INTERNATIONAL JOURNAL OF RESEARCH AND SCIENTIFIC INNOVATION (IJRSI)
ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue VI June 2026

AI-Enhanced Personalized Learning in Higher Education: Integrating Machine Learning With Moodle

[*1]Sibusisiwe Dube, [2]Arthur Madzore, & [3]Sinokubekezela Princess Dube

[1]Lecturer, National University of Science and Technology, Department of Informatics and Analytics, Zimbabwe

[2]Student, National University of Science and Technology, Department of Informatics and Analytics, Zimbabwe

[3]Student. The University of Zambia, School of Engineering, Zambia

[*]Corresponding Author

DOI: https://doi.org/10.51244/IJRSI.2026.1306000417

Received: 22 June 2026; Accepted: 27 June 2026; Published: 15 July 2026

ABSTRACT

Learning Management Systems (LMSs) have been rapidly adopted in higher education. The emergence of the COVID-19 pandemic not only disrupted normal, traditional teaching and learning but also revolutionized pedagogical approaches and learning methodologies. However, most LMS platforms, such as Moodle, utilize static content delivery methods that are not sufficiently catered to the diverse learning needs and abilities of students. The study, motivated by the results from our previous article based on a systematic literature review, aimed to design and evaluate an AI-enabled adaptive learning framework to enhance Moodle's ability to provide personalized learning experiences. This paper used a quantitative experimental research design and a data set that contained demographic, behavioral, engagement, and academic performance data from 213,000 students. The proposed framework involved the use of Extreme Gradient Boosting (XGBoost) models for learner performance prediction and at-risk student identification, along with a hybrid recommendation system for personalized content delivery. The results showed a remarkable predictive power, with the at-risk detection model achieving 97.7% accuracy and the learner performance prediction model achieving 97.3% accuracy. The feature importance analysis suggested that the top predictors of academic outcomes included learner engagement, peer interaction, attendance, time spent on the platform, and academic skills. Moreover, the hybrid recommendation system was able to generate personalized learning resources based on learners' performance, deficiencies, and learning preferences. The research results indicate that the combination of AI and machine learning techniques in Moodle can greatly enhance adaptive learning, learner engagement, and early intervention strategies, resulting in improved educational outcomes in higher education settings.

Keywords: Adaptive learning systems; Artificial intelligence; Higher education; Machine learning; Moodle; Personalized learning

INTRODUCTION

With the rise of digital learning environments around the world, there has been a major shift within educational organizations, especially after the COVID-19 pandemic outbreak, which triggered the use of virtual and hybrid learning systems. Learning management systems (LMS) like Moodle have become integral tools for the dissemination of course material, assessment of students, communication, and remote learning. Their versatility, scalability, and affordability have played a significant role in their widespread acceptance in universities globally. Despite such improvements, however, current LMS systems have some major drawbacks. Most traditional e-learning solutions use static content delivery and apply identical approaches to all users, without taking into account their learning styles, engagement patterns, intellectual abilities, or previous academic performance. Such an approach is likely to lower user engagement, prevent proper learner assistance, delay interventions with underperforming learners, and negatively affect academic success.

While Moodle is quite effective in terms of being an open-source LMS system, this platform uses only human guidance and simple reporting mechanisms. Although this solution provides great administrative control, its adaptation capabilities are not so strong, and no predictive algorithms can be used for identification of at-risk learners. Consequently, teachers will experience difficulties with progress monitoring, learning problem detection, and personalized instruction. In turn, the application of artificial intelligence (AI) and machine learning (ML) can provide ways of dealing with the aforementioned disadvantages. An intelligent educational system using the capabilities of artificial intelligence and machine learning can analyze huge amounts of information about learners collected from digital learning environments, which includes behavioral patterns, assessment scores, attendance data, interaction, and engagement patterns.

This paper is a follow-up to a systematic literature review conducted by Dube et ql (2026), which revealed several gaps in existing literature. The findings of that research revealed that recent trends in the field of educational data mining and intelligent tutoring systems show the high potential of AI-enabled learning environments to enhance students' engagement, academic performance, and their general satisfaction from the learning process. It has been proven that machine learning techniques including XGBoost, Decision Trees, Artificial Neural Networks, and SVMs provide high prediction ability within the educational area. Moreover, modern recommendation systems and generative AI techniques are successfully implemented into LMS platforms as well. In the current research, a new approach to improving Moodle platform is suggested based on applying AI methods to increase students' engagement and enhance educational results. To achieve these goals, it was decided to use XGBoost-based predictive models and a recommendation system as an effective combination for enhancing Moodle learning experience.

