FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 10 No. 16, June, 2026, pp 475 – 480
DOI: https://doi.org/10.33003/fjs-2026-1016-5876

A Personalized, Adaptive Learning Platform for Tertiary Education

***Iriagbonse Amanda Inyang and Orie Cynthia Eloho**

[1]Department of Computer Science, Faculty of Computing, Benson Idahosa University, Benin City, Edo State, Nigeria.

*Corresponding authors' email: iinyang@biu.edu.ng

ABSTRACT

The continuous increase of digital education has exposed the limitations of traditional, uniform learning models that fail to account for individual learner differences. A Personalised Learning Platform with Adaptive Content (PLPAC), which is AI-driven, was developed to deliver tailored learning experiences through real-time adaptation. The system incorporates the mathematical Bayesian Knowledge Tracing (BKT) model, a hybrid collaborative and content-based recommendation engine, and mastery-based progression, adjusting content difficulty, format, sequence, and assessment in response to each learner's evolving profile. The system was built using a five-layer, multi-tier architecture across six two-week Agile sprints, and was then evaluated using a 12-week, mixed-methods, quasi-experimental design involving 250 tertiary-level students (125 in the PLPAC experimental group, 125 in a conventional Learning Management System control group). Results showed statistically significant gains across all four evaluated dimensions: large normalized learning gains for PLPAC (Hake's $g = 0.43$) relative to the control group ($g = 0.20$), with a large effect size (Cohen's $d = 1.76$); a 42% higher module completion rate ($\chi^2(1) = 38.47$, $p < .001$); substantially higher engagement across six behavioural metrics (77%–225% increases); and a disproportionately larger gain for the lowest-performing quartile of learners, which narrowed the gap in learning gains (though not the absolute post-test score gap) between low- and high-achieving learners relative to the control group. User satisfaction averaged 4.27 out of 5, exceeding the System Usability Scale benchmark. This research provides strong empirical support for AI-powered adaptive learning as a mechanism for simultaneously improving academic performance, engagement, satisfaction, and equity in tertiary education, and concludes with a scalable framework for institutional adoption.

Received: 15 Aug. 2026

Accepted: 26 Aug. 2026

Published: 03 Aug. 2026

Keywords: Adaptive Learning; Personalized Learning; Bayesian Knowledge Tracing; Recommendation Engine; Learning Analytics; Educational Technology; Tertiary Education

INTRODUCTION

Traditional learning follows a defined pattern whereby the same content, pace, and instructional approach are delivered to all learners, irrespective of their prior knowledge, learning pattern, or acquired skill. This pattern, common in traditional teaching practice, is a significant disadvantage because it fails to account for the needs of different learners (Shelle et al., 2018; Soofi and Ahmed, 2019). The rise in educational digitalisation, especially during the COVID-19 pandemic, has not fully resolved this problem: many e-learning platforms still replicate the static content and uniform progression paths of the traditional classroom, which can result in sub-optimal engagement and learning outcomes for a large proportion of users.

Research consistently shows that a one-size-fits-all strategy under-challenges high-achievers while frustrating and disengaging struggling students, widening achievement gaps over time (Tan et al., 2025). Conventional Learning Management Systems (LMS) generally lack the ability to adjust in real time, leading to high dropout rates, low retention, and inequitable access to quality instruction, particularly in resource-constrained settings (Gligorea et al., 2023). Personalised learning and adaptive content delivery have shown promise in addressing these issues, enabling instruction to be tailored to individual learners and encouraging progression based on demonstrated mastery rather than time spent (Mustapha, 2025; Chen et al., 2025).

Advances in Artificial Intelligence (AI) and Machine Learning (ML) have improved adaptive learning by enabling systems to build dynamic learner models from interaction data, assessment results, and engagement signals, and to use these models to determine optimal learning paths in real time (Tan et al., 2025; Gligorea et al., 2023). Despite these advances, a critical gap remains: comprehensive, empirically validated, and openly accessible adaptive learning platforms suited to diverse tertiary education settings are scarce. Existing commercial solutions are frequently proprietary, costly, and difficult to integrate with institutional infrastructure (Twyman, 2018; Lagos-Castillo et al., 2025).

