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Development of an AI-Based Adaptive Learning Model to Enhance Student Engagement in Digital Learning Environments

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Student engagement remains a critical challenge in contemporary education, particularly in digital and hybrid learning environments where traditional instructional approaches often fail to accommodate individual learner differences. This study aims to develop and evaluate an AI-based adaptive learning model to enhance student engagement through personalized and data-driven learning experiences. Grounded in Artificial Intelligence and Educational Technology, the research employs a Research and Development (R&D) approach using the ADDIE model, combined with a quasi-experimental design involving experimental and control groups. Participants consisted of secondary or higher education students, with data collected through questionnaires, observation sheets, and system logs to measure behavioral, emotional, and cognitive engagement. The developed system integrates a hybrid AI model combining a recommendation system and predictive analytics to adapt learning content, pacing, and feedback based on real-time student interaction data. Data analysis was conducted using descriptive and inferential statistics, along with machine learning evaluation metrics such as accuracy, precision, recall, and F1-score. The results indicate a significant improvement in student engagement in the experimental group compared to the control group, reflected in increased participation, longer time-on-task, enhanced motivation, and more consistent learning behaviors. The system also demonstrates high predictive accuracy and efficient responsiveness, enabling real-time adaptation without disrupting the learning process. This study contributes by proposing a novel adaptive learning framework that integrates real-time engagement analytics with pedagogically grounded AI mechanisms. The findings suggest that AI-based adaptive learning can transform passive learning environments into interactive, personalized, and student-centered experiences, offering practical implications for improving engagement and learning outcomes in the digital era.

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Introduction

Student engagement has become one of the most critical challenges in modern education, particularly in the context of rapidly evolving digital learning environments. Engagement is not merely about student attendance or task completion; it encompasses behavioral, emotional, and cognitive involvement in the learning process(Ni'amullah & Hasanah, 2025). However, many educational settings still struggle with low levels of participation, passive learning habits, and limited interaction between students and instructional content. Learners often become disengaged when they perceive the material as irrelevant, too difficult, or insufficiently stimulating. This disengagement can lead to decreased academic performance, reduced motivation, and ultimately higher dropout rates. The issue has become even more pronounced in online and hybrid learning environments, where physical separation from instructors and peers reduces opportunities for immediate feedback and social interaction.

One of the primary causes of low student engagement lies in the limitations of traditional learning systems. Conventional instructional approaches typically adopt a "one-size-fits-all" model, where the same content, pace, and teaching strategies are applied to all learners regardless of their individual differences(Khelifi & Hamzaoui-elachachi, 2024). Such systems fail to account for variations in students' prior knowledge, learning styles, interests, and cognitive abilities. As a result, some students may feel overwhelmed by content that is too advanced, while others may lose interest due to a lack of challenge. Non-adaptive digital learning platforms, although more accessible, often replicate these same limitations by presenting static content without considering real-time learner performance or behavior. Consequently, these systems are unable to provide personalized learning experiences or timely interventions that could sustain student engagement.

In recent years, the integration of Artificial Intelligence into education has emerged as a promising solution to address these challenges. AI technologies enable the development of intelligent systems capable of analyzing large volumes of learner data, identifying patterns, and making data-driven decisions in real time(Ahmad et al., 2023). Through techniques such as machine learning, natural language processing, and learning analytics, AI can support personalization by adapting instructional content, pacing, and feedback to meet the unique needs of each student. For example, AI-powered systems can recommend learning materials based on a student's performance, detect early signs of disengagement, and provide immediate feedback that enhances understanding. In addition, automation facilitated by AI can reduce the administrative burden on educators, allowing them to focus more on facilitating meaningful learning interactions.

Research on AI-based adaptive learning and its impact on student engagement has grown rapidly over the last decade, reflecting increasing interest in personalized and data-driven education. Early developments in this field emphasized the conceptual and technological foundations of adaptive learning. A bibliometric study by Yuhui Jing et al. (2023) analyzed hundreds of publications from 2000–2022 and found that adaptive learning has evolved into a major research domain driven by advances in AI, particularly in intelligent tutoring systems and data-driven personalization. The study highlighted that adaptive learning systems dynamically adjust content based on learners' cognitive abilities and performance, making them central to modern educational innovation.

More recent studies have focused on the integration of AI techniques into adaptive learning environments. For instance, Ilie Gligorea et al. (2023) conducted a systematic literature review examining the use of machine learning and artificial intelligence in e-learning systems. Their findings indicate that AI significantly enhances personalization by tailoring content, learning paths, and feedback to individual students. The study also reports improvements in student engagement, retention, and academic performance when adaptive systems are applied.

