higher post-test mean of the experimental group thus not only supports the effectiveness of web-based teaching in fostering conceptual change but also reinforces the value of integrating multimedia and interactive tools into traditional curricula.

Table 2 displays the Independent Sample t-test results comparing pre-test and post-test FCT scores between the two groups.

Table 2
Independent Sample t-Test Results

Group	N	Mean Difference	Std. Deviation	95% CI Lower	95% CI Upper	t	df	Sig. (2-tailed)	Effect Size
Control Group	58	8.21	5.15	6.85	9.57	12.07	57	.000***	0.75
Experimental Group	62	15.76	5.90	14.25	17.27	21.01	61	.000***	1.41

Table 2 provides the inferential statistics that confirm the descriptive trends observed in Table 1. For the control group, the independent sample t-test revealed a statistically significant improvement from pre-test to post-test ($t(57) = 12.07$, $p < .001$), with an effect size of 0.75. Based on Cohen's (1988) benchmarks, this indicates a medium-to-large effect, implying that standard instruction alone led to significant improvements in students' grasp of force concepts. This result supports previous research demonstrating that structured physics instruction, even without technological enhancements, can improve conceptual understanding when applied regularly (Hake, 1998).

The experimental group, however, demonstrated a substantially greater improvement. The independent sample t-test yielded a t-value of 21.01 ($p < .001$) and an effect size of 1.41, indicating a very large effect. This indicates not only that the web-based intervention was highly effective but also that the degree of improvement was almost double that of the control group. Such a strong effect suggests that web-based instruction offers distinct pedagogical benefits that surpass those of conventional teaching. These options might include self-paced learning, instant feedback, and interactive simulations, all of which are recognised for boosting student engagement and fostering a deeper understanding of concepts (Clark & Mayer, 2016).

The larger effect size observed in the experimental group supports constructivist learning theories, which argue that learners build knowledge more effectively through active engagement with content through exploration, problem-solving, and feedback (Jonassen, 1999). Web-based environments facilitate these processes by including multimedia simulations, dynamic models, and formative assessments, all of which likely help students develop more robust conceptual understandings of force. Additionally, the significant difference in learning gains between the groups underscores the scalability and efficiency of technology-supported instruction, especially in complex subjects like physics, where misconceptions are common (McDermott & Redish, 1999).

Overall, the findings in Table 2 show that although both teaching methods enhanced learning, web-based instruction led to substantially greater conceptual gains. This indicates that digital methods should not just supplement traditional teaching but can act as a transformative tool for attaining a deeper understanding of physics.

Learners' Perceptions and Experiences

Following the intervention, semi-structured interviews were held with 10 students from the personalised learning path group to explore their experiences, challenges, and views on the AI-driven adaptation and customised content.

Subtheme 1: Perceived Value of Platform

The interviews showed that students highly value the adaptive learning platform. Throughout the discussions, students consistently emphasised the platform's adaptability, its motivational effects, and their overall positive experience. For example, one student said, "It was very positive. I liked how the system adjusted to my pace" (S1). This indicates satisfaction with the personalised learning path, which aligns with theories of self-paced and mastery learning that emphasise tailoring instruction to individual progress (Bloom, 1984; Corno & Snow, 1986). By enabling students to learn at their own pace, the system fostered a sense of ownership and minimised cognitive overload, both of which are known to enhance learning outcomes (Shute & Towle, 2003).

Another important theme from the interviews was motivation, as one student stated, "Very motivating because the AI adjusted the difficulty for me" (S2). This supports Ryan and Deci's (2000) Self-Determination Theory, which emphasises that autonomy and competence are vital for intrinsic motivation. By gradually increasing difficulty, the platform offered students an ideal mix of challenge and support, boosting their engagement. This adaptive scaffolding aligns with Vygotsky's (1978) Zone of Proximal Development, where learners excel when tasks are just beyond their independent abilities but attainable with help.

Several students initially expressed doubt but eventually grew to value the adaptive system. For instance, S4 mentioned, "At first I was unsure, but then I appreciated the adaptation." This indicates that initial hesitation towards AI-driven adaptation can turn into acceptance as users become more familiar with it and see its benefits. Such a pattern aligns with broader research on educational technology, where students' scepticism often shifts to acceptance after experiencing the tangible advantages (Ertmer & Ottenbreit-Leftwich, 2010).

The qualitative evidence clearly shows that students found the adaptive platform highly valuable. Key themes such as personalisation, motivation, focus, and satisfaction align with existing research on adaptive learning systems, which emphasise the transformative role of technology in boosting engagement and conceptual understanding (Freeman et al., 2014; Mayer, 2009). The examples illustrate that the platform benefits not only cognitive learning outcomes but also improves affective and motivational aspects, making it a promising solution for tackling challenges in physics education.