This study addresses this gap by designing, developing, and empirically evaluating the Personalised Learning Platform with Adaptive Content (PLPAC). The major aim is to develop a personalized, adaptive learning platform for tertiary education.

Related Works

Numerous studies support the use of adaptive and intelligent tutoring systems. Early knowledge-tracing work by Corbett and Anderson (1994) established the statistical basis for modelling learner mastery from sequential assessment data, a foundation extended by more recent machine-learning-based adaptive systems (Tan et al., 2025). Meta-analyses of intelligent tutoring systems report positive effects on learning outcomes relative to conventional instruction (Ma et al., 2014; Steenbergen-Hu and Cooper, 2014; VanLehn, 2011), and systematic reviews of adaptive learning systems in tertiary education report consistent, if heterogeneous, benefits across disciplines (Martin et al., 2020; Kabudi et al., 2021). More recent studies have explored AI-powered adaptive systems using GPT-based architectures (Lagos-Castillo et al., 2025), reinforcement learning, and generative AI tutors (Hernández-Herrera, 2026), reflecting rapid technical evolution in the field.

Motivational and self-regulatory theory also informs this study. Self-Determination Theory (Deci and Ryan, 2000) identifies competence support, autonomy support, and relatedness as core drivers of intrinsic motivation, while Vygotsky's Zone of Proximal Development (ZPD) framework holds that optimal learning occurs when content is calibrated just above a learner's current competency. Gamification research (Urh et al., 2015) and studies of self-regulated learning in online environments (Viberg et al., 2018; Kizilcec et al., 2017) further support the design choices adopted in PLPAC.

Several gaps remain in the existing literature. Existing solutions are often proprietary and commercially restricted (for example, Knewton, ALEKS, Realizeit), limiting institutional access and customisation. Many empirical studies are domain-specific and short in duration, limiting generalisability across undergraduate disciplines (du Plooy, 2024; Hariyanto, 2025). Others show poor interoperability with standard LMS infrastructure, or insufficient focus on equity-driven design for learners from heterogeneous cultural, economic, and technological backgrounds (Mustapha, 2025; Lagos-Castillo et al., 2025). To date, no single study or platform has offered an accessible, fully integrated, and empirically tested architecture that combines dynamic learner profiling, real-time adaptive content sequencing, intelligent recommendation, mastery-based progression, and rigorous multi-disciplinary validation in one scalable system for tertiary education, This is what this study seeks to addresses .

MATERIALS AND METHODS

The Design Science Research (DSR) paradigm was adopted as a mixed-methods research strategy (Hevner et al., 2004), supporting the design, production, and assessment of novel IT artefacts that address acknowledged practical problems. Quantitative data were gathered using pre-tests, post-tests, system-generated analytics, and structured survey instruments, while qualitative data were obtained through semi-structured interviews and open-ended survey feedback (Creswell and Creswell, 2018). The research followed a pragmatist philosophical stance, in which methodological choice is guided by the research objectives and the practical usefulness of the resulting information rather than allegiance to a single paradigm (Tashakkori and Teddlie, 2010).

The PLPAC prototype was developed using Agile Software Development, specifically the Scrum framework, organised into six two-week sprints over three months (Sommerville, 2016). A pilot test involving 20 students preceded the main evaluation. The final prototype was deployed on an AWS EC2 cloud instance supporting up to 300 concurrent users, with average response times of 1.4 seconds for content delivery and 0.8 seconds for adaptive recommendation requests. The technology stack comprised a React.js front end, a Node.js/Express back end, PostgreSQL and MongoDB for structured and unstructured data respectively, and scikit-learn/TensorFlow for the machine learning components.

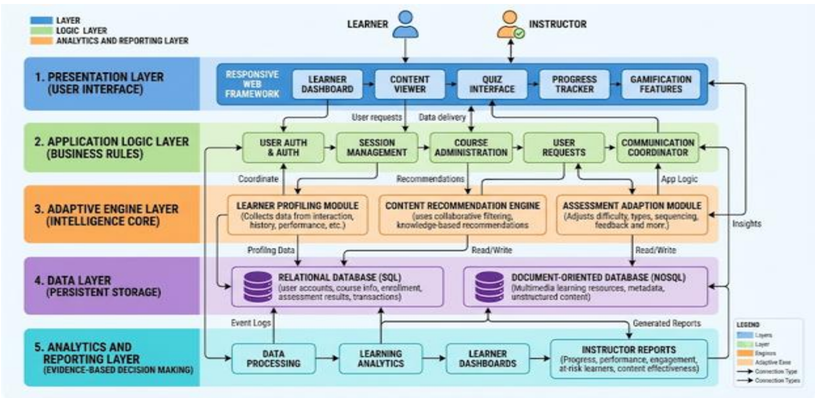

Figure 1: Proposed System Architecture of a Personalized Learning Platform with Adaptive Content (PLPAC)

