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Beyond One-Size-Fits-All Learning: An AI-Driven Personalized Learning Pathway Framework

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Abstract

Artificial intelligence has accelerated the evolution of personalized learning, yet most learning management systems continue to rely on static instructional pathways that inadequately accommodate learners' cognitive and behavioral diversity. This study evaluated an AI-driven Personalized Learning Pathway (PLP) framework that integrates learner analytics, intelligent content recommendation, and adaptive assessment within a unified learning environment to enhance student engagement and academic achievement. A mixed-methods quasi-experimental design was conducted with 240 undergraduate students from four universities across Southeast Asia. Students in the experimental group learned through an AI-augmented learning management system, while the control group used a conventional platform. The findings demonstrate that the AI-driven PLP framework consistently improved student engagement, motivation, course completion, and academic achievement compared with traditional learning management systems. Students also exhibited stronger learning adaptability and more effective responses to personalized feedback, both of which emerged as key contributors to academic success. By integrating behavioral analytics with real-time instructional adaptation, the proposed framework moves beyond content personalization toward a responsive learning ecosystem. This study contributes a scalable AI-enabled instructional framework that supports learner-centered higher education and provides practical guidance for implementing adaptive digital learning environments.

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INTRODUCTION

Artificial intelligence (AI) technologies are advancing rapidly and are beginning to offer opportunities and innovative ways for personalization and learner-centered instructional design in higher education (Dahlan, 2026; Ahda et al., 2025; Jannah et al., 2025). As institutions continue to move towards entirely online and blended teaching and learning, the challenges of accommodating different students' abilities and preferences in education and engagement are becoming more pressing (Hill & Smith, 2023; Mulenga & Shilongo, 2025). Most Learning Management Systems (LMS)

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employ a ‘one-size-fits-all’ approach and offer duplicate content and assessments that do not ‘model’ to the learner’s progress and challenges (Riady et al., 2025; Khalil et al., 2024; Ulfah et al., 2026). Due to the rigidity in the learning system, students are likely to become disengaged and demotivated, and exhibit poor and inconsistent performance, especially those with diverse behavioral and cognitive profiles (Española & Ouano, 2024; Siska & Franzhardi, 2025). Personalized learning, the modification of pedagogy to focus on the individual needs and learning rates of students, has become a paradigm of educational practice over the past several years (Bernacki et al., 2021; Amin et al., 2025). However, the operationalization of personalization on a large scale remains a paradox. Traditional approaches to personalization are heavily reliant on time-consuming, manual processes performed by instructors. This is not realistic in large, classroom, or remote learning environments (Chattaraj & Parakkate, 2021; Zakharova et al., 2024). This is a critical example of the existing gaps in the learning ecosystem and the operationalization of personalized learning. The gaps are especially pronounced in learning environments characterized by the use of technology.

In the present study context, preliminary LMS observations showed that students using conventional LMS environments demonstrated inconsistent engagement patterns. Before the intervention, the average session duration was only 39.4 minutes, while the content completion rate was 72.5%. These figures indicate that conventional LMS use may not sufficiently sustain learner participation and learning persistence. Therefore, a more adaptive system is needed to support students through personalized learning pathways, real-time feedback, and continuous monitoring of learning behavior.

Previous studies have examined multiple AI-based approaches to advance educational personalization, ranging from systematic frameworks for integrating artificial intelligence into teaching and learning. Beyond adaptive learning systems, recent research has demonstrated the growing adoption of AI-powered educational technologies to support academic writing, self-regulated learning, and technology-enhanced instruction, indicating that artificial intelligence is increasingly embedded across diverse educational contexts (Yakubu et al., 2025). Other studies have proposed systematic AI integration frameworks, combined AI with emerging technologies such as augmented reality and STEAM education, as well as bibliometric analyses that map the evolution of AI-driven educational research and identify future directions for adaptive learning systems (Arif et al., 2025; Rusmansyah et al., 2025; Zainuddin et al., 2025). Technologies like Knewton and Carnegie Learning use adaptive learning algorithms to modify content based on a learner’s performance (S. Dutta et al., 2024; Kurkure, 2025). Other recent studies use learning analytics to identify student performance in order to create instructional interventions (Alalawi et al., 2025).

Nevertheless, the majority of adaptive systems are still about predicting performance and/or content adaptation. While Knewton and Carnegie Learning have evidenced the instructional personalization potential of AI, their methods are mostly performance-driven; they primarily adjust the difficulty of content based on learner responses. These systems optimize the learning process to maximize the acquisition of content in the short-term. However, they do not incorporate behavioral engagement and learner feedback in real-time. Learning analytics have improved the educational systems by employing the predictive capabilities of identifying at-risk learners and proposing intervention strategies. However, they mostly act as diagnostic methods and not as adaptive systems, because they offer recommendations without changing the learning environment based on the learners’ actions in real-time.