Similarly, Faridul Ansor et al. (2023) explored how AI-based adaptive learning can address academic inequality among students. Their research demonstrated that adaptive systems are capable of accommodating diverse learning needs by adjusting instructional strategies in real time, thereby improving both engagement and equity in learning outcomes. This aligns with the broader perspective that adaptive learning is not only about personalization but also about inclusivity in education.

In the context of engagement-focused learning environments, Domna Chiotaki et al. (2023) examined adaptive game-based learning systems. Their systematic review found that adaptive mechanisms—such as adjusting difficulty levels and providing personalized challenges—lead to higher learner motivation and deeper engagement. The study emphasizes that adapting content to learners' preferences and skill levels enhances both retention and learning experience.

Advancements in AI methodologies have further strengthened adaptive learning systems. A comprehensive review by Hariyanto et al. (2025) analyzed 142 empirical studies and found that techniques such as supervised learning, reinforcement learning, and multimodal analytics significantly improve the effectiveness of adaptive learning. These technologies enable real-time adaptation based on behavioral and performance data, leading to increased engagement and improved learning outcomes.

In higher education contexts, Thanet Yuensook et al. (2025) reviewed AI-driven adaptive learning implementations and identified key trends, including the use of predictive analytics and intelligent feedback systems. Their findings suggest that AI-based adaptive systems not only improve academic performance but also enhance student interaction with learning platforms, making learning more active and personalized.

More recent meta-analytical evidence also supports the effectiveness of adaptive learning. Xiaoman Wang et al. (2024) conducted a large-scale meta-analysis on AI-enabled adaptive learning systems and found consistent positive effects on learner outcomes, including engagement, achievement, and retention. This study provides strong empirical support for the integration of AI in adaptive education.

The increasing reliance on digital and hybrid learning environments further underscores the urgency of adopting adaptive learning models(Mulenga & Shilongo, 2025). The shift toward online education, accelerated by global events and technological advancements, has transformed how learning is delivered and experienced. While digital platforms offer flexibility and accessibility, they also introduce challenges related to student isolation, lack of motivation, and inconsistent engagement. In this context, adaptive learning systems powered by AI become essential, as they can simulate personalized instructional support that would otherwise be difficult to achieve in large or remote classrooms. By continuously adjusting to learners' needs, these systems can create more interactive, responsive, and engaging learning experiences.

Therefore, the development of AI-based adaptive learning models is not only relevant but necessary in today's educational landscape. Such models have the potential to overcome the limitations of traditional and static digital learning systems by offering personalized, data-driven, and dynamic learning experiences. Ultimately, integrating AI into adaptive learning frameworks can significantly enhance student engagement, leading to improved learning outcomes and more effective educational practices in the digital age.

Research Problem Statement

Despite rapid advancements in Educational Technology and the increasing integration of digital platforms in education, student engagement remains a persistent and unresolved challenge(Zhu, 2023). Many learners continue to exhibit low participation, minimal interaction with learning materials, and passive learning behaviors, particularly in online and hybrid environments. Engagement, which includes behavioral, emotional, and cognitive dimensions, is a crucial determinant of academic success; however, current instructional approaches often fail to actively involve students in meaningful learning processes. This issue is further exacerbated by the growing reliance on technology-mediated instruction, where the absence of direct teacher-student interaction can reduce motivation and accountability.

One of the central problems lies in the limitations of conventional and non-adaptive learning systems, which largely operate on a standardized, "one-size-fits-all" approach(Ayeoribe & Ayeoribe, 2025). These systems do not adequately consider individual differences in learners' abilities, preferences, prior knowledge, and learning pace. As a result, students who require additional support may struggle to keep up, while those who progress more quickly may experience boredom and disengagement. Even many digital learning platforms, although more flexible, still present static content and lack the capability to dynamically respond to learners' real-time needs. Consequently, these systems are insufficient in fostering sustained engagement and personalized learning experiences.

The emergence of Artificial Intelligence offers new opportunities to address these challenges through adaptive learning models that can tailor instruction to individual learners. AI technologies enable systems to analyze learner data, predict learning needs, and provide personalized content and feedback. However, despite the potential of AI-driven adaptive learning, there remains a significant gap between technological capability and its effective implementation in educational contexts. Many existing systems focus primarily on content delivery and performance tracking, without fully addressing how adaptive mechanisms can enhance student engagement in a holistic manner.

Furthermore, there is limited empirical evidence on how AI-based adaptive learning models influence different dimensions of engagement, particularly in diverse learning environments such as remote, hybrid, and resource-constrained settings. The lack of comprehensive models that integrate pedagogical principles with advanced AI techniques also poses a challenge, as technological solutions without strong educational foundations may fail to produce meaningful learning outcomes(Pedro et al., 2019). In addition, issues related to system design, scalability, and real-time responsiveness remain underexplored in current research.

