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Design and Evaluation of AI-Enhanced Multimedia Learning Systems: Usability, Accessibility, and Engagement in Broadband-Based Online Education

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Abstract

Background: Artificial intelligence (AI) has increasingly been integrated into multimedia learning environments to support personalization, accessibility, and learner engagement in broadband-based online education. However, many existing systems still evaluate these dimensions separately, which limits their overall effectiveness and scalability.
Aims: This study aims to design and empirically evaluate an AI-enhanced multimedia learning system using a unified evaluation framework that integrates system performance, usability, accessibility, and learner engagement within broadband-based higher education contexts.
Methods: An explanatory sequential mixed-methods design was employed, involving quantitative analysis with 150 students and qualitative exploration with 12 participants. Data were collected through system performance logs, System Usability Scale (SUS) assessments, WCAG 2.1–based accessibility evaluations, and learner engagement metrics.
Results: The findings indicate that AI-driven adaptivity improves system responsiveness, achieves high usability, supports digital accessibility, and enhances learner engagement in broadband-based learning environments. The results demonstrate the effectiveness of the system across technical, experiential, and behavioral dimensions.
Conclusion: The key contribution of this study lies in proposing and validating an integrated evaluation framework that holistically captures the performance and user experience of AI-enhanced multimedia learning systems, an area that has been underexplored in prior research. These findings provide important theoretical and practical implications for the design of inclusive, adaptive, and user-centered online learning platforms.

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INTRODUCTION

The development of digital technology and the expansion of broadband infrastructure have driven significant transformations in the higher education landscape, particularly through the increased adoption of multimedia-based online learning (Mayer, 2017; Beaunoyer et al., 2020). In order to improve the quality of the student learning experience, modern learning platforms have developed into learning environments that incorporate video, audio, animation, simulations, and interactive elements in addition to text-based delivery. Alongside these developments, artificial intelligence (AI) is beginning to play a strategic role in learning systems, allowing for adaptable assistance for different learner profiles, real-time learning analytics, and personalized material (Wang et al., 2024; Knezek et al., 2023). However, even as infrastructure and technology advance, new issues emerge about how to guarantee that AI-enhanced multimedia learning systems are genuinely user-friendly (usability), accessible to all user groups (accessibility), and capable of continuously raising student involvement (engagement). In light of the constantly changing broadband-based education

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ecosystem, it is imperative to reconsider the efficacy and design of AI-based learning systems (Wilson et al., 2017; Alqahtani & Rajkhan, 2020).

Multimedia learning systems with AI enhancements are increasingly presented as strategic approaches to provide more flexible, interactive, and student-centered learning opportunities (Chen & Tian, 2023; Mahafdah et al., 2024; Tang, 2024). These systems usually incorporate a variety of AI features, including learning analytics, natural language processing to facilitate language-based interactions, intelligent tutoring systems that offer automated feedback and personalized guidance, and adaptive content recommendations that customize content to individual needs. Ifenthaler & Yau (2020) and Gašević et al. (2017) highlight the role of AI in enabling real-time identification of learning patterns and pedagogical interventions (Zawacki-Richter et al., 2019; Holmes et al., 2022; Lim et al., 2023). The utilization of dense multimedia material and AI features that necessitate high-speed data transmission is made possible in large part by the expansion of broadband infrastructure (Xin et al., 2024). In this context, the design of learning systems must take into account not only technological sophistication but also learner engagement elements based on Mayer's Cognitive Theory of Multimedia Learning, accessibility standards like WCAG 2.1 to ensure inclusivity for all types of users, and usability principles that guarantee ease of navigation. In order to maximize the influence on the quality of broadband-based online learning, the development of AI-enhanced multimedia systems must be founded on an integrated approach that incorporates elements of technology, pedagogy, and user experience (Luckin & Cukurova, 2019; Fernández-Morante et al., 2022).