The Personalized Learning Platform with Adaptive Content (PLPAC) design artefact comprises five primary layers as shown in figure 1, with clearly defined responsibilities to promote modularity, scalability, maintainability, and adaptability.

Presentation Layer

The presentation layer serves as the user interface through which learners and instructors interact with the system. This layer is implemented using a responsive web framework that ensures accessibility across multiple devices. Key components include the learner dashboard, content viewer, quiz interface, progress tracker, and gamification features that enhance learner engagement and motivation.

Application Logic Layer

The Application Logic Layer coordinates the core business processes of the platform. This layer manages user authentication and authorisation, session management, course administration, user requests, and communication between the presentation layer and the underlying adaptive services, while ensuring the seamless integration of system functionalities and enforcing business rules.

Adaptive Engine Layer

The adaptive engine layer forms the intelligence core of the PLPAC system, comprising three principal modules:

Learner Profiling Module

*S*ystematically constructs and continuously updates individual learner profiles using interaction history, assessment performance, time-on-task, navigation behaviour, and other engagement indicators.

Content Recommendation Engine
Uses collaborative filtering and knowledge-based recommendation techniques to identify and deliver learning resources that best match each learner's needs, preferences, and demonstrated competency.

Assessment Adaptation Module
personalises assessments by adjusting question difficulty, question types, sequencing, and feedback based on the learner's current mastery level, supporting continuous formative assessment.

Data Layer
The Data Layer provides persistent storage for both structured and unstructured information. It uses a relational database for managing user accounts, course information, enrolment records, assessment results, and system transactions, together with a document-oriented database for storing multimedia learning resources, metadata, and other unstructured content assets.

Analytics and Reporting Layer
This layer handles the collection, processing, and visualisation of learning analytics to support evidence-based decision-making. It generates dashboards and reports for learners and instructors, highlighting learning progress, performance trends, learner engagement, at-risk-learner identification, and content effectiveness. These insights facilitate timely interventions and continuous improvement of the learning experience.
Collectively, these five layers provide a robust and extensible architectural foundation that supports personalised learning, adaptive content delivery, real-time assessment, and comprehensive learning analytics while maintaining clear separation of concerns across the system.

Evaluation Design and Sample
The evaluation followed a 12-week, quasi-experimental, nonequivalent control-group design involving 250 tertiary-level undergraduate students from Sciences, Social Sciences, and Humanities disciplines. Participants were assigned to a PLPAC experimental group ($n = 125$) or a conventional LMS control group ($n = 125$) by pre-existing course cohort rather than by individual random assignment; this design, common in institutional field evaluations where randomising individual students across course sections is impractical, is quasi-experimental rather than a true randomised-controlled-trial design, and the study's terminology has been aligned accordingly throughout this paper. Throughout the evaluation period, all experimental participants completed an onboarding session and had access to in-platform help-desk and email support. An independent-samples t-test confirmed pre-test equivalence between the groups ($t(248) = 0.55$, $p = .581$), ruling out pre-existing ability differences as an explanation for subsequent outcome differences (Table 1).

Table 1: Pre-test Equivalence Statistics

Group	N	Pre-test Mean	Std. Deviation	t-value	p-value
PLPAC (Experimental)	125	51.3	9.87	0.55	.581
Conventional LMS (Control)	125	50.6	10.12	—	—

Adaptive Algorithms
Learner mastery was modelled using Bayesian Knowledge Tracing (BKT), implemented in Python and coupled to the platform's back-end API. Each knowledge component was parameterised by four values: prior probability of mastery (L0), probability of learning (T), probability of slip (S), and probability of guess (G), initialised from a 500-interaction calibration dataset collected during the pilot phase and updated after every learner response (Table 2). The recommendation engine combined collaborative filtering (55% weighting) and content-based filtering (45% weighting), a split determined empirically during piloting, to compute a composite score for each candidate resource. During the live evaluation, the engine processed an average of 2,847 recommendation requests per day at a mean latency of 0.83 seconds, achieving an overall recommendation acceptance rate of 73.4%.