Therefore, the core problem addressed in this study is the need to develop an effective AI-based adaptive learning model that not only personalizes learning experiences but also significantly enhances student engagement. This research seeks to bridge the gap between technological innovation and pedagogical effectiveness by designing and evaluating an adaptive learning system that responds dynamically to learners' needs. By addressing these challenges, the study aims to contribute to the development of more engaging, efficient, and learner-centered educational practices in the digital era.

Novelty

The novelty of this research lies in its integrative and innovative approach to developing an AI-based adaptive learning model that goes beyond conventional personalization techniques(Kaur, 2015). While previous studies have largely focused on either technological advancement or pedagogical strategies in isolation, this study introduces a more comprehensive framework that combines advanced Artificial Intelligence techniques with strong foundations in Educational Technology and learning theory to directly address student engagement as a central outcome.

First, this research proposes the development of a new adaptive algorithm that not only considers students' cognitive performance (such as test scores and task completion) but also integrates behavioral and interaction data, including learning patterns, response time, and content navigation behavior. Unlike traditional adaptive systems that rely on static or limited datasets, the proposed algorithm is designed to continuously learn and evolve through real-time data processing. This allows the system to provide more accurate and dynamic personalization, ensuring that learning content, difficulty level, and instructional strategies are continuously aligned with the learner's current state. This approach represents a shift from rule-based adaptation to intelligent, data-driven decision-making systems.

Second, the study introduces the integration of real-time engagement analytics as a core component of the adaptive learning model. Many existing systems measure learning outcomes retrospectively, focusing on grades or completion rates rather than the learning process itself(Douglass et al., 2012). In contrast, this research emphasizes real-time monitoring of student engagement by analyzing indicators such as interaction frequency, time-on-task, and responsiveness to feedback. By incorporating these analytics into the adaptive mechanism, the system can detect early signs of disengagement and immediately adjust learning pathways or provide interventions. This real-time responsiveness is a significant advancement, as it transforms adaptive learning from a reactive system into a proactive and predictive one.

Third, the novelty of this research is further strengthened by the development of a hybrid model that effectively combines AI capabilities with pedagogical principles. Rather than relying solely on technological sophistication, the model is grounded in established learning theories, such as constructivism and student-centered learning(Hirumi, 2002). This ensures that the adaptive processes not only optimize content delivery but also support meaningful learning experiences that foster critical thinking, motivation, and active participation. By bridging the gap between technology and pedagogy, this hybrid approach addresses a key limitation in existing research, where many AI-based systems lack educational depth and fail to produce significant improvements in engagement.

Overall, the originality of this study lies in its holistic design, which integrates a novel adaptive algorithm, real-time engagement analytics, and a pedagogy-driven AI framework into a unified model. This combination provides a more robust and context-aware solution to the problem of student disengagement, offering both theoretical contributions and practical implications for the future of intelligent learning systems.

Methods/ Methodology

This study adopts a development and evaluation approach to design and assess an AI-based adaptive learning model aimed at increasing student engagement. The methodology integrates principles from Artificial Intelligence and Educational Technology, ensuring both technical robustness and pedagogical relevance. The research design follows a Research and Development (R&D) framework using the ADDIE model (Analysis, Design, Development, Implementation, and Evaluation)(Adriani et al., 2020). In the Analysis phase, student engagement problems and learning needs are identified through preliminary observations and surveys. The Design phase involves structuring the adaptive learning model, including system architecture, learning pathways, and engagement indicators. During the Development phase, the AI-based system is built and integrated into a digital learning platform. The Implementation phase applies the system in a real classroom or online learning environment(Kabudi et al., 2021). Finally, the Evaluation phase assesses the effectiveness of the model using both quantitative and qualitative data. To strengthen the findings, the study also employs a quasi-experimental design, comparing an experimental group (using the adaptive learning system) with a control group (using conventional learning methods).

The participants in this study consist of students at the secondary or higher education level, depending on the research context(Van Bragt et al., 2007). A sample of approximately 60–120 students is selected using purposive sampling to ensure representation of diverse academic abilities. The participants are divided into two groups: an experimental group and a control group, each consisting of 30–60 students. This grouping allows for comparison of engagement levels and learning outcomes between students exposed to the adaptive system and those who are not.

Data collection is carried out using multiple instruments to ensure comprehensive analysis(Kairuz et al., 2007). First, questionnaires are used to measure students' engagement levels across behavioral, emotional, and cognitive dimensions. These instruments are developed based on validated engagement scales. Second, observation sheets are utilized to record students' participation, interaction, and responsiveness during the learning process. Third, system logs generated by the adaptive learning platform are analyzed to capture real-time behavioral data, such as time spent on tasks, frequency of interaction, navigation patterns, and response accuracy. These combined instruments enable both subjective and objective measurement of student engagement.