AI learning systems currently in use have made notable advancements to adaptive education concerning the prediction of learner performance, customization of content, and analysis of learner behavior. However, most existing systems remain disjointed. Most adaptive systems are concerned with modifying the content based on learner responses. Most systems for learning analytics are intended to predict student performance or determine the risk a student may pose. Although significant by themselves, the systems described above do not provide the means to resolve the combination of behavioral engagement, feedback, content recommendation, and adaptive assessment along a given learning pathway. Thus, the main contribution of this research is the development of a real-time model of Personalized Learning Pathway (PLP) that is integrated with learner analytics and AI to provide the means to recommend content and conduct adaptive assessments to support learners in engaging and achieving.

Fragmentation of systems described above, perhaps more importantly, demonstrates a fundamental lack of AI-based educational technologies. This is most evident when seeking to adaptively recommend content and assess learners in real time. Existing systems either predict and adapt or provide and engage. There is a critical need for a unified model that predicts learner performance and, within the same model, adapts to the cognitive and behavioral changes of the learner in real time.

According to Johar et al, (2023) and Tretow-fish & Khalid, (2023), no model currently integrates learner analytics with adaptive feedback and behavioral engagement. Most studies reviewed focused on system accuracy, often neglecting the educational impact, e.g., the personalization of AI and its effects on learner engagement, motivation, and on maintaining a positive level of accomplishment (Alenezi, 2023; Hartono et al., 2024; Saleem et al., 2025). The model of the AI-based Personalized Learning Pathway (PLP) proposed in this study attempts to address this issue by delineating three components (Figure 1) that incorporate: (1) behavioral and performance analytics, (2) content recommendation, using AI and semantic similarity to create personalized educational content, and (3) adaptive assessment, that alters the difficulty and/or types of assessment items based on the learner's previous answers. The model intends to work within conventional Learning Management Systems (LMS) to transform a static LMS into a responsive and personalized system for continual adjustment and engagement.

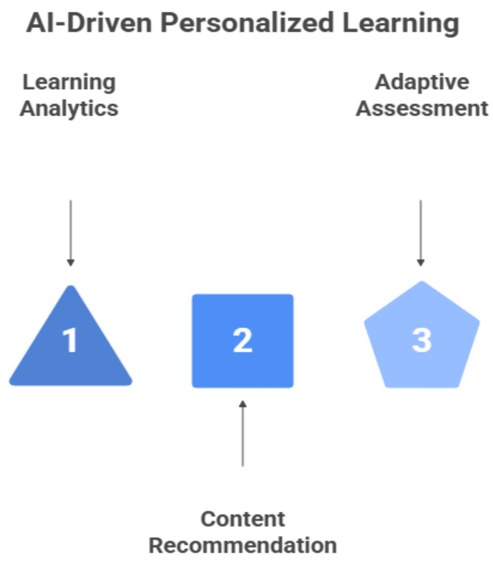

Figure 1. AI-Driven Personalised Learning Pathway

This research evaluates post-secondary AI-driven PLP models and their impact on learner engagement and academic results. This study has two main objectives. The first is to compare the PLP and the traditional LMS Models and assess the PLP Model's impact on the levels of student motivation, engagement, and achievement. The second objective is to understand the impact of learning adaptability, feedback sensitivity, and other variables on the predictive factor of academic achievement in AI-based learning systems. This research combines behavioral and performance indicators to demonstrate AI-based LMS personalization. This research also analyzes the AI-based Personalized Learning Pathway model and its impact on the variables of student interest and student participation. Additionally, it analyzes the impact of learning adaptability and feedback-driven learning on the student's performance and the potential of the AI-based learning system.

METHOD

Research Design

To measure the impact of the AI-based Personalized Learning Pathways (PLP) Model on the engagement and achievement of learners, a mixed-methods research design with a quasi-experimental approach was adopted. A quasi-experimental design was used to take into account the constraints of the real world, as in other choosing methods, it may not be possible to randomly assign research subjects to different groups (Chi et al., 2022). Notably, the design used a treatment group and a control group to allow for the drawing of causal conclusions. This study employed a triangulation design to incorporate different types of data, which in turn provided a better description of the learning experience on the cognitive and affective dimensions.