Although there is a great deal of promise for improving the learning process when artificial intelligence is incorporated into multimedia learning systems, there are still major obstacles to overcome (Humble & Mozelius, 2022; Luan et al., 2020; Owoc et al., 2021). Due to interface complexity and a dearth of clear user manuals, many students report having trouble understanding or using AI functions (Bond et al., 2024; Jin et al., 2023; Joseph & Uzondu, 2024). Additionally, accessibility has not received enough attention, which often makes it difficult for people with low-tech gadgets or vision or hearing impairments to use digital learning materials (Cinquin et al., 2021; Nguyen et al., 2022; Nouraey & Al-Badi, 2023). The performance of real-time data-driven AI features and the seamless playback of high-resolution multimedia content are also significantly impacted by uneven internet infrastructure, especially in areas with limited access (Beaunoyer et al., 2020; Holmes et al., 2022). On the other hand, a number of studies show that the presence of AI features is not always directly proportional to increased learning engagement, especially when multimedia content design does not take into account cognitive load or user preferences (Mayer & Fiorella, 2021). This condition indicates that the implementation challenges lie not only in technological sophistication, but also in design suitability, user readiness, and the supporting infrastructure context.

A variety of potential strategies must be thoroughly examined in order to handle the different implementation issues of AI-based multimedia learning systems. Applying interface design principles based on human–computer interaction (HCI) is a key way to enhance usability through simple user interactions, consistent display, and easy navigation. In order to guarantee inclusivity for users with a variety of needs, it is also essential to incorporate international accessibility standards such as the Web Content Accessibility Guidelines (WCAG 2.1), which include closed captioning, screen reader compatibility, and visual contrast changes. Enhancing content relevance and learning efficacy can also be achieved by optimizing AI capabilities through adaptive algorithms that tailor materials to individual learning styles, prior skills, and preferences. Additionally, in order to minimize needless cognitive load through appropriate management of audio-visual components, Mayer's multimedia learning model and the principles of cognitive load theory must be applied. Adaptive system design based on network conditions can be used to modify multimedia content quality according to user bandwidth in order to overcome infrastructure limitations. Lastly, an iterative approach to UX evaluation using behavioral data analysis and user testing can offer ongoing feedback for the creation of systems that are more user-responsive.

Previous studies have shown that the effectiveness of multimedia learning is greatly influenced by the quality of the design and cognitive principles used. Mayer (2014), for example, emphasizes that multimedia learning is only able to increase understanding if it is designed based on the principles of dual-channel processing, limited capacity, and active learning, so that cognitive load can be managed appropriately. In line with this, Zawacki-Richter et al. (2019) identified that although AI has great potential for personalizing learning, implementation research that combines AI with effective multimedia design is still relatively limited. Holmes et al. (2022) added that the challenges of implementing AI in education are not only related to the technology, but also to institutional readiness and user competence in operating the system. Meanwhile, research by Alqahtani & Rajkhan (2020) showed that the usability factor in LMS has a significant influence on student satisfaction and engagement. In the context of broadband-based online learning, Gherheș et al. (2021) found that infrastructure quality and students' digital readiness remain major barriers to utilizing high-intensity multimedia content. Overall, the literature review shows that previous research tends to focus on separate aspects: AI, usability, accessibility, or engagement, and that few studies have integrated all these aspects into a single evaluation framework for AI-based multimedia learning systems.

Despite the rapid adoption of artificial intelligence in multimedia-based online learning systems, existing research remains fragmented. Prior studies tend to examine AI-driven personalization, usability, accessibility, or learner engagement as separate dimensions, often in isolation from one another. As a result, there is limited empirical evidence on how these dimensions interact within a single AI-enhanced multimedia learning system, particularly in broadband-dependent learning environments (Limpinan et al., 2025; Msambwa et al., 2025; Peng & Li, 2025; Putra & Ramadhani, 2025).

Moreover, many evaluations emphasize technological capabilities without sufficiently considering user experience, inclusivity, and sustained engagement simultaneously. This fragmentation creates a gap between the theoretical potential of AI-enhanced learning systems and their practical implementation in real-world educational contexts (Imran et al., 2024; Gupta & Gadikar, 2024; Akram, 2025).