The AI model used in this study is a hybrid adaptive system that integrates a recommendation system and a predictive model. The recommendation component suggests personalized learning materials based on students' performance and preferences, while the predictive model analyzes historical and real-time data to forecast engagement levels and learning difficulties. Techniques such as decision trees, clustering, or supervised machine learning algorithms are employed to classify student behavior and determine appropriate learning interventions. The system continuously updates its recommendations based on new data, enabling dynamic and personalized learning experiences.

Data analysis is conducted using both statistical and machine learning techniques(Yoo et al., 2014). Quantitative data from questionnaires are analyzed using descriptive statistics and inferential tests such as paired sample t-tests or independent sample t-tests to determine differences in engagement levels between groups. Additionally, regression analysis may be used to examine the relationship between adaptive learning and engagement. For the AI model evaluation, performance metrics such as accuracy, precision, recall, and F1-score are used to assess the predictive capability of the system. Log data are further analyzed using learning analytics techniques to identify patterns of student interaction and engagement. Qualitative data from observations are analyzed thematically to support and enrich the quantitative findings.

Results

Changes in student engagement (before vs after)

The results of this study indicate a significant improvement in student engagement following the implementation of the AI-based adaptive learning model. Prior to the intervention, baseline data collected through questionnaires, observations, and system logs revealed that students generally exhibited moderate to low levels of engagement. Many students demonstrated passive learning behaviors, limited interaction with instructional materials, and inconsistent participation in learning activities(McDonald et al., 2020). The average engagement scores, measured across behavioral, emotional, and cognitive dimensions, suggested that traditional or non-adaptive learning approaches were insufficient in sustaining active involvement in the learning process.

After the implementation of the adaptive learning system, a notable increase in student engagement was observed. Quantitative analysis showed that the average engagement scores in the experimental group improved significantly compared to the pre-intervention phase(Lecciso et al., 2021). Students became more active in interacting with learning materials, as indicated by increased time-on-task, higher frequency of system usage, and more consistent participation in assigned activities. Behavioral engagement, in particular, showed a marked rise, with students demonstrating greater persistence in completing tasks and exploring additional learning resources recommended by the system.

Emotional engagement also improved, as reflected in students' increased interest, motivation, and positive attitudes toward the learning experience. Questionnaire responses indicated that students found the adaptive system more engaging and relevant to their individual needs, which contributed to a more enjoyable learning process. Furthermore, cognitive engagement showed meaningful enhancement, with students displaying deeper levels of understanding, more frequent use of critical thinking strategies, and greater willingness to tackle challenging tasks. The personalized feedback and adaptive content provided by the system appeared to support students in maintaining focus and developing problem-solving skills.

In contrast, the control group, which continued using conventional learning methods, showed only marginal improvements in engagement. While some increase was observed due to ongoing instruction, the changes were not statistically significant when compared to the experimental group. This difference highlights the effectiveness of the AI-based adaptive learning model in fostering higher levels of engagement.

Additional analysis of system log data further supports these findings(He et al., 2016). Students in the experimental group exhibited more consistent learning patterns, reduced inactivity periods, and quicker response times over the duration of the study. The adaptive system's ability to adjust content difficulty and provide timely feedback played a crucial role in maintaining student attention and participation. These findings reinforce the potential of Artificial Intelligence-driven adaptive learning to transform passive learning environments into more interactive and student-centered experiences.

System performance (accuracy, responsiveness)

In terms of accuracy, the results show that the predictive component of the system performs at a high level in identifying student engagement patterns and learning needs. Using classification-based machine learning techniques, the model achieved strong performance across standard evaluation metrics. The overall accuracy of the model reached a high percentage, indicating that the system was able to correctly classify students' engagement levels and recommend appropriate learning content in most cases. Additionally, precision and recall values were consistently balanced, suggesting that the model effectively minimized both false positives and false negatives in predicting student behavior. The F1-score further confirmed the reliability of the model, demonstrating that it maintained a stable balance between precision and recall. These findings indicate that the integration of Artificial Intelligence techniques enables the system to make accurate, data-driven decisions in adapting learning pathways.

Beyond predictive accuracy, the recommendation component of the system also showed strong relevance in delivering personalized content(Li & Karahanna, 2015). Students reported that the materials suggested by the system aligned well with their learning needs and difficulty levels. This alignment is supported by system log data, which show increased acceptance rates of recommended content and reduced instances of skipped or abandoned tasks. Such results suggest that the system's adaptive mechanism successfully interprets user data and translates it into meaningful instructional adjustments.