Problem Statement

Although Moodle's open-source nature offers an extensible architecture for intelligent services (such as automated grading or learning analytics), research into large-scale, policy-driven integration that ensures ethical governance and pedagogical alignment remains in its infancy (Sofianos, 2026). In addition to this problem, despite Moodle's popularity compared with other platforms, the scalability and deep AI integration in such systems still require further research (Angeioplastis, 2026; Sofianos, 2026). This is because there is limited literature demonstrating how to integrate machine learning with Moodle to enhance personalized learning.

Much current literature tends to focus on the investigation of various types of AI technologies in isolation from each other, instead of considering them as one integrated system (Long, 2026; Wang, Zhang, & Zhou, 2026). Furthermore, much research typically assesses the efficiency of individual technological applications, like AI-powered chatbots for language training, without considering their integration into larger adaptive learning systems (Wang, Zhang, & Zhou, 2026)). Moreso, many AI applications in educational practice depend on static evaluation rather than longitudinal and field-based use (Niyazova, 2026; Sangwa, 2026). Adding to this is the realization that current empirical evidence is not yet available with regard to the effects of adaptive algorithms and intelligent feedback in practical, skill-related university classes (Yermaganbetova, 2026).

Most importantly, many Learning Management Systems (LMS) continue to function primarily as administrative and static content repositories rather than intelligent, inclusive environments (Angeioplastis, 2026). There is therefore a need for a holistic approach where AI is integrated with other systems, such as Moodle, to enable multiple tasks, including cognitive scaffolding, real-time feedback, and instructional management (Long, 2026; Yermaganbetova, 2026). For example, literature provides evidence that numerous studies employ historical data sets to check whether algorithms would operate properly, while the reality requires an approach that could account for "the sense-decide-act cycle" (Niyazova, 2026).

Research Objectives

This study aims at filling in these gaps through the proposal and analysis of an AI-based adaptive learning model for enhancing Moodle e-learning tool by incorporating the capabilities of artificial intelligence and machine learning to promote personalization and adaptation to learning in higher education.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue VI June 2026

The specific objectives of this research are to:

1. Personalize the learning process with a focus on the learner's performance.
2. Identify weaknesses of learners using continuous evaluation and prediction.
3. Enhance learner engagement by providing interactive learning resources.
4. Provide educators with intelligent information regarding the progress and engagement of their learners.

Related Work

Conventional systems of education are mainly based on behaviorists and cognitive models of learning, where teaching is usually teacher-centered and standardized, while learning involves passively acquiring knowledge. Personalized e-learning systems have, however, been found to borrow much from social constructivist and connectivist theories of learning.

According to social constructivism, learning is viewed as a social process where knowledge is socially constructed using various digital technologies. Connectivism further stresses the importance of technology-mediated social connections in the construction of knowledge and learning. The use of AI-enabled learning systems corresponds with these modern theories through providing an environment where learners take charge of their educational experience. The adaptive learning system enables learners to create their own knowledge through personal interaction, thus enhancing their learning experience.

The latest research indicates that the integration of AI into the curriculum facilitates collaboration and self-regulation among students by creating opportunities for them to design learning paths based on their capabilities and preferences. This new paradigm in which learners construct knowledge is a marked departure from the old approach of learning, were learners passively consumed information.

Traditional Versus Personalized E-Learning

The development of digital learning spaces has changed traditional learning practices. The standard e-learning system usually uses a linear learning model that delivers uniform content and learning paths for everyone enrolled in the program. While these systems have increased access and flexibility, they do not cater to the unique needs of each student. Traditional LMS does not have a flexible component that can adapt to changes in student interest, ability, and achievement levels. This means that some students may lack motivation, engagement, and academic support. On the other hand, personalized e-learning systems make use of artificial intelligence to provide an adaptive environment for learning. Personalized e-learning uses AI to track the learner’s performance and behavior to personalize the instructional material. Current LMS systems like Moodle are not just limited to serving as databases but can also be used to facilitate intelligent tutoring using artificial intelligence.