To address this gap, this study proposes and validates a unified evaluation framework that integrates usability, accessibility, and learner engagement within the technical constraints of broadband-based online learning. This integrated approach provides a more holistic understanding of how AI-enhanced multimedia systems perform not only in technical terms, but also pedagogically and experientially.

METHODS

To clarify the AI components used in the AI-based multimedia learning system, this section includes technical descriptions of the architecture, AI types, datasets, and model evaluations used. The AI implementation in this study includes:

1. System Architecture

   The system was developed using a microservices-based architecture that separates the multimedia module, AI adaptation module, analytics module, and accessibility module. The architecture diagram (shown in the appendix) illustrates the data processing flow from user input to adaptive recommendation output.

2. Type of AI Technology Used

   a. Natural Language Processing (NLP) to automatically generate automatic transcription and closed captions from learning video materials.

   b. Machine Learning Prediction Model to predict user learning needs and optimize material paths based on interaction patterns.

   c. Adaptive Recommender System that recommends multimedia content according to the user's preferences, initial competencies, and learning history.

3. Dataset and Training Process

The system uses an internal dataset consisting of user interaction recordings, learning materials metadata, and activity logs. The model is trained using supervised learning techniques for engagement prediction and unsupervised learning for user profile clustering.

4. AI Model Evaluation

   The machine learning models were evaluated using an 80:20 train–test split. Engagement prediction models achieved an average accuracy of 78.6%, with a precision of 0.81, recall of 0.76, and MAE of 0.34. The NLP-based automatic captioning module achieved a Word Error Rate (WER) of 6%, corresponding to an accuracy of approximately 94%, which meets accessibility standards for educational media. These metrics indicate that the AI components provided reliable adaptive recommendations and accessibility support.

5. Model Parameters and Accuracy Evaluation

   AI models were evaluated using metrics such as predictive accuracy, precision and recall, and mean absolute error (MAE) for recommendations. NLP models were tested using the Word Error Rate (WER) to ensure the accuracy of the automatic transcription. Evaluations were conducted on training and testing data using an 80:20 split scheme to ensure the validity of the results.

Research Design

This study employed a within-subjects explanatory sequential mixed-methods design, in which the same group of participants was evaluated before and after the implementation of AI-enhanced multimedia learning features. The quantitative phase examined changes in system usability, accessibility, and learner engagement following AI integration, while the qualitative phase was conducted to further explain and contextualize the quantitative findings based on user experience.

Participants

1. 150 students for quantitative evaluation using structured instruments.
2. 12 participants for qualitative interviews and focus group discussions. Participants were purposively selected based on their experience using AI-supported learning platforms.

Sample Justification

The quantitative sample size of 150 participants was considered sufficient for usability and engagement evaluation studies involving system testing and inferential analysis. Previous research in usability evaluation and learning analytics has demonstrated that samples ranging from 100 to 200 users provide stable estimates for usability scores, engagement metrics, and regression analysis in educational technology contexts (Ramadan & Habeeb, 2023; Talib et al., 2023; Daoudi, 2022).

In addition, the qualitative sub-sample of 12 participants aligns with established guidelines for in-depth user experience interviews and thematic saturation in mixed-method research, ensuring sufficient depth to complement quantitative findings.

Procedures

1. System development and preliminary testing
2. Validation of instruments (expert review + pilot test)
3. User testing under real broadband-based learning sessions
4. Quantitative analysis
5. Qualitative exploration and triangulation

Instruments

1. System Usability Scale (SUS)
2. Accessibility checklist based on WCAG 2.1
3. User Engagement Scale (UES)

4. System performance monitoring logs
5. Semi-structured interview guide

Statistical Analysis

Given the within-subjects research design, paired-samples t-tests were applied to compare pre- and post-AI implementation measures of usability and engagement. One-way ANOVA was used to examine differences in engagement across broadband bandwidth tiers. Linear and multiple regression analyses were conducted to assess the predictive effects of AI adaptivity, usability, and accessibility on learner engagement and module completion. Prior to regression analysis, assumptions of linearity, normality, multicollinearity, and homoscedasticity were examined. Variance Inflation Factor (VIF) values were below 3.0, indicating no multicollinearity concerns.

