AI-Driven Adaptive Learning for Personalized Higher Education E-Learning

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Abstract: The rapid expansion of digital learning environments in higher education has increased the demand for personalised learning experiences that accommodate diverse learner needs, preferences, and learning trajectories. Artificial intelligence (AI)-driven adaptive learning systems have emerged as a promising solution by providing personalised content recommendations, adaptive feedback, and data-informed learning pathways. This study examines the influence of AI-driven adaptive learning on personalised learning experiences, student engagement, and learning outcomes in higher education e-learning environments. Drawing upon Self-Regulated Learning Theory and Constructivist Learning Theory, the study proposes a conceptual model in which personalised learning experience and student engagement serve as key mechanisms through which adaptive learning technologies enhance educational outcomes. A quantitative explanatory research design was employed using survey data collected from 320 undergraduate students enrolled in AI-supported e-learning courses at several higher education institutions. Data were analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM Ver. 3.0). The measurement model demonstrated satisfactory reliability and validity, with Cronbach's alpha and composite reliability exceeding 0.70 and average variance extracted exceeding 0.50. The structural model revealed that AI-driven adaptive learning significantly influenced personalised learning experience ($\beta = 0.545$, $p < 0.000$) and student engagement ($\beta = 0.701$, $p < 0.000$). Personalised learning experience positively affected learning outcomes ($\beta = 0.424$, $p < 0.000$), while student engagement also exerted a significant positive influence ($\beta = 0.321$, $p < 0.000$). Mediation analysis indicated that personalised learning experience partially mediated the relationship between AI-driven adaptive learning and learning outcomes ($\beta = 0.231$, $p < 0.000$). The findings suggest that AI-driven adaptive learning enhances higher education e-learning by fostering more personalised and engaging learning experiences, which in turn improve student achievement. This study contributes to the growing literature on AI in education by providing empirical evidence of the mechanisms by which adaptive learning technologies support effective, learner-centered digital education.

Keywords: Artificial Intelligence, Adaptive Learning, Personalised Learning, Student Engagement, Learning Outcomes, Higher Education E-Learning.

1. Introduction

Digital and online learning has become a central feature of contemporary higher education, particularly through blended and fully online formats. These modalities provide flexibility but also create challenges for maintaining engagement and academic achievement. Evidence from large-scale online learning indicates that students may experience reduced engagement and lower achievement when digital environments are inadequately designed or supported (Fan and Tian, 2022). Student engagement is therefore widely regarded as an important indicator of educational quality and predictor of learning outcomes, achievement, and satisfaction (Wang and Ji, 2021; Hua and Wang, 2023). Importantly, engagement encompasses behavioral, cognitive, and emotional dimensions, which may contribute differently to educational outcomes.

These challenges are complicated by learner diversity. Students differ in prior preparation, learning strategies, motivation, and other characteristics that may influence achievement through engagement-related mechanisms (Meng and Zhang, 2023). Students' perceptions of technology-mediated environments also influence their satisfaction and achievement, yet the interaction between perceptions, engagement, and technology-rich instructional designs remains insufficiently understood (Tossell *et al.*, 2024). Consequently, higher education requires approaches that move beyond standardised, one-size-fits-all digital instruction toward learning environments responsive to individual differences.

Artificial intelligence (AI) offers opportunities to address these limitations by enabling personalised and adaptive learning. AI applications in higher education include intelligent tutoring, adaptive learning, learning analytics, automated assessment, and competency-based learning pathways (Dastane, Turner and Nankervis, 2024). AI-driven systems can analyse learner data and adjust content, feedback, pacing, and learning pathways according to individual progress. Empirical evidence suggests that appropriately integrated AI-supported interventions can enhance achievement-related skills and learning performance (Mayasari *et al.*, 2024). However, technological

capability alone does not guarantee educational effectiveness. Learners' perceptions, trust, motivation, and engagement can shape their responses to AI-supported environments (Tossell *et al.*, 2024). Equity, access, infrastructure, privacy, and the digital divide further influence whether AI-enabled personalisation benefits diverse learners (Wafik *et al.*, 2024).