During the eight weeks of the study, the AI system used predictive modeling to adjust its suggestions to users. The suggestions were based on the users' learning histories and were designed to target the system's control parameters of academic engagement, feedback-driven learning, and task completion. The system used flexible control to target different types of learning. The system used short-term control to reduce the variation in the data. The data were pre-processed to control for the model's flexibility. The following is a flow chart of this research (Figure 2).

Figure 2. Research Flowchart

The overall research procedure for this study is described in the 'Research Flowchart' (Figure 2). Recruitment of participants and baseline assessment formed the starting point of the procedure. The AI-based Personalized Learning Pathway (PLP) model was implemented with the research participants in the experimental group. The Control group was taught with the Learning Management System (LMS) as is. During the eight-week period of the study, the Learning Management System (LMS) was used to collect data on learning interactions, assessments, and feedback. Data collected was cleaned, and the effects of the PLP model and its personalization on engagement, motivation, and achievement were assessed using descriptive statistics, inferential, and predictive analytics. The PLP model of personalization is based on AI, and the flow of the procedure used in the study demonstrates its systematic and repeatable nature.

Participants and Sampling

A total of 240 undergraduate students were recruited from four higher education institutions representing diverse geographical and educational contexts in Southeast Asia, namely Universitas Bengkulu and Universitas Bina Darma in Indonesia, INTI International University in Malaysia, and Shinawatra University in Thailand. Natural learning environments were preserved by using whole-class sections to form the two study groups. Each institution's focus was on 80 participants, with 40 in the experimental group and 40 in the control group. Accordingly, 120 participants formed the experimental group and interacted with the AI-embedded LMS supplemented with the PLP model, while the standard LMS was used by the other 120 participants in the Control group. Baseline equivalence was assessed using pre-intervention motivation scores, prior GPA, and pre-test scores. Based on the results, no significant differences were observed between the study groups ($p > 0.05$) as shown in Table 1, and the groups were comparable before the intervention.

Table 1. Summary of Study Participants

Category	Description	Details
Total Participants	Number of undergraduate students involved in the study	240 students
Participating Institutions	Universities representing diverse geographical and institutional contexts	1. Universitas Bengkulu, Indonesia 2. Universitas Bina Darma, Indonesia 3. INTI International University, Malaysia 4. Shinawatra University, Thailand
Sampling Method	Participant selection approach	Purposive sampling targeting students in blended learning courses utilizing an LMS
Learning Platform	Type of digital environment used	Learning Management System (LMS)
Group Division	Experimental and control conditions	B Used AI-augmented LMS with PLP model - Control Group (n = 120): Used standard LMS without AI personalization
Ethical Approval	Research ethics compliance	Approved by institutional review boards of all participating universities
Disciplinary Coverage	Academic background of participants	Students from both STEM and social science disciplines
Study Objective for Group Comparison	Comparative evaluation goal	To assess differences in engagement and achievement between AI-personalized LMS and standard LMS users

Participants were purposefully sampled as outlined in Table 1. The focus was on participants enrolled in a blended learning course that utilized a Learning Management System (LMS). Participants were assigned to two main groups: Experimental Group (n = 120): utilized the AI-augmented LMS with an Embedded PLP model. Control Group (n = 120): utilized a non-AI-based personalization LMS. All participants gave their informed consent. The model's applicability was ensured with the representation of both social sciences and STEM participants. Ethical clearance to collect and analyse data was obtained from the relevant boards.

AI-Based Personalized Learning Pathway Model

Three elements comprise the Personalized Learning Pathway (PLP) Model to form an active learning environment. The first component is the Learner Analytics Engine, in which the Moodle Learning Management System (LMS) records a variety of learner data, including students' login and logout times, time spent on each learning module, quiz results, and quiz participation. These data are subsequently transformed into multidimensional learner profiles encompassing the cognitive, emotional, and behavioral dimensions of learning. The second component is the Content Recommendation System, which suggests learning resources based on students' levels of understanding by employing collaborative filtering and semantic similarity techniques. Learning needs are semantically matched with appropriate instructional materials according to topic, difficulty level, and learning mode using a state-of-the-art BERT model. The third component is the Adaptive Assessment Module, which utilizes the Bayesian Knowledge Tracing (BKT) and Item Response Theory (IRT) frameworks to customize assessments based on learners' previous responses. Through this approach, students receive assessment items that are aligned with their current level of understanding, ensuring that they remain optimally challenged and continuously engaged throughout the learning process. All components worked in unison, built using a central AI orchestration based on Python and TensorFlow, to modify and provide on-the-fly feedback through the LMS interface.