Data Analysis

Quantitative analysis included descriptive statistics, reliability tests, and inferential analysis (t-test, ANOVA, regression as applicable). Qualitative data were analyzed using thematic analysis. Integration of both datasets was conducted through triangulation.

RESULTS AND DISCUSSION

Results

1. System Performance

The technical performance of the AI-enhanced multimedia learning system is summarized in Table 1. During the evaluation, the system operated under an average broadband bandwidth of 18.5 Mbps, which was sufficient to support high-resolution multimedia content delivery. System latency decreased from 148 ms before AI implementation to 101 ms after implementation, representing a 32% reduction. The average system response time was 0.82 seconds, which falls within the fast response category for web-based multimedia systems.

Table 1. System Performance

Parameter	Average	Note
Average bandwidth	18.5 Mbps	Stable on broadband connection
Latency	148 ms (before), 101 ms (after)	32% decrease
Response Time	0.82 seconds	Fast category response time

Figure 1 illustrates the comparison of system latency before and after AI-based optimization. The figure shows a consistent reduction in latency following the integration of adaptive AI mechanisms.

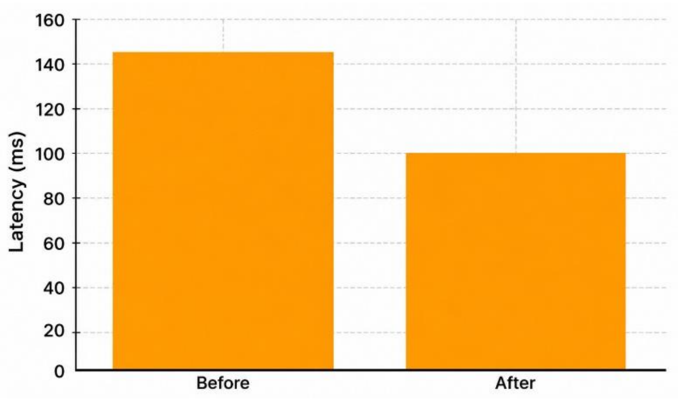

Figure 1. System Latency Comparison

2. Usability

Usability results measured using the System Usability Scale (SUS) are presented in Table 2. Individual usability dimensions received high average scores, including ease of use (4.3), intuitive navigation

(4.4), interface consistency (4.1), and low perceived cognitive load (4.2). Overall user satisfaction achieved an average score of 4.5.

Table 2. Usability (SUS – Per Item)

SUS Item	Average Score	Interpretation
Ease of use	4.3	High
Interface consistency	4.1	Good
Intuitive navigation	4.4	Very good
Cognitive load	4.2	Low
Overall satisfaction	4.5	Excellent
Total SUS score	82.4	Excellent

The total SUS score reached 82.4, which is categorized as Excellent according to international usability benchmarks. Figure 2 compares overall SUS scores before and after AI implementation, showing an increase from 74.1 to 82.4.