Despite increasing interest in AI-driven adaptive learning, an important research gap remains regarding **how** personalisation translates into improved learning outcomes in higher education e-learning. Engagement may represent a critical mechanism because it can mediate relationships between learner characteristics, instructional experiences, and academic achievement (Hua and Wang, 2023; Meng and Zhang, 2023). Thus, evaluating AI systems solely on technological functionality may overlook the pedagogical processes by which adaptive technologies influence student success.

Accordingly, this study investigates the mechanisms through which AI-driven adaptive learning influences learning outcomes, focusing on personalised learning experiences and student engagement. It addresses five research questions: (1) How does AI-driven adaptive learning influence personalised learning experiences? (2) What is its effect on student engagement? (3) How do personalised learning experiences affect learning outcomes? (4) How does student engagement contribute to learning outcomes? and (5) Does personalised learning experience mediate the relationship between AI-driven adaptive learning and learning outcomes?

2. Literature Review

2.1 E-Learning in Higher Education

E-learning is now widely embedded in higher education, particularly after COVID-19 accelerated institutional adoption of online and blended learning, which has expanded flexible participation across geographical and temporal boundaries (Yıkıcı *et al.*, 2022; Aldraiweesh and Alturki, 2023). However, engagement, motivation, and satisfaction remain critical determinants of persistence and learning outcomes (Essa, Çelik and Human-Hendricks, 2023). Poorly designed online instruction may reduce engagement and reinforce limitations of one-size-fits-all approaches (Almekhlafi *et al.*, 2024; Komolafe *et al.*, 2025). Consequently, AI-enabled adaptive learning is increasingly used to identify knowledge gaps, personalise content and pacing, and provide targeted feedback (Ahmed, 2024). Such personalised approaches respond to learner differences and may improve engagement and outcomes across heterogeneous student populations (Aithal and Aithal, 2023).

2.2 Artificial Intelligence in Education

Artificial intelligence in education (AIED) uses AI to provide personalised and automated educational services across teaching, assessment, and learner support (Almekhlafi, Abdelaziz and Shabaan, 2024). Key applications include intelligent tutoring systems, learning analytics, natural language processing, pedagogical agents, and automated assessment (Aldraiweesh and Alturki, 2023). Intelligent tutoring and adaptive systems use learner data to personalise instruction and feedback (Li, 2022), while predictive analytics can identify learning patterns and students at risk, enabling timely interventions (Yıkıcı *et al.*, 2022). However, effective AIED implementation requires responsible attention to algorithmic bias, fairness, privacy, transparency, security, and ethical use.

2.3 Adaptive Learning Systems

Adaptive learning systems use AI to personalise instruction by dynamically adjusting content, pathways, pacing, and feedback according to learners' needs, knowledge, and progress (Aldraiweesh and Alturki, 2023). Unlike uniform e-learning, adaptive platforms combine learner and domain models to recommend resources and learning pathways in real time (Essa, Çelik and Human-Hendricks, 2023). Adaptation may employ expert-defined rules or AI techniques, including machine learning, predictive analytics, reinforcement learning, and natural language processing (Li, 2022). By identifying knowledge gaps and individual learning trajectories, these systems can provide targeted support that strengthens learner engagement and improves academic outcomes.

2.4 Conceptual Framework and Hypotheses Development

Based on the literature, AI-driven adaptive learning is expected to enhance personalised learning experiences by delivering customised content, adaptive recommendations, and individualised feedback. Personalised learning experiences are subsequently anticipated to improve learning outcomes by increasing content relevance, learner autonomy, and learning effectiveness. Similarly, adaptive learning systems are expected to

enhance student engagement through interactive, responsive learning experiences. Higher engagement levels are likely to contribute positively to academic achievement and overall learning outcomes. Accordingly, the following hypotheses are proposed:

- **H1:** AI-Driven Adaptive Learning positively influences Personalised Learning Experience.
- **H2:** AI-Driven Adaptive Learning positively influences Student Engagement.
- **H3:** A personalised learning experience positively influences Learning Outcomes.
- **H4:** Student Engagement positively influences Learning Outcomes.
- **H5:** Personalised Learning Experience mediates the relationship between AI-Driven Adaptive Learning and Learning Outcomes.