In terms of responsiveness, the system demonstrated efficient real-time performance in adapting to student interactions. The average response time for generating recommendations and feedback was observed to be within an acceptable range, allowing students to receive immediate support without noticeable delays. This near real-time responsiveness is crucial in maintaining engagement, as delayed feedback can disrupt learning flow and reduce motivation. The system was also able to continuously update its recommendations based on new input data, reflecting a dynamic and iterative learning process.

Furthermore, system stability and scalability were evaluated during the implementation phase. The platform maintained consistent performance even when multiple users accessed the system simultaneously, indicating its capability to function effectively in classroom or large-scale learning environments. Minor latency issues were observed under peak usage conditions; however, these did not significantly affect the overall user experience.

User interaction data

The analysis of user interaction data provides deeper insight into how students engaged with the AI-based adaptive learning system throughout the implementation phase. Unlike self-reported measures, interaction data derived from system logs offer objective evidence of student behavior, allowing for a more precise evaluation of engagement patterns and learning dynamics. The findings indicate a substantial increase in the frequency and consistency of student interactions after the implementation of the adaptive system. Students in the experimental group accessed the learning platform more regularly and demonstrated higher levels of activity compared to the baseline period. System logs revealed that the number of sessions per student increased, along with a more even distribution of learning activities over time. This suggests that the adaptive system encouraged continuous engagement rather than sporadic or last-minute participation, which is commonly observed in traditional learning environments.

In terms of time-on-task, the data show that students spent significantly more time engaging with learning materials. The adaptive system's ability to present personalized content at an appropriate level of difficulty appears to have reduced cognitive overload and boredom, enabling students to remain focused for longer periods(Sottilare & Goldberg, 2012). Additionally, the average duration of each session increased, indicating that students were more willing to invest time in completing tasks and exploring recommended materials. This sustained interaction reflects a higher level of behavioral engagement and commitment to the learning process.

Navigation patterns within the system also provide important evidence of enhanced engagement. Students demonstrated more structured and purposeful learning paths, frequently following the recommendations generated by the system. The rate of skipped content decreased, while the completion rate of assigned tasks increased significantly. Moreover, students were more likely to revisit previously accessed materials, suggesting the development of reflective learning behaviors and a deeper approach to understanding the content.

Another key finding relates to response behavior. The system recorded faster response times to prompts, quizzes, and feedback, indicating improved attentiveness and familiarity with the learning environment(Siau et al., 2006). At the same time, the accuracy of responses improved over time, reflecting not only increased participation but also better comprehension. The adaptive feedback mechanism, supported by Artificial Intelligence, appears to have played a crucial role in guiding students toward correct answers and reinforcing learning.

Furthermore, interaction data show a reduction in inactivity periods and dropout tendencies within the learning sessions. Students were less likely to abandon tasks midway and demonstrated greater persistence in completing challenging activities. This suggests that the adaptive system successfully maintained student motivation by continuously adjusting content and providing timely support.

Discussion

Why the model improves (or does not improve) engagement

First, the model enhances engagement by addressing individual differences among learners. Traditional learning environments often fail to accommodate variations in students' prior knowledge, learning pace, and cognitive abilities. In contrast, the adaptive system continuously analyzes learner data and adjusts content difficulty, learning pathways, and feedback accordingly. This personalization reduces the likelihood of cognitive overload for struggling students while preventing boredom among advanced learners. As a result, students are more likely to remain actively involved in the learning process because the material is consistently aligned with their current level of understanding.

Second, the improvement in engagement can be attributed to the system's real-time responsiveness. The model provides immediate feedback and dynamically adapts to student interactions, which plays a critical role in sustaining attention and motivation. From a psychological perspective, timely feedback reinforces learning behavior and helps students correct mistakes before frustration builds. This aligns with principles of formative assessment, where continuous feedback supports deeper learning and ongoing engagement(Rushton, 2005). The system's ability to detect early signs of disengagement such as reduced interaction or prolonged inactivity and respond with appropriate interventions further strengthens its effectiveness.

Third, the integration of engagement analytics contributes significantly to the model's success. By monitoring indicators such as time-on-task, interaction frequency, and response patterns, the system gains a comprehensive understanding of student behavior beyond simple performance metrics. This allows the model to not only react to academic outcomes but also proactively support the learning process. The shift from outcome-based evaluation to process-oriented adaptation helps maintain consistent engagement throughout the learning experience.

Moreover, the model's foundation in pedagogical principles enhances its impact. Unlike purely technology-driven systems, this adaptive learning model incorporates elements of student-centered learning and constructivist approaches, encouraging active participation and knowledge construction(Hirumi, 2002). Students are not merely passive recipients of information; instead, they interact with content, receive tailored guidance, and engage in problem-solving activities that promote deeper cognitive involvement. This alignment between technology and pedagogy is a key factor in improving engagement.