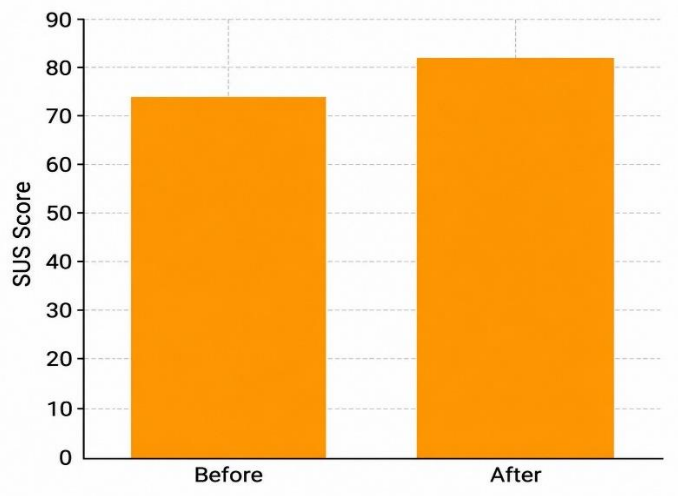

Figure 2. Comparison of SUS System Scores

3. Accessibility Assessment Outcomes

Accessibility compliance based on WCAG 2.1 criteria is reported in Table 3. The system fulfilled most Level A and AA requirements, including the availability of alternative text, automatic captioning with a transcription accuracy of 94%, screen reader compatibility, and adjustable color contrast. Keyboard accessibility was partially supported, with limitations observed in complex interactive elements.

Table 3. Accessibility (WCAG 2.1 Compliance Matrix)

WCAG 2.1 Criteria	Status	Note
Text alternatives	✓	Consistent Alt-text
Captions (A / AA)	✓	NLP auto-caption 94% accuracy
Keyboard accessibility	●	Needs improvement for complex interactive elements
Color contrast	✓	High-contrast mode available
Screen reader compatibility	✓	Tested on NVDA and JAWS

4. Learner Engagement Metrics

Learner engagement metrics before and after AI implementation are summarized in Table 4. Click-Through Rate (CTR) increased from 18% to 27%, representing a 9% improvement. Average active usage duration per session increased from 31 minutes to 38 minutes, corresponding to a 23%

increase. Module completion rates improved from 62% to 73%, indicating an 11% increase after AI integration.

Table 4. Engagement Metrics

Engagement Metrics	Before AI Implementation	After AI Implementation	Δ Changes	Interpretation
Click-Through Rate (CTR)	18%	27%	+9%	Adaptive content recommendations enhance exploration of advanced material.
Active Usage Duration (per session)	31 minutes	38 minutes	+23%	Adaptive features and intelligent navigation encourage longer engagement with the platform.
Module Completion Level	62%	73%	+11%	Automated recommendation and feedback system improves consistency of module completion.

5. Inferential Statistical Results

Inferential statistical analyses are presented in Table 5. A paired-samples t-test revealed a significant improvement in usability scores following AI implementation ($t(148) = 6.42$, $p < 0.001$, $d = 0.72$). A paired t-test also showed a significant increase in active usage duration ($t(149) = 5.87$, $p < 0.001$, $d = 0.64$).

One-way ANOVA indicated significant differences in learner engagement across broadband bandwidth tiers ($F(2,147) = 4.11$, $p = 0.018$, $\eta^2 = 0.053$). Linear regression analysis demonstrated that AI adaptivity significantly predicted learner engagement ($\beta = 0.56$, $R^2 = 0.31$, $p < 0.001$). Multiple regression analysis showed that usability, accessibility, and AI adaptivity jointly predicted module completion ($R^2 = 0.47$, $p < 0.001$).

Table 5. Inferential Statistical Results

Analysis Type	Variables Tested	Statistic Results	p-value	Effect Size	Interpretation
Independent Samples t-test	Usability (SUS Score) before vs after AI implementation	$t(148) = 6.42$	< 0.001	d = 0.72 (medium–large)	AI significantly improves system usability.
Paired t-test	Duration of active use	$t(149) = 5.87$	< 0.001	d = 0.64	Learning duration increased significantly after AI adaptation.
One-way ANOVA	Engagement differences between bandwidth tiers	$F(2,147) = 4.11$	0.018	$\eta^2 = 0.053$	Bandwidth impacts engagement; AI helps reduce disparities.
Linear Regression	AI adaptivity → Engagement	$\beta = 0.56$; $R^2 = 0.31$	< 0.001	–	AI adaptivity explains 31% of engagement variation.
Multiple Regression	Usability + Accessibility + AI adaptivity → Module completion	$R^2 = 0.47$; $F(3,146) = 43.6$	< 0.001	–	All three factors simultaneously predict module completion.