3. Research Methodology

3.1 Research Design

This study used a quantitative, explanatory, cross-sectional survey to examine associations among AI-Driven Adaptive Learning (AIAL), Personalised Learning Experience (PLE), Student Engagement (SE), and Learning Outcomes (LO) in higher-education e-learning, leveraging single-time-point data collection appropriate for modeling relationships among learning engagement and outcomes in AI-supported contexts (Agbong-Coates, 2024). Hypotheses (including mediation paths) were tested with PLS-SEM Ver. 3.0 because it supports prediction-oriented, complex latent-variable models and mediation analysis, and is tolerant of non-normal data and Likert-type measures (Khương, Nguyen, and Huy, 2025). The study targeted higher-education institutions using AI-supported e-learning; respondents had ≥1 semester of platform experience, consistent with prior AI-integration survey designs linking AI use to engagement and learning quality (Agbong-Coates, 2024).

3.2 Population and Sample

The population comprised undergraduate students enrolled in online or blended courses using AI-driven adaptive e-learning at Institut Teknologi dan Bisnis Bina Sarana Global, Tangerang, Indonesia. Purposive sampling recruited students meeting predefined eligibility criteria, consistent with context-specific participant selection (Muñoz & Canese, 2024). Data were collected electronically in accordance with established online survey practices (Agbong-Coates, 2024). PLS-SEM was selected for its suitability for complex predictive models, while sample adequacy was considered beyond simplistic heuristics (Agbong-Coates, 2024; S.IP & To, 2025). Of 350 questionnaires distributed, 320 complete and valid responses were retained, yielding a 91.4% usable response rate.

3.3 Instrument Development

Data were collected using a structured questionnaire adapted from validated instruments in the fields of educational technology, adaptive learning, and online learning research. All items were measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire consisted of two sections (see Table 1).

Table 1: Questionnaire Structure and Measurement Constructs

Section	Variable/Construct	Code	Number of Items	Description
A. Demographic Information	Gender	GEN	1	Respondent gender (Male/Female)
	Age	AGE	1	Respondent age category
	Academic Discipline	AD	1	Field of study of the respondent
	Year of Study	YS	1	Current academic year/semester
	Prior Experience with E-learning	PEE	1	Duration of experience using e-learning systems
	Frequency of AI Platform Usage	FAI	1	Frequency of using AI-supported learning platforms

Section	Variable/Construct	Code	Number of Items	Description
B. Research Constructs	AI-Driven Adaptive Learning	AIAL	5	Measures perceptions of adaptive recommendations, personalised feedback, intelligent support, predictive analytics, and adaptive learning pathways(Azpiazu, Rodríguez-Fernández and Palacios, 2021)
	Personalised Learning Experience	PLE	5	Measures perceived personalisation, flexibility, autonomy, content relevance, and individualised learning support (Yan, Wu and Dai, 2025)
	Student Engagement	SE	5	Measures behavioral, emotional, and cognitive engagement in e-learning activities (Wastira and Tekad, 2025)
	Learning Outcomes	LO	5	Measures perceived knowledge acquisition, academic achievement, learning effectiveness, problem-solving ability, and overall performance (Jarudin and Dedi, 2026).
Total	—	—	26 Items	6 demographic items and 20 construct measurement items

A pilot study involving 30 students was conducted to assess clarity, reliability, and content validity before the main data collection phase.