Table 2: Calibrated BKT Parameters by Subject Domain

Subject Domain	L0 (Prior Mastery)	T (Learning Rate)	S (Slip Rate)	G (Guess Rate)
Sciences	0.31	0.18	0.09	0.21
Social Sciences	0.28	0.21	0.11	0.19
Humanities	0.35	0.16	0.08	0.23

Mathematical Formulation of the Adaptive Algorithms
From Table 2, let $P(L_t)$ be the probability that a learner has mastered the component after the t-th opportunity. This can be demonstrated, with prior mastery L0, learning rate T, slip rate S, and guess rate G calibrated per domain. Following an observed response $u_t \in \{\text{correct, incorrect}\}$, the mastery estimate is first revised using Bayes' rule conditioned on the observed outcome, then adjusted for the possibility of learning between opportunities:

$$P(L_t \mid \text{correct}) = [P(L_{t-1})(1 - S)] \div [P(L_{t-1})\cdot(1 - S) + (1 - P(L_{t-1}))\cdot G] \quad (1)$$

$$P(L_t \mid \text{incorrect}) = [P(L_{t-1})\cdot S] \div [P(L_{t-1})\cdot S + (1 - P(L_{t-1}))\cdot(1 - G)] \quad (2)$$

$$P(L_t) = P(L_t \mid u_t) + [1 - P(L_t \mid u_t)]\, T \quad (3)$$

This two-step update — Bayesian revision given the observed response, followed by a transition term accounting for learning — is applied after every formative-assessment interaction, allowing the mastery estimates reported in the Results and Discussion section to be continuously refined over the 12-week evaluation period (Corbett and Anderson, 1994).
The recommendation engine's composite score $S(u, r)$ for candidate resource r and learner u combines collaborative and content-based signals:

$$S(u, r) = \alpha\, SCF(u, r) + (1 - \alpha)\cdot SCBF(u, r \quad (4)$$

where $\alpha = 0.55$, matching the empirically determined collaborative-filtering weighting reported above; $SCF(u, r)$ is the cosine similarity between learner u's interaction vector and the aggregated interaction vectors of peers with similar mastery profiles; and SCBF (u, r) is the TF-IDF cosine similarity between resource r's metadata and the knowledge components in which learner u has been assessed as below the mastery threshold. Candidate resources are ranked by S(u, r) in descending order, with the top-ranked resources returned to the Application Logic Layer for rendering.

RESULTS AND DISCUSSION

The PLPAC group showed a mean pre-test score of 51.3 (SD = 9.87), which rose to a post-test mean of 72.4 (SD = 8.31), a statistically significant within-group gain of 21.1 percentage points ($t(124) = 19.64$, $p < .001$, $d = 1.76$). The control group gained 9.8 percentage points, from 50.6 to 60.4 ($t(124) = 10.23$, $p < .001$, $d = 0.91$), as shown in Table 3.

Table 3: Pre-test and Post-test Learning Outcome Comparison

Group	Pre-test Mean	Post-test Mean	Mean Gain	Norm. Gain (g)	Cohen's d	p-value
PLPAC	51.3	72.4	+21.1	0.43	1.76	< .001
Conventional LMS	50.6	60.4	+9.8	0.20	0.91	< .001

Expressed as Hake's normalized gain, $g = (post - pre) \div (100 - pre)$, PLPAC achieved $g = 0.43$ (medium-high), compared with $g = 0.20$ (low) for the control group, indicating that PLPAC learners closed a substantially larger share of the room available for improvement. The figures derive from the two separate within-group paired-samples tests, establishes that each group improves significantly over time but do not, by themselves, formally test whether the size of that improvement differs significantly between groups. A one-way ANCOVA on post-test scores with pre-test score as covariate, or an equivalent 2×2 mixed factorial ANOVA (Group × Time) reporting the F-statistic and partial eta-squared, is recommended to confirm the between-group effect in any subsequent submission of this research; the raw data needed to compute this test (individual-level scores) were not retained in the dataset available for the present analysis.