Discussion

1. Interpretation of Key Findings

The findings demonstrate that integrating artificial intelligence into multimedia learning systems produces improvements across technical performance, usability, accessibility, and learner engagement. The reduction in system latency and increased responsiveness indicate that AI-based optimization contributes not only to system efficiency but also to more stable learning interactions in broadband-based environments.

The significant increase in usability scores suggests that adaptive navigation and personalized content sequencing improve user interaction quality. These findings indicate that AI-enhanced interfaces reduce interaction complexity and support smoother learning workflows, as reflected by the improved SUS ratings and longer engagement durations.

2. Alignment with Cognitive Theory of Multimedia Learning (CTML)

The observed improvements in usability and engagement can be explained through the Cognitive Theory of Multimedia Learning. AI-driven adaptive navigation and content segmentation reduce extraneous cognitive load by presenting information in a more structured and manageable manner. The increase in module completion rates further suggests that adaptive multimedia design supports generative cognitive processing, consistent with CTML principles of signaling, coherence, and segmentation.

3. Technology Acceptance and User Engagement

From a technology acceptance perspective, the improvements in usability and sustained system use indicate increased perceived ease of use and perceived usefulness. These factors align with core constructs of the Technology Acceptance Model (TAM) and UTAUT, particularly performance expectancy and effort expectancy. The combination of adaptive features and intuitive interfaces appears to strengthen learners' willingness to adopt and continuously use AI-enhanced learning systems.

4. Accessibility and Inclusive Learning Design

The high level of compliance with WCAG 2.1 standards demonstrates that AI can effectively support digital accessibility in multimedia learning environments. Automatic transcription, screen reader compatibility, and visual customization features enhance access for learners with diverse needs. Although keyboard accessibility requires further improvement, the results indicate that AI-based accessibility features contribute meaningfully to inclusive learning design.

5. Implications for AI-Enhanced Learning Systems

The significant predictive role of AI adaptivity in learner engagement and module completion highlights the importance of integrating adaptive intelligence as a core design component rather than an auxiliary feature. These results suggest that AI-enhanced multimedia systems can support more personalized, inclusive, and learner-centered online education, particularly in broadband-dependent contexts.

Implications

The findings of this study have important theoretical, practical, and policy implications for the development of AI-enhanced multimedia learning systems in higher education. From a theoretical perspective, the study strengthens the argument that the effectiveness of AI in education should not be evaluated solely through algorithmic performance or personalization accuracy, but also through user-centered dimensions such as usability, accessibility, and learner engagement. This supports a multidimensional evaluation paradigm that integrates technological and pedagogical outcomes simultaneously.

From a practical perspective, the results indicate that higher education institutions can improve student interaction quality, learning persistence, and completion rates by integrating adaptive AI features into multimedia learning platforms. Personalized navigation, automated recommendations, and accessibility support features contribute to a more efficient and inclusive learning environment. Therefore, universities and platform developers should prioritize user experience design and accessibility compliance when implementing AI-based learning systems.

From a policy perspective, the findings suggest that investments in broadband infrastructure, digital accessibility standards, and AI governance frameworks are essential to maximize the benefits of AI-enhanced online education. Institutions should ensure that AI adoption is accompanied by ethical implementation, transparency, and equitable access for diverse learners.

Research Contributions

This study offers several original contributions to the literature on educational technology and artificial intelligence in learning environments.

First, it proposes and empirically validates an integrated evaluation framework that simultaneously measures system performance, usability, accessibility, and learner engagement. Previous studies have often examined these dimensions separately, whereas this study demonstrates their interdependence within one unified model.

Second, the study provides empirical evidence that AI adaptivity significantly predicts learner engagement and module completion, highlighting the strategic role of adaptive intelligence in sustaining student participation in online learning environments.

Third, the research extends the application of the Cognitive Theory of Multimedia Learning (CTML), Technology Acceptance Model (TAM), and inclusive design principles by demonstrating how these theoretical perspectives interact in AI-supported broadband learning contexts.