3.4 Data Collection Procedure

Data were collected over six weeks using a web-based questionnaire, enabling efficient access to geographically dispersed participants (Aktuna, 2023). Participation was anonymous and voluntary, consistent with established online survey practices (Mohammed *et al.*, 2022), while electronic surveys can provide reliable primary data (Nie *et al.*, 2022). Data screening removed incomplete, duplicate, and potentially invalid submissions, addressing risks associated with remote data collection (Vilenchik *et al.*, 2025; Hu, Kuang and Lu, 2024). Following screening, **320 valid responses** were retained for statistical analysis.

3.5 Data Analysis Techniques

Data analysis was conducted using SmartPLS 3 following the two-stage PLS-SEM procedure: measurement and structural model evaluation (Liang *et al.*, 2025). Descriptive statistics summarised respondent characteristics and variable distributions (Tian *et al.*, 2023). The measurement model assessed factor loadings, Cronbach's alpha, composite reliability, AVE, and HTMT (Won, Chiu and Bravo, 2023). The structural model evaluated path coefficients, R^2, f^2, and Q^2, with bootstrapping used to determine statistical significance (Lněnička *et al.*, 2022). Mediation was assessed through bootstrapped indirect effects and confidence intervals excluding zero (Rios, Riquelme and Comai, 2023).

4. Results

4.1 Respondent Demographics

A total of 320 valid responses were analysed. Table 2 presents the demographic characteristics of the participants.

Table 2: Respondent Demographics (N = 320)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	142	44.4
	Female	178	55.6
Age	18–20 years	96	30.0
	21–23 years	158	49.4
	≥24 years	66	20.6
Academic Discipline	Social Sciences	104	32.5
	Business	88	27.5

Characteristic	Category	Frequency	Percentage (%)
	Engineering	71	22.2
	Education	57	17.8
Experience with E-learning	<1 year	72	22.5
	1–3 years	168	52.5
	>3 years	80	25.0

The results indicate that female students constituted the majority of respondents (55.6%). Most participants were aged between 21 and 23 years (49.4%) and had between one and three years of experience using e-learning platforms (52.5%). The sample represents diverse academic disciplines, suggesting broad exposure to AI-supported learning environments.

4.2 Descriptive Statistics

Table 3 presents the descriptive statistics of the study variables. The results indicate generally positive perceptions of AI-driven adaptive learning, personalised learning experiences, student engagement, and learning outcomes, with all constructs recording high mean scores above 4.00, suggesting favorable evaluations of the AI-supported e-learning environment.

Table 3: Descriptive Statistics of Research Variables

Variable	Mean	SD	Category
AI-Driven Adaptive Learning	4.18	0.63	High
Personalised Learning Experience	4.11	0.59	High
Student Engagement	4.06	0.61	High
Learning Outcomes	4.14	0.57	High

The mean values indicate positive perceptions of AI-supported adaptive learning. AI-Driven Adaptive Learning received the highest evaluation (M = 4.18), suggesting that students generally perceived adaptive recommendations, personalised feedback, and intelligent learning support as effective.

4.3 Measurement Model Assessment

The measurement model assessment was conducted to evaluate the reliability and validity of the research constructs. Figure 1 presents the indicator loadings and the relationships among the latent variables, providing evidence of construct adequacy before testing the structural model and the research hypotheses.