However, it is also important to acknowledge conditions under which the model may not fully improve engagement. For instance, the effectiveness of the system depends on the quality and completeness of input data. Inaccurate or limited data can lead to inappropriate recommendations, which may reduce the relevance of the learning experience. Additionally, students who lack digital literacy or intrinsic motivation may not fully benefit from the adaptive features, as they may not engage sufficiently with the system for it to function optimally. Technical limitations, such as system latency or interface complexity, can also hinder user experience and reduce engagement if not properly addressed.

In summary, the improvement in student engagement is primarily driven by the model's ability to deliver personalized content, provide real-time feedback, and integrate behavioral analytics within a pedagogically grounded framework. These features collectively transform the learning environment into a more interactive, adaptive, and student-centered experience. At the same time, the discussion highlights that the success of such models depends on proper implementation, data quality, and user readiness, suggesting important considerations for future development and application.

Comparison with previous studies

The findings of this study are largely consistent with, yet also extend, previous research on AI-based adaptive learning and student engagement. Prior studies in Educational Technology have generally concluded that adaptive learning systems improve engagement by personalizing content and pacing(Walkington, 2013). For example, earlier research has shown that systems using basic recommendation algorithms can increase student participation and time-on-task by aligning instructional materials with learners' abilities. These results are supported in the present study, where students demonstrated higher interaction frequency, longer engagement duration, and improved task completion rates after using the adaptive model.

However, compared to previous studies, this research demonstrates a more substantial and multidimensional improvement in engagement. Many earlier works primarily focused on cognitive outcomes such as test scores or completion rates, with limited attention to emotional and behavioral engagement(Wang & Eccles, 2012). In contrast, this study adopts a more comprehensive framework, measuring engagement across behavioral, emotional, and cognitive dimensions. The results show that the adaptive model not only enhances academic interaction but also increases students' motivation, interest, and overall learning experience. This suggests that the integration of engagement-focused indicators provides a more holistic understanding of how adaptive learning influences student behavior.

Another key difference lies in the use of real-time engagement analytics. Previous studies often relied on retrospective data analysis, where adaptations were made based on past performance rather than ongoing interaction. While such approaches improved personalization to some extent, they lacked the immediacy needed to sustain engagement during the learning process. This study advances the field by incorporating real-time data monitoring and dynamic system responses, enabling the model to detect disengagement early and intervene promptly. This proactive mechanism appears to be a major factor contributing to the higher engagement levels observed, distinguishing this research from earlier, more reactive systems.

Furthermore, while many existing adaptive learning models are heavily technology-driven, they often lack strong pedagogical integration. Some studies have reported that even technically advanced systems fail to significantly improve engagement due to poor alignment with learning theories. In contrast, this study explicitly combines Artificial Intelligence techniques with established pedagogical principles, such as student-centered learning and constructivist approaches. This hybrid design ensures that the adaptive features not only optimize content delivery but also promote active learning and critical thinking(Yang et al., 2014). As a result, the model achieves both technical effectiveness and educational relevance, addressing a gap identified in previous research.

Additionally, compared to earlier studies that often tested adaptive systems in controlled or small-scale environments, this research demonstrates the model's applicability in a more realistic learning setting. The inclusion of system log analysis, observation data, and user feedback provides stronger empirical evidence of how students interact with the system in practice. This contributes to the external validity of the findings and supports the argument that AI-based adaptive learning can be effectively implemented in real-world educational contexts.

In summary, while the results of this study align with previous findings that adaptive learning enhances student engagement, they also offer significant advancements. The incorporation of real-time analytics, a multidimensional engagement framework, and a pedagogy-driven AI model represents a meaningful contribution to the existing body of research(Sun, 2017). These improvements not only confirm the effectiveness of adaptive learning but also provide a more comprehensive and practical approach to designing engaging educational systems in the digital era.

Educational implications

The findings of this study have important implications for educational practice, particularly in the integration of technology to enhance student engagement and learning outcomes. First, the study highlights the need for a shift from teacher-centered to student-centered learning. The adaptive model empowers students to take a more active role in their learning by providing content that aligns with their individual needs, preferences, and abilities(Walkington, 2013). This suggests that educators should move beyond uniform instructional strategies and adopt more flexible approaches that accommodate diverse learners. Teachers, in this context, are not replaced by technology but instead take on the role of facilitators who guide, support, and interpret learning processes enhanced by AI systems.

Second, the results imply that personalization is a key factor in sustaining student engagement. Educational institutions should consider integrating adaptive learning systems into their curricula to ensure that learning experiences are tailored to each student. By leveraging Artificial Intelligence, schools and universities can provide differentiated instruction at scale, something that is difficult to achieve through traditional methods alone. This is particularly important in large or diverse classrooms, where individual attention from instructors may be limited.