The large effect size ($d = 1.76$) also indicates a practically, not merely statistically, meaningful impact. This aligns with Tan et al. (2025), who reported a comparable gain in adaptive systems employing real-time knowledge tracing, and with Gligorea et al. (2023), who documented substantial improvements when content sequencing was governed by mastery data rather than fixed progression. The adaptive difficulty adjustment and mastery-based gating appear to have prevented cognitive overload for lower-ability learners while sufficiently challenging high achievers, consistent with Vygotsky's ZPD theory.

Module Completion Rates

The PLPAC group achieved an overall module completion rate of 84.6%, compared to 59.5% for the control group, a 42% relative improvement ($\chi^2(1) = 38.47$, $p < .001$), consistent across all three disciplines as shown in Table 4.

Table 4: Module Completion Rates by Discipline and Group

Discipline	PLPAC Completion (%)	Control Completion (%)	Difference (%)
Sciences	86.2	61.3	+24.9
Social Sciences	83.4	58.7	+24.7
Humanities	84.1	58.4	+25.7
Overall	84.6	59.5	+25.1

This finding is practically significant given that low completion is one of the major continuous challenges in online and blended learning (Twyman, 2018). PLPAC's adaptive scaffolding and mastery-based progression appear to have addressed key drivers of dropout, including content mismatch, delayed feedback, and insufficient motivational support, while the gamification layer likely sustained engagement, consistent with Lagos-Castillo et al. (2025), who observed that gamified adaptive systems produce higher persistence than non-gamified equivalents.

Learner Engagement

System-generated analytics revealed consistently and substantially higher activity across all six engagement metrics for the PLPAC group, as shown in Table 5.

Table 5: Comparative Engagement Metrics (PLPAC vs Conventional)

Engagement Metric	PLPAC Group	Control Group	Difference
Mean weekly logins	6.3	3.1	+103%
Avg. session duration (min)	38.4	21.7	+77%
Resources accessed per week	11.2	5.4	+107%
Assessment attempts per week	4.7	2.1	+124%
Discussion contributions	3.9	1.2	+225%
Peer interaction events	5.1	1.8	+183%

The more-than-doubling of weekly logins and assessment attempts suggests that the adaptive feedback loop created a reinforcement cycle encouraging continued use, while the 225% increase in discussion contributions indicates that PLPAC's socialised learning features fostered a more collaborative learning community. These findings are consistent with Self-Determination Theory (Deci and Ryan, 2000), which identifies competence support, autonomy support, and relatedness as core drivers of intrinsic motivation.

User Satisfaction

The 28-item satisfaction survey, completed by all 125 experimental participants, was collated into four constructs, each scoring above 4.0 on a 5-point scale and exceeding the System Usability Scale (SUS) benchmark of 3.75, as shown in Table 6.

Table 6: User Satisfaction Survey Results by Construct

Satisfaction Construct	Mean Score (/5)	Std. Deviation	SUS Benchmark	Rating
Perceived Usability	4.21	0.61	3.80	Above Benchmark
Content Relevance	4.38	0.54	—	Excellent
Adaptive Feedback Quality	4.19	0.67	—	Good – Excellent
Overall Satisfaction	4.27	0.58	3.75	Above Benchmark

Content Relevance was the highest-rated construct (M = 4.38), suggesting that learners perceived the adaptive engine's recommendations as well matched to their needs. Adaptive Feedback Quality showed the widest dispersion (SD = 0.67), indicating some variability in how learners perceived automated feedback, an area flagged for future refinement. A 12% minority of participants expressed a preference for more instructor-led interaction, suggesting that some learner profiles require a blend of automated and human facilitation.
The platform's satisfaction survey used a 5-point Likert scale, whereas the standard System Usability Scale (SUS) produces a 0–100 composite score (with approximately 68 conventionally treated as the 'above-average' threshold). The 3.75/5.00 benchmark reported in Table 6 reflects a rescaling of SUS norms for comparability with this survey's 5-point format; readers seeking to compare PLPAC's usability rating against SUS scores from other studies should apply an explicit conversion (for example, mean-score ÷ 5 × 100) rather than treating the two scales as directly equivalent.