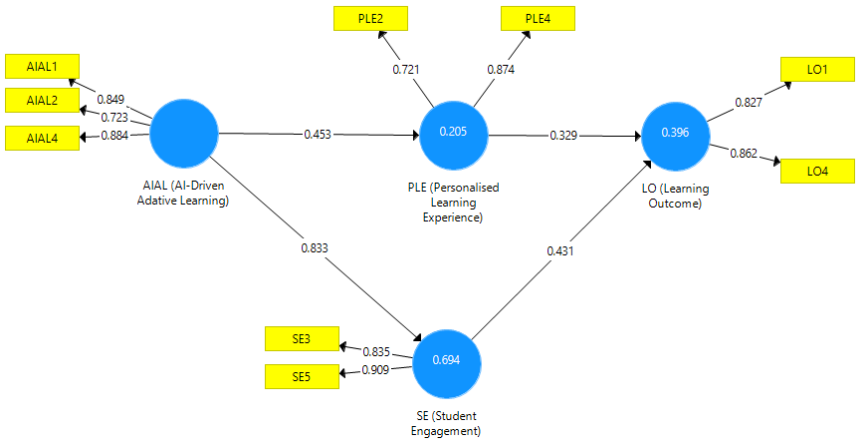


Figure 1: Results of the PSL Algorithm

Table 4 presents the measurement model assessment results, including factor loadings, internal consistency reliability, convergent validity, and discriminant validity. These indicators were evaluated to ensure that the constructs adequately measured the intended latent variables before proceeding to structural model analysis.

Table 4: Measurement Model Assessment

Construct	Loadings Factor	Cronbach's Alpha	Composite Reliability	AVE	HTMT
AIAL	0.723 - 0.884	0.758	0.861	0.675	0.597
PLE	0.721 – 0.874	0.901	0.781	0.642	0.766
SE	0.835 – 0.909	0.893	0.865	0.762	0.606
LO	0.827 – 0.862	0.918	0.833	0.714	0.797

The measurement model demonstrated satisfactory reliability and validity. Factor loadings (0.721–0.909), Cronbach's Alpha (0.758–0.918), and Composite Reliability (0.781–0.865) met recommended thresholds. AVE values (0.642–0.762) confirmed convergent validity, while HTMT values (0.597–0.797) established adequate discriminant validity.

4.4 Structural Model Assessment

The structural model was evaluated using the bootstrapping procedure with 5,000 subsamples to determine the significance and strength of the hypothesised relationships among the constructs. Path coefficients, t-statistics, and p-values were examined to assess the predictive relationships between AI-Driven Adaptive Learning, Personalized Learning Experience, Student Engagement, and Learning Outcomes (see Figure 2).

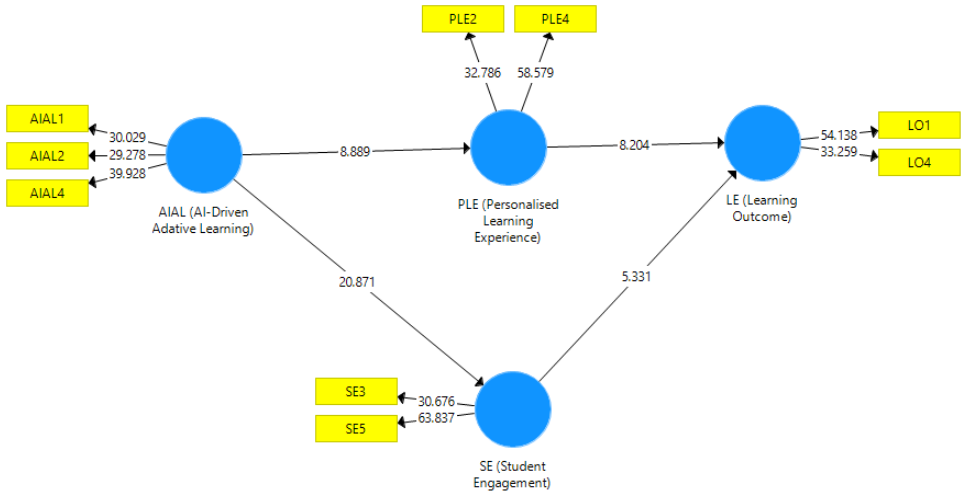


Figure 2: Results of Bootstrapping

Table 5 presents the results of hypothesis testing obtained through the PLS-SEM bootstrapping procedure. The significance of the proposed relationships was evaluated using path coefficients (β), t-values, and p-values to determine whether the hypothesised effects among the constructs were supported.