Third, the use of real-time engagement analytics introduces new possibilities for continuous assessment and early intervention. Instead of relying solely on summative assessments such as exams, educators can monitor students' engagement and progress throughout the learning process. This allows for timely support when students show signs of disengagement or difficulty, ultimately preventing learning gaps from widening. As a result, assessment practices may need to evolve toward more formative, data-informed approaches that emphasize ongoing feedback and improvement.

Moreover, the study underscores the importance of aligning technological innovation with pedagogical principles. The effectiveness of the adaptive model is not solely due to its technical capabilities but also its grounding in learning theories such as constructivism and active learning. This implies that educational institutions should carefully design and implement AI systems that are pedagogically sound, rather than adopting technology for its own sake. Training and professional development for educators are therefore essential to ensure they can effectively integrate and utilize these systems in their teaching practices.

Another key implication relates to digital readiness and infrastructure(Kozhevina et al., 2018). For adaptive learning systems to be successfully implemented, institutions must invest in reliable technological infrastructure, including learning management systems, data storage, and internet connectivity. Additionally, both teachers and students need adequate digital literacy skills to interact effectively with AI-based platforms. Without these supporting conditions, the potential benefits of adaptive learning may not be fully realized.

Finally, the study suggests that AI-based adaptive learning has the potential to promote more equitable education. By tailoring learning experiences to individual needs, such systems can help reduce disparities among students with different abilities, backgrounds, and learning speeds. This aligns with broader educational goals of inclusivity and accessibility, ensuring that all students have the opportunity to engage meaningfully with learning content.

Conclusion

In conclusion, this study demonstrates that the development and implementation of an AI-based adaptive learning model can significantly enhance student engagement in modern educational environments. By integrating principles from Artificial Intelligence and Educational Technology, the proposed model successfully addresses the limitations of traditional and non-adaptive learning systems, particularly their inability to accommodate individual differences among learners. The findings reveal that the adaptive learning model improves student engagement across behavioral, emotional, and cognitive dimensions. Students who interacted with the system showed increased participation, longer time-on-task, higher motivation, and deeper cognitive involvement compared to those in conventional learning settings. These improvements are largely attributed to the system's ability to provide personalized content, deliver real-time feedback, and dynamically adjust learning pathways based on individual performance and interaction data. In addition, the system demonstrated strong technical performance, with high accuracy in predicting student needs and efficient responsiveness in delivering adaptive recommendations. The analysis of user interaction data further confirmed that the model fosters more consistent and meaningful learning behaviors, transforming passive learners into active participants. These results highlight the effectiveness of combining advanced AI techniques with pedagogically grounded approaches to create engaging and student-centered learning experiences. This study also contributes to the existing body of knowledge by introducing a novel framework that integrates real-time engagement analytics and a hybrid AI-pedagogical model. Unlike many previous studies that focus primarily on learning outcomes, this research emphasizes the importance of the learning process itself, particularly student engagement as a key driver of academic success. As such, it provides both theoretical and practical contributions to the advancement of adaptive learning systems. However, the study acknowledges several limitations, including the scope of the sample, potential variability in digital literacy, and dependence on the quality of system data. These limitations suggest the need for further research to test the model in broader and more diverse educational contexts, as well as to refine its scalability and adaptability. Overall, this research confirms that AI-based adaptive learning is a promising approach for improving student engagement in the digital age. By offering personalized, responsive, and data-driven learning experiences, such systems have the potential to transform educational practices and support more effective, inclusive, and sustainable learning outcomes in the future.

Reference

Adriani, D., Lubis, P., & Triono, M. (2020). Teaching material development of educational research methodology with Addie Models. *3rd International Conference Community Research and Service Engagements, IC2RSE 2019, 4 December 2019, North Sumatra, Indonesia*.

Ahmad, K., Iqbal, W., El-Hassan, A., Qadir, J., Benhaddou, D., Ayyash, M., & Al-Fuqaha, A. (2023). Data-driven artificial intelligence in education: A comprehensive review. *IEEE Transactions on Learning Technologies*, *17*, 12–31.

Ayeoribe, O. P., & Ayeoribe, A. E. (2025). Implementing Adaptive Learning Systems to Support Personalized Instruction, Close Achievement Gaps, and Bridge Pedagogical Innovation with Practical, Student-Centered Technology across Diverse and Dynamic Classroom Environments. *Read the Published Version in the International Journal Evolving Sustainable and Renewable Energy Solutions ISSN*, 3068–9325.

Douglass, J. A., Thomson, G., & Zhao, C.-M. (2012). The learning outcomes race: The value of self-reported gains in large research universities. *Higher Education*, *64*(3), 317–335.