Artificial Intelligence Techniques in Personalized E-Learning

Data mining is now considered one of the most essential components of AI in education. Numerous studies have proven that machine learning algorithms can be used to predict academic performance and identify at-risk learners. Chen et al. (2026) created a multimodal early warning system based on behavioral logs and emotional analytics with a predictive accuracy of 86.3%. Wang (2025) incorporated Artificial Neural Networks, Recurrent Networks, and Support Vector Machines into a composite model that was able to predict outcomes with a predictive accuracy of 98%. Nai et al. (2024) also applied process mining and XGBoost models to predict learner outcomes based on the analysis of web interaction data with approximately 70% accuracy. Moreover, Khan et al. (2021) utilized the Decision Tree algorithm to analyze students' attendance and assessment data to identify at-risk learners with an 86% accuracy. Machine learning algorithms can be successfully applied to predict student academic performance based on the data generated by LMS.

AI and Student Engagement

Learning platforms using AI technologies have similarly demonstrated great promise in increasing learner engagement. Various technologies such as generative AI chatbots, intelligent tutoring systems, and adaptive learning agents have become common among learning platforms. According to Zhou et al. (2025), the use of AI chatbots in language learning environments increased learner engagement and listening skills. Similarly, Lee, Atif, and Kang (2026) conducted a research where GPT and natural language processing (NLP) technologies integrated within digital learning platforms were used to categorize the behaviors of students, demonstrating that adaptive, reflective AI capabilities indeed support constructivist teaching methods. In like manner, Villegas-Ch et al. (2026) created an explainable AI tutor in Moodle and found out that over 90% of suggestions made by the tutor were pertinent to the learner's situation. Overall, the findings imply that AI technology may enhance learner interaction and engagement in e-learning settings.

Student and Educator Perspectives on AI in Education

While there is no doubt that AI-based tools have a lot to contribute to education, it should be admitted that both teachers and learners have raised issues about ethics, privacy, and dependency on AI-driven solutions. There are quite a few pieces of research that suggest that learners have positive attitudes towards AI-based learning systems because of the personalized and instant feedback. Nonetheless, there are also concerns about reduced human interaction, cognitive overload, and limited opportunities for critical thinking. Educators recognize the possibilities of AI but highlight the importance of developing governance systems, ethical codes of conduct, and teacher training programs.

Challenges in AI-Enhanced E-Learning Systems

In spite of the wide usage of AI solutions in education, there are still some obstacles that affect the process of implementing them efficiently.

Technological Infrastructure

The Digital Divide and Connectivity Issues: The most significant problem of technology infrastructure is the digital divide, which hinders the equal distribution of AI-based tools. AI systems usually require an efficient network connection to receive information and analyze user behavior for personalized learning (Ordaya-Gonzales et al., 2024). Technology limitations are prevalent in less-developed countries or rural settings, low Internet speed makes it hard to implement data-hungry technologies such as Generative AI (GenAI) and real-time predictive analytics (Ntorukiri et al., 2022). This is further exacerbated by an imbalance in resources because the development of technology infrastructure varies geographically; for instance, AI research and applications are mainly conducted in the Asia-Pacific and Anglophone countries, whereas others lack even basic digital technologies (Long, et al., 2026).

Compatibility Between Modern AI Systems and Legacy Systems: Using AI systems within existing educational paradigms usually causes issues related to incompatibility between modern AI software/hardware and legacy infrastructure. This is most evident where software and hardware are incompatible: For example, some organizations use an LMS system and also have an AI-based system. The failure of these systems to work together creates challenges for educators who have to resolve the problem instead of teaching (Qiu, & Qiu, 2026; Boninger, & Nichols, 2025). Another form of the challenge relates to scalability issues regarding organizations that have AI-related policies; they may not be able to implement them due to inadequate planning for scaled use (Zakiah et al., 2025).

Security and Privacy Infrastructures for the Collection of Data

The use of artificial intelligence in the learning process is characterized by huge amounts of information collected about the learner's performance and behavioral traits. The emergence of such requirements makes it necessary to implement a cybersecurity infrastructure. Data breaches are common due to the lack of money needed to purchase modern security solutions; educational establishments may experience identity theft and become victims of data breaches (Zaid and Garai, 2024). Furthermore, ethical data protection issues exist because of the

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue VI June 2026

implementation of XAI that must be supported by proper data protection policies and procedures, especially concerning learners with disabilities (Adewale, et al., 2026). Transparency in Algorithmic Decision-Making: The critical infrastructure requirement for "explainable AI" (XAI) is crucial in providing transparency in decision-making mechanisms, including auto-grading and profiling of students (Ncube, 2023; Tunduny & Shibwabo, 2026). Without this requirement, there is a risk of algorithmic bias (Mariyono, et al., 2025). Moreso, failure to adapt to diverse cultures and languages is problematic since the technology is unable to adapt to diverse cultures and languages, thereby producing bias in the algorithms for NLP and assessments for minority learners (Adewale, et al., 2026).