Differential Gains across Performance Quartiles (Equity Analysis)

Post-test performance and gain scores were disaggregated by pre-test performance quartile, with an ANCOVA controlling for pre-test performance used to isolate PLPAC's differential effect across ability groups, as shown in Table 7.

Table 7: Post-test Performance by Quartile and Achievement Gap

Performance Quartile	PLPAC Post-test Mean	Control Post-test Mean	PLPAC Gain	Control Gain
Q1 (Low)	63.2	52.4	+19.4	+6.8
Q2 (Low-Mid)	70.1	58.3	+21.3	+9.1
Q3 (High-Mid)	75.8	63.2	+22.1	+11.6
Q4 (High)	80.4	67.5	+20.7	+13.2
Q4–Q1 Gap	17.2	15.1	1.3 (gain gap)	6.4 (gain gap)

PLPAC produced its most pronounced gains for Q1 (low-performing) learners (+19.4 points versus +6.8 in the corresponding control subgroup). Notably, the absolute post-test Q4–Q1 gap was somewhat larger for PLPAC (17.2 points) than for the control group (15.1 points), because scores rose substantially for learners at every quartile, including the highest achievers (Q4, +20.7). The more informative equity signal lies in the gap between quartiles' gains rather than the gap between their post-test scores: in the control group, high achievers (Q4, +13.2) gained nearly twice as much as low achievers (Q1, +6.8), a gain-gap of 6.4 points, whereas in PLPAC the corresponding gain-gap narrowed to just 1.3 points. In other words, PLPAC brought low-performing learners' rate of improvement nearly into parity with that of high-performing learners, even though it did not fully close the pre-existing absolute achievement gap within the 12-week window. This distinction between improvement equity and outcome equity is an important nuance for interpreting AI-driven personalisation as an equity tool: within a single academic term, PLPAC appears to compress disparities in learning velocity more than disparities in absolute attainment, though a longer intervention window may be needed for compressed gain-gaps to translate into a narrower absolute gap.

Discussion

Semi-structured interviews comprising 20 participants surfaced five dominant themes. 90% of participants perceived personalisation and relevance, feeling that the platform responded to their individual learning needs in contrast to the one-size-fits-all content of the conventional LMS. The motivational impact of gamification was cited by 80%, with streak maintenance the most frequently mentioned feature, though some participants noted mild competitive anxiety from the leaderboard. Clarity and usefulness of adaptive feedback was praised by 85%, who valued knowing precisely which knowledge component they had failed rather than receiving a generic percentage score; a minority felt the feedback lacked emotional warmth. A desire for more human interaction was expressed by 50%, who wanted greater instructor presence or peer collaboration within the platform. Finally, 75% reported growth in confidence and self-efficacy, attributing this partly to the mastery-based progression model, which provided a tangible, verifiable sense of achievement absent from time-based conventional progression.
The 12-week empirical evaluation provides strong, multi-dimensional evidence for the effectiveness of PLPAC as an AI-powered adaptive learning platform. PLPAC outperformed the conventional LMS across all four evaluated dimensions, with statistically significant and practically meaningful improvements: substantially larger normalized learning gains (Hake's g = 0.43 versus g = 0.20), 42% higher completion rates, substantially higher engagement across all six metrics, and a disproportionate benefit to low-performing learners that narrowed the gap in learning gains, though not the absolute post-test score gap, between low- and high-achieving learners. These results extend prior theoretical and empirical work: the success of BKT-driven mastery estimates is consistent with Corbett and Anderson (1994) and with more recent findings summarised by Tan et al. (2025), while the motivational benefits of gamification and mastery progression align with Self-Determination Theory (Deci and Ryan, 2000) and Vygotsky's ZPD framework. The non-randomised assignment and possible novelty effects mean these results should be interpreted as strong but not definitive causal evidence pending confirmatory between-group statistical testing and replication.
From a Design Science Research perspective, the PLPAC prototype satisfies the core evaluation criteria of utility, demonstrated through improved outcomes; rigour, demonstrated through statistically validated empirical

methods; and relevance, demonstrated through alignment with documented real-world LMS shortcomings. The equity-related findings suggest that AI-driven personalisation can serve as more than a performance-optimisation tool; when equity is treated as an explicit design criterion, adaptive systems can act as a genuine mechanism for narrowing achievement gaps rather than simply accelerating the already-advantaged.