He, S., Zhu, J., He, P., & Lyu, M. R. (2016). Experience report: System log analysis for anomaly detection. *2016 IEEE 27th International Symposium on Software Reliability Engineering (ISSRE)*, 207–218.

Hirumi, A. (2002). Student-centered, technology-rich learning environments (SCenTRLE): Operationalizing constructivist approaches to teaching and learning. *Journal of Technology and Teacher Education*, *10*(4), 497–537.

Kabudi, T., Pappas, I., & Olsen, D. H. (2021). AI-enabled adaptive learning systems: A systematic mapping of the literature. *Computers and Education: Artificial Intelligence*, *2*, 100017.

Kairuz, T., Crump, K., & O'Brien, A. (2007). Tools for data collection and analysis. *Pharmaceutical Journal*, *278*.

Kaur, J. (2015). *Personalizing AI Education for Women: A Wi-Fi-Enabled Adaptive Framework Using Reinforcement Learning*.

Khelifi, K., & Hamzaoui-elachachi, H. (2024). Beyond'One-Size-Fits-All'Teaching: Embracing the Learner-Centered Paradigm Through Differentiated Instruction. 726–708), 2(*14*, *التعليمية*.

Kozhevina, O., Salienko, N., Kluyeva, V., & Eroshkin, S. (2018). Digital readiness parameters for regional economies: Empirical research and monitoring results (Russia case study). In *Energy Management of Municipal Transportation Facilities and Transport* (pp. 247–256). Springer.

Lecciso, F., Levante, A., Fabio, R. A., Caprì, T., Leo, M., Carcagnì, P., Distante, C., Mazzeo, P. L., Spagnolo, P., & Petrocchi, S. (2021). Emotional expression in children with ASD: A pre-study on a two-group pre-post-test design comparing robot-based and computer-based training. *Frontiers in Psychology*, *12*, 678052.

Li, S. S., & Karahanna, E. (2015). Online recommendation systems in a B2C E-commerce context: a review and future directions. *Journal of the Association for Information Systems*, *16*(2), 2.

McDonald, D., Holmes, Y., & Prater, T. (2020). The Rules of Engagement: A Test of Instructor Inputs and Student Learning Outcomes in Active versus Passive Learning Environments. *E-Journal of Business Education and Scholarship of Teaching*, *14*(1), 25–39.

Mulenga, R., & Shilongo, H. (2025). Hybrid and blended learning models: innovations, challenges, and future directions in education. *Acta Pedagogia Asiana*, *4*(1), 1–13.

Ni'amullah, A., & Hasanah, R. (2025). AI-based adaptive learning in higher education: Improving student engagement and learning outcomes. *Journal of Digital Learning*, *1*(1), 39–51.

Pedro, F., Subosa, M., Rivas, A., & Valverde, P. (2019). *Artificial intelligence in education: Challenges and opportunities for sustainable development*.

Rushton, A. (2005). Formative assessment: a key to deep learning? *Medical Teacher*, *27*(6), 509–513.

Siau, K., Sheng, H., & Nah, F.-H. (2006). Use of a classroom response system to enhance classroom interactivity. *IEEE Transactions on Education*, *49*(3), 398–403.

Sottilare, R., & Goldberg, B. (2012). Designing adaptive computer-based tutoring systems to accelerate learning and facilitate retention. *Cognitive Technology*, *17*(1), 19–33.

Sun, S. Y. H. (2017). Design for CALL–possible synergies between CALL and design for learning. *Computer Assisted Language Learning*, *30*(6), 575–599.

Van Bragt, C. A. C., Bakx, A. W. E. A., Van der Sanden, J. M. M., & Croon, M. A. (2007). Students' approaches to learning when entering higher education: Differences between students with senior general secondary and senior secondary educational backgrounds. *Learning and Individual Differences*, *17*(1), 83–96.

Walkington, C. A. (2013). Using adaptive learning technologies to personalize instruction to student interests: The impact of relevant contexts on performance and learning outcomes. *Journal of Educational Psychology*, *105*(4), 932.

Wang, M., & Eccles, J. S. (2012). Adolescent behavioral, emotional, and cognitive engagement trajectories in school and their differential relations to educational success. *Journal of Research on Adolescence*, *22*(1), 31–39.

Yang, Y. C., Gamble, J. H., Hung, Y., & Lin, T. (2014). An online adaptive learning environment for critical-thinking-infused E nglish literacy instruction. *British Journal of Educational Technology*, *45*(4), 723–747.

Yoo, C., Ramirez, L., & Liuzzi, J. (2014). Big data analysis using modern statistical and machine learning methods in medicine. *International Neurourology Journal*, *18*(2), 50.

Zhu, A. (2023). Navigating the digital shift: The impact of educational technology on pedagogy and student engagement. *Journal of Education and Educational Research*, *6*(1), 11–14.