Table 5: Hypothesis Testing Results

Hypothesis	Relationship	β	t-value	p-value	Result
H1	AIAL → PLE	0.545	8.857	<0.000	Supported
H2	AIAL → SE	0.701	20.385	<0.000	Supported
H3	PLE → LO	0.424	8.269	<0.000	Supported
H4	SE → LO	0.321	5.444	<0.000	Supported

All four hypotheses were supported. AI-Driven Adaptive Learning significantly influenced Personalized Learning Experience (β = 0.545) and Student Engagement (β = 0.701). Personalized Learning Experience (β = 0.424) and Student Engagement (β = 0.321) significantly improved Learning Outcomes (all $p < 0.001$), confirming the importance of personalisation and engagement in AI-supported learning.

4.5 Coefficient of Determination (R^2)

Table 6 presents the coefficient of determination (R^2) values for the endogenous variables in the structural model. R^2 measures the proportion of variance explained by the predictor variables and indicates the model's predictive power for Personalized Learning Experience, Student Engagement, and Learning Outcomes.

Table 6: Coefficient of Determination

Endogenous Variable	R^2
Personalised Learning Experience	0.205
Student Engagement	0.694
Learning Outcomes	0.396

AI-Driven Adaptive Learning explained 20.5% of the Personalized Learning Experience and 69.4% of Student Engagement, and, together with Personalized Learning Experience, accounted for 39.6% of Learning Outcomes. These findings indicate strong predictive power for engagement and moderate explanatory capability for learning outcomes in AI-supported e-learning environments.

4.6 Effect Size (f^2)

Table 7 presents the effect sizes (f^2), which assess the magnitude of each predictor's contribution to the endogenous constructs beyond statistical significance.

Table 7: Effect Size Results

Relationship	f^2	Interpretation
AIAL → PLE	0.258	Medium
AIAL → SE	2.265	Large
PLE → LO	0.156	Medium
SE → LO	0.267	Medium

The results indicate a large effect of AIAL on SE (f^2 = 2.265), while AIAL → PLE (f^2 = 0.258), PLE → LO (f^2 = 0.156), and SE → LO (f^2 = 0.267) demonstrate medium effects. These findings suggest that AI-driven adaptive learning has the strongest influence on student engagement.

4.7 Predictive Relevance (Q^2)

The Q^2 analysis indicates that the model possesses satisfactory predictive relevance (see Figure 3).

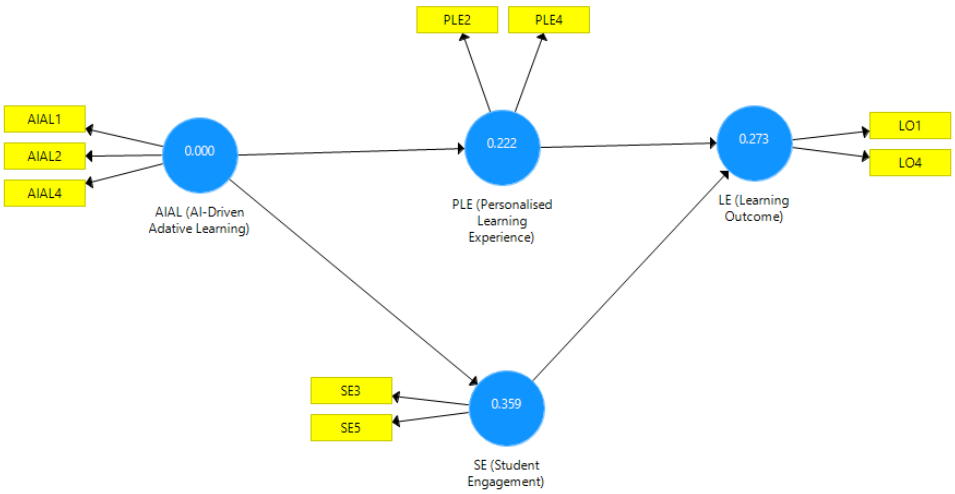


Figure 3: Results of Blindfolding

Table 8 presents the predictive relevance (Q^2) values for the endogenous constructs, which assess the model's ability to accurately predict observed data.