Preparedness of Educators

Trends 2024-2026 indicate that access to technological advancement does not necessarily imply educational preparedness. Self-efficacy and pedagogical trust: studies on pre-service teachers reveal that even if they have a high degree of "AI readiness," it does not necessarily correlate with self-efficacy in their teaching profession (Baimukhambetova et al., 2025). However, teachers tend to become more confident in their ability to use the AI tool only after training that helps them understand how AI abilities align with their teaching goals (Murillo-Jiménez et al., 2026). The literacy divide is a persistent problem because teachers do not get the required training to integrate digital inclusion, accessibility, and AI literacy into their teaching practices (Yermaganbetova et al., 2026). Another issue regards adaptation since many educational institutions generally adapt slowly, while GAI technologies advance quickly. There is a "dual responsibility" placed on teachers to both adopt the technology and train their students on AI literacy skills (Gravino et al., 2024). In countries like Latin America, structural barriers such as workload, lack of incentives, and mandatory self-paid professional development make teachers resistant to embracing the AI technology (Yermaganbetova et al., 2026).

Privacy and Ethical Issues

Privacy Concerns and Ethical Issues: Ethical discourse in AI-enabled education is no longer subsidiary but essential for responsible and beneficial use of such technology (Arsian, 2026). AI algorithms rely on massive amounts of data, such as students' grades, behaviors, and learning approaches, which brings up the issues of privacy violations and access to confidential information (Gökçe, 2026). Furthermore, algorithms perpetuate any form of bias embedded in their datasets, which leads to biased grading and discrimination against women or marginalized groups due to their background or financial standing (Gökçe, 2026; Marcos, 2026). The emergence of LLMs such as GPT-4 poses challenges to authorship and authentic learning, as it may cause students to refrain from cognitive development in favor of relying on AI-generated content (Alblooshi, 2025). Explainable AI is crucial for transparency on how such AI will make important judgments regarding students' progress, avoiding the "black box problem" (Arslan, 2026). Infrastructure Limitations: The first challenge posed by AI integration is the incapacity of existing technological infrastructure to support demanding AI applications. For example, poor Connectivity and the Digital Divide: High-speed connectivity is essential for real-time processing of AI algorithms. The digital divide, characterized by inadequate connectivity and expensive devices, is a form of "structural constraint" (Ramroop, 2026). Another infrastructure related challenge is the interoperability Issues: The implementation of advanced AI technology into pre-existing learning management systems often causes interoperability problems, as the old systems are not compatible enough to provide seamless communication between new technologies (Ramroop, 2026).

Lack of Communication and Collaboration Opportunities

The introduction of AI-assisted learning platforms has raised some issues concerning the loss of social presence and the dehumanizing effect of education. There is an interactive distance because AI systems can unintentionally increase feelings of loneliness. The concept of "interactive distance" is defined as the absence of human interaction in communication, which results in alienation and lack of motivation (Kyrou et al., 2026). There is also an absence of social presence because overuse of digital and AI tools may prevent individuals from establishing valuable relationships, thus preventing essential cognitive and emotional development (Marcos, 2026). The other challenge is that there is a conflict between humans and AI partnerships: Although various models of "Teacher-AI Cooperation" (TAC) have been proposed, too much automation may interfere with teaching and limit a teacher's capacity to define relational educational goals (Chan, 2025). On the other hand, students may engage in intellectual surrender when dealing with an AI system without proper support from peers and teachers (Muhanguzi, 2025).

METHODOLOGY

The experiment was conducted using an experimental design of quantitative research in order to create and assess artificial intelligence-based adaptive learning models in Moodle. The research design included four stages: data gathering, data pre-processing, machine learning model building, and model assessment and recommendation generation.. The research design concentrated on assessing the effectiveness of machine learning algorithms in predicting performance and identifying at-risk students.

Dataset Description

The experiment employed an adaptive learning dataset that comprised 213,003 students' information and 29 features. These consisted of demographic, behavior, academic, and engagement features created via digital learning interactions. Important features consisted of Age, Gender, Mother tongue, English language proficiency, and learning method. Attendance rate, Feedback score, Quiz score, Engagement score, Usage time on the learning platform, Peer interaction score, and Final exam score. Two target features were constructed as follows: Performance Level — a multiclass classification feature that classifies students as low, moderate, and high performers and At-Risk — a binary classification feature that recognizes students at risk of performing poorly academically.