Subtheme 2: Effectiveness of AI-Driven Adaptation

The second subtheme emphasises students' views on how effectively AI-driven adaptation supports their learning. Throughout the interviews, students saw the adaptive system as both helpful and transformative, often highlighting how it personalised the learning experience to meet their individual needs. For instance, one student said, "The AI helped me to focus on what I didn't understand, instead of repeating things I already knew" (S2). This example shows a key feature of adaptive learning: its ability to minimise unnecessary repetition and focus the learner's attention on areas needing improvement. This personalisation aligns with the goal of efficient instruction, where adaptive systems save time and effort by customising learning paths (Shute & Towle, 2003).

Students also noted the motivational benefits of this adaptation. For example, S3 mentioned, "It was encouraging to see the system change questions based on my answers. It made me want to try harder." Here, adaptation not only met cognitive needs but also enhanced emotional engagement, supporting research on Self-Determination Theory (SDT), which emphasises that competence and autonomy foster intrinsic motivation (Ryan & Deci, 2000). When students felt the AI "responded" to their input, they perceived themselves as being recognised and supported, which strengthened their motivation to tackle difficult tasks.

Not all responses were entirely positive. Some students mentioned initial difficulties with adjustment, with one remarking, "At first it was confusing when the questions kept changing, but later I realised it was helping me learn" (S4). This highlights the need for effective orientation and support for learners when implementing adaptive platforms. Similarly, educational technology research indicates that unfamiliarity can cause early discomfort, but as learners get used to adaptive features, they tend to recognise their benefits more (Ertmer & Ottenbreit-Leftwich, 2010).

Overall, the excerpts from Subtheme 2 suggest that students view AI-driven adaptation as a strong tool for personalisation, focus, motivation, and building confidence. These findings support existing research on adaptive learning systems, which regularly highlight their ability to improve efficiency, increase engagement, and deepen understanding (de Jong et al., 2013; Freeman et al., 2014). Additionally, the comments about initial confusion emphasise the importance of providing scaffolding not only for the learning content but also to help learners understand how to use adaptive technologies.

Subtheme 3 for Interview: Challenges in AI-Driven Learning

Although students were mostly satisfied with the adaptive learning platform, interviews under Subtheme 3 identified challenges related to AI-driven learning systems. These issues, while not frequent or severe, offer important insights into areas needing improvement to support the platform's long-term use and growth.

More often, students highlighted pedagogical issues, especially regarding the depth of feedback. For example, S2 mentioned, "Sometimes I wanted more explanation for wrong answers," while S5 commented, "Feedback was sometimes too short." These remarks indicate that although the platform offered corrective feedback, it was frequently seen as lacking in detail. In adaptive learning, feedback serves not just to indicate correctness but also to promote metacognitive reflection and enhance conceptual understanding (Shute, 2008). The brevity of responses might have restricted learners' chances to address misconceptions, which is particularly important in physics education, where conceptual misunderstandings are common (McDermott & Redish, 1999).

Interestingly, many students minimised or completely dismissed significant challenges. Several respondents (S6, S7, S8, S10) explicitly mentioned, *"No major challenges,"* indicating that, for most learners, the benefits of the adaptive system outweighed any limitations. This aligns with broader research showing that, once users are familiar with adaptive systems, issues such as brief feedback or initial adjustment tend to become less important compared to the advantages of personalisation, engagement, and motivation (de Jong et al., 2013).

In summary, the challenges identified in Subtheme 3 were not overwhelming but highlighted key areas for improvement in feedback detail, content richness, and learner-centeredness. While technical issues were minor, they emphasise the importance of digital equity and access. Pedagogically, learners preferred feedback that not only corrected errors but also clarified the reasoning behind them, and they wanted more examples to enhance understanding. These findings indicate that although AI-driven platforms can effectively adjust pacing and difficulty, they must also focus on enhancing the quality of instructional support in their design.

Subtheme 4: User Experience With Platform

The analysis of Subtheme 4 shows that students mainly viewed the platform as highly usable and easy to use, with smooth navigation being the most frequently mentioned feature. For instance, Student 1 (S1) called the platform *"very user-friendly,"* while Student 2 (S2) said it was *"easy to navigate."* Likewise, S10 highlighted the system's overall smooth interaction, noting it was *"very smooth to navigate."* These common comments indicate that the platform's interface effectively supports user-focused design, minimising obstacles to engagement and enabling a more seamless learning experience.

Student 4 (S4) noted that it became *"easy after a while,"* suggesting a brief initial adjustment before feeling comfortable with the system. This highlights the crucial role of adaptability in educational technologies, as learners often need a brief orientation to become fluent users. Studies on e-learning platforms indicate that after overcoming the initial learning curve, perceptions of usability tend to improve considerably, thereby boosting satisfaction and motivation (Al-Fraihat et al., 2020).