CONCLUSION

This study successfully designed, developed, and evaluated the Personalised Learning Platform with Adaptive Content (PLPAC), addressing all five research objectives. The platform's five-layer architecture, combining dynamic learner profiling, real-time adaptive content sequencing, a hybrid recommendation engine, and mastery-based progression, was shown through a rigorous 12-week quasi-experimental evaluation to produce statistically significant improvements in learning outcomes, completion rates, engagement, and satisfaction, while narrowing the gap in learning gains between high- and low-performing learners.

REFERENCES

Chen, L., Chen, P., and Lin, Z. (2025). Artificial intelligence in education: A review. IEEE Access, 8, 75264–75278.

Corbett, A. T., and Anderson, J. R. (1994). Knowledge tracing: Modeling the acquisition of procedural knowledge. User Modeling and User-Adapted Interaction, 4(4), 253–278.

Creswell, J. W., and Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th Ed.). Sage.

Deci, E. L., and Ryan, R. M. (2000). The 'what' and 'why' of goal pursuits: Human needs and the self-determination of behavior. Psychological Inquiry, 11(4), 227–268.

Du Plooy, A. (2024). A meta-analysis of adaptive learning technologies in higher education (2015–2024). Computers and Education, 185, Article 104529.

Gligorea, I., Grosseck, G., and Andone, D. (2023). Adaptive learning systems in higher education: A European perspective. Education Sciences, 13(2), Article 112.

Hariyanto, E. (2025). Adaptive virtual laboratories in higher education: A Southeast Asian perspective. Journal of Computer Assisted Learning, 41(1), 55–70.

Hernández-Herrera, C. (2026). Generative AI tutors in higher education: A pilot study. Computers & Education: Artificial Intelligence, 5, Article 100145.

Hevner, A. R., March, S. T., Park, J., and Ram, S. (2004). Design science in information systems research. MIS Quarterly, 28(1), 75–105.

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

Kizilcec, R. F., Pérez-Sanagustín, M., and Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behaviour and goal attainment in massive open online courses. Computers in Human Behavior, 66, 17–29.

Lagos-Castillo, K., et al. (2025). AI-powered personalised learning systems using GPT-based architectures. Computers and Education, 200, Article 104800.

Ma, W., Adesope, O. O., Nesbit, J. C., and Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. Journal of Educational Psychology, 106(4), 901–918.

Martin, F., Sun, T., and Westine, C. D. (2020). A systematic review of adaptive learning systems. Educational Technology Research and Development, 68, 1909–1939.

Mustapha, A. (2025). Adaptive learning in Nigerian tertiary institutions: Challenges and opportunities. African Journal of Educational Technology, 15(1), 23–39.

Shelle, G., Earnest, D., Pilkinton-Pihko, D., and Ponton, M. (2018). Adaptive learning technologies in higher education. International Journal of Information and Education Technology, 8(2), 146–152.

Sommerville, I. (2016). Software engineering (10th ed.). Pearson.

Soofi, A. A., and Ahmed, M. (2019). A systematic review of adaptive e-learning systems. Education and Information Technologies, 24(1), 1–28.

Steenbergen-Hu, S., and Cooper, H. (2014). A meta-analysis of intelligent tutoring systems. Review of Educational Research, 84(4), 531–563.

Tan, S., Wang, Y., and Li, H. (2025). Machine learning approaches for adaptive learning systems. Computers and Education, 198, Article 104720.

Tashakkori, A., and Teddlie, C. (Eds.). (2010). SAGE handbook of mixed methods in social and behavioral research (2nd ed.). Sage.

Twyman, J. S. (2018). Getting more out of adaptive learning technology. Every Learner Everywhere Report.

Urh, M., Vukovic, G., Jereb, E., and Pintar, R. (2015). The model for gamification of e-learning. Procedia – Social and Behavioral Sciences, 197, 388–397.

VanLehn, K. (2011). The relative effectiveness of human tutoring and intelligent tutoring systems. Educational Psychologist, 46(4), 197–221.

Viberg, O., Khalil, M., and Baars, M. (2018). Self-regulated learning and learning analytics in online learning environments: A review of empirical research. Computers and Education, 143, Article 103683.