Data Preprocessing

Data preprocessing started with the detection and imputation of missing data. Missing numeric values were imputed by the median, whereas mode imputation was used to fill up missing categorical values. Duplicate rows were detected and eliminated to ensure high-quality data. After data preprocessing, there remained a dataset of about 213,000 rows ready for use. Label encoding was used for encoding categorical variables into numeric values. Examples of these categories include gender, type of learner, engagement, and proficiency in the English language. In feature selection, selected features were made according to relevancy and predictability. These included measures of engagement, academic achievements, behavior, and demographics. The Gender column was standardized to normalize values such as F or female and m or Male.

Target Variable Creation

This study provided two prediction targets: Performance Levels and “AT-Risk” status. On the performance level, the scores for the final exams were graded as Low Performance – score less than 60, Medium Performance – score between 60 and 74; and High Performance – score greater than 75. The students who scored below 60 on the final exam were “At Risk” and those that scored above 60 were “Not At Risk.” The Final_exam_score column was removed before training the model, this was important because both target variables were derived from Final_exam_score, hence excluding it from the features helped prevent direct data leakage.

Dataset Splitting

The data was then partitioned into training and testing sets following an 80% to 20% ratio. Sampling approaches were stratified to maintain balance in class distribution between the datasets.

RESULTS

Dataset Exploration and Class Distribution

The exploratory analysis of the dataset indicated an imbalance between classes in the dataset. The percentage of high-performing students was found to be 69.1%, whereas the percentage of low-performing students was just 2.25%. The XGBoost handled class balancing by giving more weights to the fewer “at risk class”. Likewise, in terms of being at-risk, 2.25% of the students belonged to this category. Performance in Detecting At-Risk

Students The XGBoost model used for detecting at-risk students had outstanding prediction performance with an overall accuracy of 97.7%. Other prediction measures included Precision: 95.6%, Recall: 97.7%, F1-Score: 96.6%; and ROC-AUC: 95.9%. The confusion matrix showed the robustness of prediction in detecting at-risk students while minimizing the rate of false negatives. This implies that AI-based predictive analysis could be instrumental in intervention systems in Moodle. humans and AI partnerships: Although various models of "Teacher-AI Cooperation" (TAC) have been proposed, too much automation may interfere with teaching and limit a teacher's capacity to define relational educational goals (Chan, 2025). On the other hand, students may engage in intellectual surrender when dealing with an AI system without proper support from peers and teachers (Muhanguzi, 2025)

Performance Prediction Results

The performance predicting algorithm gave 97.3% accuracy in its predictions. On the other hand, the accuracy rate showed some limitations of having a highly imbalanced class dataset when predicting the performance of learners. The model showed that it was very accurate in predicting high-performing students. On the other hand, there were lower recalls in the minority performance categories of low- and medium-performing students.

Feature Importance Analysis

A feature importance analysis helped us identify several factors that could predict both good academic results and potential academic risks. The most important features are the Attendance percentage. Learning platform time usage, Peer interaction score, Writing skills score, Listening skills score, Vocabulary improvement, Engagement score, and Socioeconomic status. All the above-mentioned findings prove previous research studies that indicate a close connection between learner engagement and interaction patterns and their academic results.

Cross Validation Findings

Five-fold cross validation revealed the robustness and high level of generalization ability of the models under consideration. The model predicting performance showed an average accuracy of 97.13%, while the at-risk detection model yielded an average accuracy of 97.70%. The minimal variance obtained in this process points to the stability of the models.

Performance of the Hybrid Recommendation System

The hybrid recommendation system was able to provide personalized learning recommendations for each individual learner depending on his or her weaknesses, engagement, preferred learning style, and performance trends. This means that such a recommendation system would have the capability to provide learning materials tailored to specific learners, increase engagement, offer adaptive pacing, promote self-regulated learning, and offer personalized instructional support

DISCUSSION

The results of this research have shown how effectively adaptive learning and support can be improved with the help of integrating AI and machine learning methods into Moodle platforms. For instance, experiments reveal that merging single classifiers (Neural Networks, Logistic Regression, and SVM) into a heterogeneous group through voting methods like soft-voting and stacking provides higher predictive power (Evangelista & Sy, 2022; Saini, 2025). This view confirms an earlier study by Injadat et al. (2020), which concluded that the ensembles of learners performed exceptionally well in terms of their predictive accuracy and low false-positive rate in detecting the at-risk students. In acknowledgement, Zhao et al. (2025) show that the use of tree-based ensembles, such as Random Forests, generates better precision, recall, and F1-scores compared to traditional classifiers.