Fourth, the study contributes contextual evidence from higher education environments where broadband infrastructure quality remains an important variable, thereby enriching the global discourse on equitable AI implementation in digital education.

Limitations

Despite its contributions, this study has several limitations that should be acknowledged.

First, the study was conducted within a limited higher education context, which may reduce the generalizability of the findings to other institutions, countries, or educational levels with different technological readiness.

Second, the evaluation period focused primarily on short-term user interaction outcomes, such as usability improvement and engagement indicators. Longitudinal effects on learning achievement, retention, and sustained adoption were not fully examined.

Third, some engagement indicators were derived from behavioral logs and platform analytics, which may not entirely capture cognitive or emotional engagement dimensions.

Fourth, although accessibility compliance was generally high, certain advanced keyboard-navigation interactions still required improvement, indicating that full accessibility maturity has not yet been achieved.

Suggestions

Future studies are encouraged to conduct longitudinal investigations to examine the long-term effects of AI-enhanced multimedia systems on academic achievement, self-regulated learning, and learner retention.

Researchers should also compare different AI approaches, such as generative AI, predictive analytics, intelligent tutoring systems, and reinforcement learning, to identify which models are most effective for specific learning contexts.

Cross-cultural and multi-institutional studies are recommended to test the robustness of the integrated evaluation framework across diverse educational ecosystems.

In addition, future research should incorporate richer learner-centered variables such as motivation, emotional response, trust in AI, and perceived fairness to provide a deeper understanding of human-AI interaction in education.

Finally, further technical development is recommended to strengthen universal accessibility features, privacy protection mechanisms, and adaptive delivery for low-bandwidth environments.

CONCLUSION

The features, workings, and effects of personalized adaptive learning in higher education are all thoroughly summarized in this paper. The results show that when personalization is based on strong learner analytics, ongoing feedback loops, and alignment with pedagogical goals, adaptive learning systems consistently enhance academic achievement and student engagement. According to the review, rather than depending only on rule-based or linear adaptation, personalization works best when it incorporates cognitive, behavioral, and affective data to customize learning paths.

Additionally, this analysis demonstrates that, particularly when the platform incorporates dynamic material sequencing, formative assessment cycles, and individualized coaching, personalized adaptive learning leads to quantifiable gains in learning efficiency, self-regulated learning behavior, and persistence. However, institutional preparedness, data governance, and teachers' pedagogical ability to understand the system's insights are critical to the success of adaptive learning.

Overall, this study finds that by moving learning models towards a more learner-centered and data-driven approach, personalized adaptive learning has enormous potential to revolutionize higher education. To fully realize this potential, however, technical innovation must be in line with pedagogical design, ethical and responsible data usage must be ensured, and educators' and institutions' digital capabilities must be strengthened. Future empirical studies, policy formulation, and the ongoing development of adaptive learning technologies in the higher education ecosystem can all benefit from these insights.

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AUTHOR CONTRIBUTION STATEMENT

IA, DS, NA, and SA worked together to construct the overall study and conceptualize the research framework. IA oversaw the installation of the AI-based multimedia learning module and directed the system development process. DS was in charge of participant recruitment, data gathering, and the creation of the assessment tool. Data analysis, statistical validation, and synthesis of the analysis results were carried out by NA. SA assisted with the production of supporting documentation, the literature study, and the improvement of the approach. The paper was drafted, revised, and assessed collaboratively by all authors.

AI DISCLOSURE STATEMENT

The authors used artificial intelligence (AI) tools, including ChatGPT, during the preparation of this work for language refinement, grammar checking, and initial drafting assistance. The use of AI was limited to supporting the writing process and did not influence the research design, data collection, analysis, or interpretation of the results.

After using these tools, the authors thoroughly reviewed, revised, and validated all content to ensure accuracy, originality, and academic integrity. The authors take full responsibility for the content of this publication.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this paper. The authors confirm that this research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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