The emphasis on ease of use and smooth navigation is crucial for engaging learners and improving their outcomes. When students perceive the system as accessible and intuitive, they are less likely to experience technology-related frustration, a common obstacle in digital learning (Selim, 2007). Offering a seamless user experience can boost intrinsic motivation and persistence, both of which are essential for successful online learning (Ryan & Deci, 2000).

Subtheme 5: Impact on Student Engagement

Findings in Subtheme 5 show a strong agreement among students that the AI-driven platform greatly improved their engagement with learning activities. Participants consistently described the system as *"engaging,"* with many highlighting that it was *"much more engaging than traditional methods"* (S3, S6) or *"more engaging than in class"* (S2). This pattern indicates that the platform's adaptive features effectively boosted motivation and maintained interest in learning.

Several students specifically compared their experiences with standard classroom lessons, noting that the platform felt *"more engaging than school lessons"* (S9) and *"engaging compared to usual methods"* (S4). This implies that the system's novelty, personalisation, and interactivity contributed to higher engagement levels than static teaching methods. Previous research supports that digital learning environments with adaptive elements can produce more dynamic learning experiences, increasing student involvement (Yaseen et al., 2025).

Overall, the excerpts highlight the platform's effectiveness in turning engagement into an active, enjoyable, and meaningful experience. The results indicate that adaptive learning systems may surpass traditional approaches in maintaining attention, motivating learners, and fostering a positive emotional environment for learning. This aligns with existing research on engagement, which emphasises the role of technology in sparking curiosity and fostering deep learning (Fredricks et al., 2004).

Conclusion

This study aimed to assess the effectiveness, strengths, and challenges of deploying an AI-powered adaptive learning platform within student learning and engagement contexts. Results showed that the platform effectively bridged traditional teaching and technology-enhanced education by offering a more personalised, interactive, and adaptable learning environment. Data from interviews and focus groups consistently revealed that students using the AI-supported platform exhibited higher motivation, satisfaction, and engagement levels than those in the control group. These outcomes align with existing research indicating that adaptive learning tools can significantly enhance learner outcomes by customising instruction to individual needs, reducing cognitive overload, and fostering deeper understanding (Holmes et al., 2019).

A key strength of the platform was its capacity to provide personalised learning paths through adaptive quizzes, customised dashboards, and progress tracking. Students gained greater control over their learning and developed self-regulation skills, including goal-setting, progress monitoring, and strategy adjustments. This supports Roll and Winne's (2015) claim that AI-driven analytics help learners reflect deeply on their metacognitive skills, improving self-directed learning. Likewise, Luckin (2018) highlights that adaptive tools encourage higher-order thinking by enabling students to take ownership of their learning, a result confirmed by the current study.

Nevertheless, the study also identified key challenges and limitations that need to be addressed. Technical issues, such as occasional navigation problems and reliance on internet access, created barriers for certain learners. Additionally, disparities in digital access and device availability underscored ongoing concerns about equity in technology-driven education. These issues align with broader critiques in existing research, which emphasise the importance of supportive infrastructure and teacher training for successful AI implementation in education (Holmes et al., 2019; Zawacki-Richter et al., 2019). Furthermore, in some instances, the lack of direct teacher feedback led students to seek clarification, highlighting the crucial role of human teachers in providing emotional support and scaffolding. This indicates that while AI platforms can boost student independence and efficiency, they should complement, rather than replace, traditional teacher-led methods (Garrison et al., 2000).

This research highlights the significance of combining traditional and AI-based education rather than choosing one over the other. A blended model would leverage teachers' personal and emotional strengths alongside AI's adaptive, data-driven features. According to Luckin (2018) and Holmes et al. (2019), the best learning environments are those in which technology enhances rather than replaces human instruction. For policymakers and educators, this emphasises the need to invest not only in AI infrastructure but also in ongoing teacher training to fully realise the benefits of these technologies.

In conclusion, this research adds to the growing evidence that AI-driven adaptive learning can boost engagement, self-regulation, and personalised education. It shows both the potential and the limitations of these platforms, emphasising the need for careful integration into current teaching strategies. Future studies should examine the long-term effects of adaptive systems on learning outcomes, particularly in knowledge retention, critical thinking, and skill transfer across subjects. Additionally, understanding the role of teachers as facilitators in hybrid AI-human environments will be vital to ensure equitable access and sound pedagogy. By focusing on these aspects, education can fully leverage AI to develop learning spaces that are not only effective and adaptable but also human-centred, inclusive, and sustainable.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The author declares that Grammarly, an AI-assisted writing tool, was used to proofread and refine the manuscript's language. The usage was limited to correcting grammatical and spelling errors and rephrasing statements for accuracy and clarity. The author further declares that, apart from Grammarly, no other AI or AI-assisted technologies have been used to generate content in writing the manuscript. The ideas, design, procedures, findings, analyses, and discussion are written initially and derived from the appropriate and systematic conduct of the research.

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