The results of this research also show that XGBoost-based predictors were capable of providing highly accurate results, which corresponds well with previous literature. For example, studies conducted on specific gradient boosting systems such as CatBoost show that optimized hyperparameter ensemble models decrease classification errors immensely relative to conventional baselines, achieving precision levels surpassing 92 percent (Joshi et al., 2021) Likewise, a recent study by Nasreddine et al., (2025) shows that when addressing cases involving highly imbalanced data in organizational settings, implementing XGBoost with data balancing algorithms provides substantial enhancements in multi-level classification over single classifiers. All this can be seen as evidence that proves the effectiveness of using ensemble learning in the context of academic forecasting.

CONCLUSION

This paper focused on the integration of artificial intelligence and machine learning into Moodle to support adaptive and personalized learning processes in higher education institutions. The results of this study clearly indicate that AI and machine learning can be utilized to boost engagement, academic performance tracking, and early intervention processes. The XGBoost predictive models proved efficient in detecting at-risk learners and predicting academic performance outcomes. The hybrid recommendation system succeeded in generating personalized learning pathways for students. Thus, this paper provides an important contribution to the existing literature as it presents a scalable and sustainable framework that can be used to implement adaptive learning processes in open-source LMSs. Nevertheless, there is room for improvement, as there are still some limitations associated with this project, which include technological, ethical issues, and class imbalance problems. Future research may focus on the development of real-time adaptive learning systems, explanation methods for AI models, integration of generative AI algorithms, and longitudinal study design. In conclusion, adaptive learning systems enhanced by AI technologies can make higher education much smarter, responsive, and individualized.

REFERENCES

1. Adewale, O. A., Rane, N. L., Ogbonna, M. O., & Rane, J. (2026). Inclusive education through artificial intelligence: Opportunities, challenges, and ethical considerations. International Journal of Applied Resilience and Sustainability, 2(2), 455-472, https://doi.org/10.70593/deepsci.0202018
2. AlBlooshi, S. (2026). Artificial intelligence in higher education, opportunities, and challenges: A review. Frontiers in Education, 10, Article 1683968. https://doi.org/10.3389/feduc.2025.1683968
3. Angeioplastis, A., Konstantakis, M., Aliprantis, J., Ordoumpozanis, K., Varsamis, D., & Tsimpiris, A. (2026). AI for All: Adaptive, Accessible, and Inclusive Learning Experiences in the Age of Intelligent LMSs. Information, 17(2), 216., https://doi.org/10.3390/info17020216
4. Arslan, A. (2026). The Ethical Compass of Digital Classrooms: Teachers' Perspectives on AI Ethics in Education. Türk Akademik Yayınlar Dergisi (TAY Journal), 10(1). https://doi.org/10.29329/tayjournal.2026.1427.04
5. Baimukhambetova, K., Ybyraimzhanov, K., Moldabek, K., Akhatayeva, U. B., Zhetkizgenova, A., & Uaidullakyzy, E. (2025). Evaluating the Relationship Between Pre-Service Teachers' Artificial Intelligence Readiness and Professional Self-Efficacy. Education Sciences, 16(1), 43. https://doi.org/10.3390/educsci16010043
6. Boninger, F., & Nichols, T. P. (2025). Fit for Purpose? How Today's Commercial Digital Platforms Subvert Key Goals of Public Education. National Education Policy Center, http://nepc.colorado.edu/publication/digital-platforms
7. Chan, C. K. Y. (2025). AI as the therapist: Student insights on the challenges of using generative AI for school mental health frameworks. Behavioral Sciences, 15(3), Article 287. https://doi.org/10.3390/bs15030287
8. Dube, S, Madzore, A, Dube, S, P and Mpande, B (2026). Enhancing Personalized E-Learning Systems in Higher Education Through Artificial Intelligence: A Rapid Systematic Literature Review. , 10(2), https://doi.org/10.47772/IJRISS.2026.10200008.
9. Evangelista, E. D. L., & Sy, B. D. (2022). An approach for improved students' performance prediction using homogeneous and heterogeneous ensemble methods. International Journal of Electrical and Computer Engineering, 12(5), 5226, https://doi.org/10.11591/ijece.v12i5.pp5226-5235
10. Gökçe, A. T. (2026). Revolutionizing Education with AI: Ethical Considerations in K-12 Settings. IntechOpen. https://www.intechopen.com/online-first/1230172
11. Gravino, C., Iannella, A., Marras, M., Pagliara, S. M., & Palomba, F. (2024). Teachers interacting with generative artificial intelligence: a dual responsibility. In CEUR Workshop Proceedings (Vol. 3762, pp. 83-88). https://ceur-ws.org/Vol-3762/579.pdf