Table 8: Predictive Relevance Results

Endogenous Variable	Q^2
Personalised Learning Experience	0.222
Student Engagement	0.359
Learning Outcomes	0.273

All Q^2 values exceed zero, indicating satisfactory predictive relevance. Student Engagement shows the highest predictive relevance (Q^2 = 0.359), followed by Learning Outcomes (Q^2 = 0.273) and Personalised Learning Experience (Q^2 = 0.222). These results confirm that the model possesses adequate predictive capability for all endogenous constructs.

4.8 Mediation Analysis

Table 9 presents the mediation analysis results, examining whether Personalised Learning Experience mediates the relationship between AI-Driven Adaptive Learning and Learning Outcomes. The significance of the indirect effect was assessed using bootstrapping procedures.

Table 9: Mediation Analysis Results

Indirect Relationship	β	t-value	p-value
AIAL → PLE → LO	0.231	4.736	<0.000

The indirect effect of AI-Driven Adaptive Learning on Learning Outcomes through Personalized Learning Experience was significant (β = 0.231, t = 4.736, p < 0.001). This finding supports the mediation hypothesis, indicating that AI-driven adaptive learning enhances learning outcomes by improving students' personalised learning experiences. The results suggest that personalisation serves as an important mechanism through which adaptive learning technologies contribute to educational effectiveness in higher education e-learning environments.

5. Discussion

5.1 Impact of AI-Driven Adaptive Learning

Interpreting *AI-driven adaptive learning* as e-learning functionality that dynamically adjusts content, feedback, and support, the observed positive links to Personalised Learning Experience (β = 0.545) and Student Engagement (β = 0.701) are consistent with evidence that e-learning system characteristics (e.g., usability, system quality, information quality, and enjoyment) shape learners' motivational and performance-related outcomes (Yahiaoui *et al.*, 2022), and that higher education e-learning effectiveness depends on interaction, cognitive reflection/communication, and instructor facilitation of meaningful outcomes (Miguel *et al.*, 2021). In crisis-driven online contexts, overall e-learning "net benefits" are commonly operationalised as multidimensional learning outcomes, reinforcing the plausibility that technology-enabled adaptation can yield measurable educational benefits rather than serving as a merely peripheral tool (Rabih and Yammine, 2025). Methodologically, estimating these relationships via variance-based path models aligns with prior higher-education research using PLS-SEM for prediction-oriented models with multiple direct and indirect paths (Ng, Wut, and Chan, 2022).

5.2 Role of Personalised Learning Experience

The significant effect of Personalised Learning Experience → Learning Outcomes (β = 0.424) is congruent with broader findings that e-learning adoption and perceived learning/academic performance improve when learners perceive the system as useful, enjoyable, and supportive of learning (learning assistance and academic performance) (Yahiaoui *et al.*, 2022). Framed through established acceptance mechanisms, perceived usefulness and ease of use can shape favorable attitudes and intentions toward learning technologies, providing a theoretical basis for why personalisation that increases relevance and reduces friction can support achievement

(Khan *et al.*, 2023). The partial mediation result (β = 0.231) aligns with prior extensions of information systems success perspectives in higher education, in which technology features affect learning outcomes through learners' perceived benefits (Rabih and Yammine, 2025).

5.3 Student Engagement and Learning Outcomes

The Student Engagement → Learning Outcomes path (β = 0.321) accords with evidence that motivation-related factors are reliably associated with student outcomes in e-learning, including perceived learning and academic performance (Yahiaoui *et al.*, 2022). Moreover, higher education e-learning success models emphasise socially collaborative interaction and cognitively meaningful participation as central mechanisms for achieving learning outcomes, supporting engagement as a proximal driver of performance (Miguel *et al.*, 2021).