12. Injadat, M., Moubayed, A., Nassif, A. B., & Shami, A. (2020). Systematic ensemble model selection approach for educational data mining. Knowledge-Based Systems, 200, 105992.
13. Jafarov, J. (2026). Core Quality Components in Contemporary Teacher Education Systems. TOJET: The Turkish Online Journal of Educational Technology, 25(1). https://files.eric.ed.gov/fulltext/EJ1497809.pdf
14. Joshi, A., Saggar, P., Jain, R., Sharma, M., Gupta, D., & Khanna, A. (2021). CatBoost—An ensemble machine learning model for prediction and classification of student academic performance. Advances in Data Science and Adaptive Analysis, 13(03n04), 2141002, https://doi.org/10.1142/S2424922X21410023
15. Kyrou F, Vergis P, Rogari G, Saiti A and Manousou E (2026) Crisis management in distance education in the age of artificial intelligence: opportunities, challenges and ethical dimensions. Front. Educ. 11:1791475. doi: 10.3389/feduc.2026.1791475, https://doi.org/10.3389/feduc.2026.1791475
16. Lee, H., Atif, A., & Kang, K. (2026). Analysing AI utilisation in education through learner question types: A constructivist approach. Australasian Journal of Educational Technology, 42(1), 79-96.
17. Long, D. Y., Wang, S., Md Rashid, S., & Lu, X. T. (2026, February). Artificial intelligence in higher education: a systematic review of its impact on student engagement and the mediating role of teaching methods. In Frontiers in Education (Vol. 10, p. 1648661). Frontiers, https://doi.org/10.3389/feduc.2025.1648661
18. Marcos, L. T. A Systematic Review on Artificial Intelligence in Education: Opportunities, Challenges, and Ethical Implications. Preprints 2026, 2026010448. https://doi.org/10.20944/preprints202601.0448.v1
19. Mariyono D, Nur Alif Hd A (2025), "AI's role in transforming learning environments: a review of collaborative approaches and innovations". Quality Education for All, Vol. 2 No. 1 pp. 267–290, doi: https://doi.org/10.1108/QEA-08-2024-0071
20. Muhanguzi, N. (2025). AI in Education: Navigating Fears, Embracing Possibilities, and Charting a Path Forward. RUFORUM BLOG. https://news.ruforum.org/wp-content/uploads/2025/12/Nimrod-AI-in-Education-.pdf
21. Murillo-Jiménez, H., Centeno-Alarcón, M., Buele, J., & Yumbla, F. (2025). Analyzing barriers to the effective implementation of technological tools in inclusive education: a scoping review. In Frontiers in Education (Vol. 10, p. 1687664). Frontiers Media SA, https://doi.org/10.3389/feduc.2025.1687664
22. Nai, R., Zheng, J., Wang, M., & Yang, Y. (2024). Leveraging process mining and XGBoost for predictive learning analytics based on student web interactions. International Journal of Distance Education Technologies, 22(1), 1–18. https://doi.org/10.4018/IJDET.346740
23. Nassreddine, G., Saleh, L., Al Majzoub, M., & El Arid, A. (2025, July). SHAP Explainability: An Ensemble Learning Approach for Student Performance Prediction. In 2025 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT) (pp. 432-438). IEEE, https://ieeexplore.ieee.org/document/11100707
24. Ncube. (2023). The impact of artificial intelligence on human resource management practices: An investigation. SA Journal of Human Resource Management. https://doi.org/10.4102/sajhrm.v21i0.2960
25. Niyazova, G. Z., Duisekeyeva, B. M., Berdi, D. K., Usembayeva, I. B., & Mindetbayeva, A. A. (2026, April). The effects of gamified AI-supported digital learning environments on personalized learning and student engagement in school education: a systematic review and meta-analysis. In Frontiers in Education (Vol. 11, p. 1754080). Frontiers Media SA, https://doi.org/10.3389/feduc.2026.1754080
26. Ntorukiri, T. B., Kirugua, J. M., & Kirimi, F. (2022). Policy and infrastructure challenges influencing ICT implementation in universities: a literature review. Discover Education, 1(1), 19, https://doi.org/10.1007/s44217-022-00019-6
27. Ordaya-Gonzales, K., Cortez Restuccia, J. C., Cossio Bolaños, W. J., & Arriola-Montenegro, J. (2024). From crisis to connectivity: Exploring the role of information and communication technologies in medical education during the COVID-19 pandemic. Cureus, 16(5), Article e60302. https://doi.org/10.7759/cureus.60302
28. Qiu, X., & Qiu, N. (2026). Cognitive load and pedagogical tension in multi-platform online learning: Evidence from Chinese higher education. PloS one, 21(4), e0347566.

29. Ramroop, N., & Reddy, K. (2026). Challenges in the use of e-learning technologies for teaching and learning at universities of technology. African Journal of Inter/Multidisciplinary Studies, 7(2), Article 2656. https://doi.org/10.51415/ajims.v7i2.2656
30. Saini, B. K. (2025). Optimizing student academic performance prediction using heterogeneous ensemble learning. European Journal of Artificial Intelligence and Machine Learning, 4(4), 1-6, https://pmc.ncbi.nlm.nih.gov/articles/PMC13098912/
31. Sangwa, S., Murungu, E., Iradukunda, A., Umutoni, J., Hackman, C., Ssekiziyivu, N., ... & Lugero, T. (2026). Toward a Systems-Level Theory of AI-Experiential Learning Orchestration (AIELO). Open Research Africa, 9, 9, https://doi.org/10.12688/openresafrica.14652.1
32. Sofianos, K. C., Kaponis, A., Stefanidakis, M., Maragoudakis, M., Pappas, T., & Bukauskas, L. (2026). Artificial Intelligence and Moodle: Advancing Intelligent Learning and Digital Marketing in Education. Engineering, Technology & Applied Science Research, 16(2), 32978-32988, https://doi.org/10.48084/etasr.13756
33. Tunduny T, Shibwabo B. Explainable AI Approaches in Federated Learning: Systematic Review. JMIR AI. 2026 Feb 3;5:e69985. doi: 10.2196/69985. PMID: 41632959; PMCID: PMC12914235, https://doi.org/10.2196/69985
34. Villegas-Ch W, Palacios P, Jaramillo-Alcázar A and Guevara V (2026). Modeling informal learning as a dynamic interaction process in digital learning environments. Front. Educ. 11:1776945. doi: 10.3389/feduc.2026.1776945Wang, Y., Zhang, Z. J., & Zhou, H. (2026). Artificial Intelligence in Language Learning: A Twenty-Year Scoping Review of Applications, Research Methods, and Outcomes. Research Synthesis in Applied Linguistics, 1-38, https://doi.org/10.1080/29984475.2026.2647961
35. Yermaganbetova M, Ashimbekova A, Kaibassova D, Akhitova R and Dyussembina E (2026) Evaluating the impact of an AI-integrated learning platform on student performance: a quasi-experimental study. Front. Educ. 11:1792353. doi: 10.3389/feduc.2026.1792353, https://doi.org/10.3389/feduc.2026.1792353
36. Zaid, T., & Garai, S. (2024). Emerging trends in cybersecurity: a holistic view on current threats, assessing solutions, and pioneering new frontiers. Blockchain in healthcare today, 7, 10-30953, https://doi.org/10.30953/bhty.v7.302
37. Zakiah, D., Kurniadi, B., Wahyunanda, I., Sijabat, P. S., Utama, Y. P., & Ahmadi, P. V. (2025). Technological Advancements in Maritime Education: A Collaborative Approach. Jurnal Penelitian Sekolah Tinggi Transportasi Darat, 16(1), 97-107, http://jurnal.ptdisttd.net/
38. Zhao, S., Zhou, D., Wang, H., Chen, D., & Yu, L. (2025). Enhancing Student Academic Success Prediction Through Ensemble Learning and Image-Based Behavioral Data Transformation. Applied Sciences, 15(3), 1231. https://doi.org/10.3390/app15031231
39. Zhou, Q., Hashim, H., & Sulaiman, N. (2025). Integrating AI chatbots in informal digital English learning: Impacts on listening competencies in Chinese higher education. Education and Information Technologies, 30(18), 27031–27059. https://doi.org/10.1007/s10639-025-13811-2