5.4 Contributions to E-Learning Theory

This study advances e-learning theory by positioning AI-driven adaptive learning as a technological capability that shapes personalised learning experiences and student engagement, thereby influencing learning outcomes, consistent with IS-success perspectives (Rabih and Yammine, 2025). The findings reinforce Self-Regulated Learning Theory by demonstrating how AI-enabled personalisation supports autonomous and self-regulated learning (Harati *et al.*, 2021). They also support constructivist perspectives, whereby adaptive systems tailor learning interactions to facilitate active knowledge construction and engagement (Ariely, Nazaretsky and Alexandron, 2024), while identifying personalisation as a mediating mechanism linking technology with learning outcomes (Rabih and Yammine, 2025).

5.5 Practical Implications

The findings suggest that higher education institutions should invest in AI-driven adaptive learning systems to enhance personalisation, engagement, and learning outcomes. Instructional designers should develop flexible, learner-centred content, while educators can utilise learning analytics for targeted support. For example, AI-based adaptive learning platforms can analyse students' quiz performance and automatically recommend additional materials or adjust task difficulty according to individual mastery levels. Similarly, intelligent tutoring systems can provide real-time personalised feedback, identify learning difficulties, and suggest appropriate learning pathways based on student progress. These applications enable educators to provide timely interventions while allowing students to learn at an appropriate pace. Technology developers should therefore prioritise transparency, explainable AI, data privacy, and adaptive feedback mechanisms to ensure that AI-supported e-learning environments remain effective, trustworthy, inclusive, and responsive to diverse learner needs.

6. Conclusion

This study investigated how AI-Driven Adaptive Learning enhances Personalized Learning Experience, Student Engagement, and Learning Outcomes in higher education e-learning. AI-Driven Adaptive Learning significantly influenced Personalized Learning Experience (β = 0.545, $p < 0.001$) and Student Engagement (β = 0.701, $p < 0.001$). Personalized Learning Experience (β = 0.424, $p < 0.001$) and Student Engagement (β = 0.321, $p < 0.001$) subsequently improved Learning Outcomes. Moreover, Personalized Learning Experience significantly mediated the relationship between AI-Driven Adaptive Learning and Learning Outcomes (β = 0.231, $p < 0.001$). The findings extend Self-Regulated Learning and Constructivist perspectives by demonstrating how AI-enabled personalisation supports learner autonomy, engagement, and knowledge construction. Practically, universities should integrate adaptive learning platforms, personalised learning pathways, and learning analytics to provide targeted instructional support and create more responsive, learner-centred digital learning environments.

Despite these contributions, the study is limited by its cross-sectional design, reliance on self-reported data, and focus on students using AI-supported e-learning systems. Self-report bias may particularly influence the measurement of Learning Outcomes, as students may overestimate or underestimate their achievement based on personal perceptions, satisfaction with the AI system, social desirability, or recent learning experiences. Consequently, perceived learning outcomes may not fully correspond with actual academic performance. Future research should employ longitudinal and experimental approaches and triangulate self-reported outcomes with objective indicators, such as examination scores, course grades, task performance, and learning analytics. Additional factors, including digital literacy, self-efficacy, and technology acceptance, should also be examined.

Further investigation into explainable AI, data privacy, algorithmic transparency, and ethical considerations will be essential to support the responsible implementation of adaptive learning technologies in higher education.

Acknowledgment

The authors sincerely acknowledge the participating higher education institutions, students, lecturers, and academic staff for their valuable support and participation in this study. Appreciation is also extended to the experts who contributed to validating the research instruments and provided constructive feedback throughout the research process. Their cooperation and contributions were essential to the successful completion of this study.

Ethics Declaration

This study was conducted in accordance with institutional ethical guidelines (Ref. No. 016/KE/LPPM/2026). Participation was voluntary, informed consent was obtained, and respondent anonymity and confidentiality were maintained. No personally identifiable information was collected, and the authors reported no conflicts of interest.

AI Declaration

Artificial intelligence (AI) tools were used solely to support language refinement, grammar checking, and manuscript preparation. All research design, data analysis, interpretation, and final content were reviewed and approved by the authors.

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