Dataset and Data Collection

Data were collected over an eight-week learning period. The data collection process consisted of four stages. First, in Week 1, all participants completed a baseline academic test and responded to the Student Engagement Instrument (SEI) and Intrinsic Motivation Inventory (IMI). Second, from Week 2 to Week 7, students participated in learning activities through the LMS. The experimental group used the AI-driven PLP system, while the control group used the standard LMS. Third, LMS interaction data were automatically recorded, including login frequency, learning duration, module access, quiz attempts, assignment submissions, and forum participation. Fourth, in Week 8, all participants completed the post-test and post-intervention survey. In total, the study generated 18,400 interaction logs, 1,920 assessment records, and 480 survey responses from pre-test and post-test measurements. The data were anonymized before any form of analysis. The data cleaning process took place within the parameters of the analytic framework, where incomplete sessions were deleted, timestamps were standardized, and a KNN imputation approach was used to address absent values (Jena & Dehuri, 2022).

Experimental Setup

The implementation of the experiment was completed via the institution's LMS, where, in both the control and experimental arms, the students had the same course structure, materials, and assessments. The only differentiating factor was the implementation of the PLP model in the experimental group. Data from students were collected through baseline assessments, which were used to evaluate the participants' prior knowledge and motivation levels. During this time, the PLP model was in the AI-driven adaptive learning phase, designed to revise in real-time. GBRs and RNNs were used in the model to predict a learner's engagement and design a learning pathway, respectively, in the model's system of predictors (Wang & Wang, 2025). The learning progress of each student in the study was monitored in terms of system responsiveness, defined as improvement from the baseline measure, and feedback slack, defined as the elapsed time to attain an accurate solution after a system suggestion from the model.

Data Analysis

Quantitative data analysis was performed using Python (NumPy, SciPy, Scikit-learn) (Lavrova et al., 2023) and SPSS 22 for statistical validation (Purwanto et al., 2021). The analysis began with descriptive statistics to summarize engagement frequency, learning time, and mean performance scores (Brahim, 2022). Subsequently, inferential statistical analyses, including independent *t*-tests and Analysis of Covariance (ANCOVA), were conducted to compare pre- and post-intervention scores between the experimental and control groups while controlling for baseline differences (Yoon et al., 2023). Furthermore, regression models were employed to examine the predictive power of learning adaptability, feedback responsiveness, and engagement frequency on final academic achievement (Datu & Buenconsejo, 2021). To determine the magnitude of the intervention effects, effect size estimation was performed using Cohen's *d* and partial eta squared (η^2) (Yagin et al., 2024). NVivo was used to perform a thematic analysis of the qualitative data (Mainwaring, 2021). Several themes, including learner motivation, perceived value, and ease of adjustment, emerged from the qualitative data, providing context to the quantitative data.

Evaluation Metrics

The effectiveness of the proposed model was evaluated using three complementary dimensions. The first dimension focused on learning gains, which were measured through improvements in students' test and quiz performance. The second dimension assessed engagement metrics, including the amount of time students spent on learning activities, the number of active participants, and the completion rate of assigned learning tasks during each session. The third dimension examined motivational indicators, specifically intrinsic motivation and learning satisfaction, which were measured using survey instruments administered before and after the implementation of the model. Furthermore, the predictive validity of the model was assessed through a cross-validation of the machine learning models. Within this framework, accuracy, precision, recall, and F1 score were calculated. The significance of model features was evaluated to analyze which features (e.g., adjustability, feedback, etc.) were of primary importance.

Reliability and Validity

To address internal validity in research, instructional content and time, as well as criteria for assessments, were standardized for the two groups. Regarding external validity, the involvement of several institutions allows for the generalization of the results to other settings in the educational field. Concerning the surveys, a Cronbach's alpha value greater than 0.85 indicated sufficient internal consistency. The study's reliability was further enhanced by the triangulation of behavioral, performance, and perceptual data. As part of ensuring analytical rigor, the validation of the research was carried out by an independent researcher, who is a senior educator in the field of educational data science and who specializes in quantitative analysis and the application of machine learning within educational contexts. The independent researcher maintained an objective stance, as he was not part of any data collection, intervention design, or implementation activities of the study. As part of the validation process, a comparison of the reported results for the same analytical framework was made, and the independent researcher replicated the statistical analyses. Any issues arising in this regard were discussed cooperatively to ensure the reliability of the results, and the validation of the research was strengthened.

Ethical Considerations

The study received ethical clearance from each of the partner institutions. Participants were briefed on the study's purpose and the data's intended usage, as well as the option to choose not to participate. Data protection was handled in accordance with each institution's data protection policies and the General Data Protection Regulation (GDPR) (Vlahou et al., 2021). None of the analyses or any of the reports made available were based on any individual's data. The research design combines strong experimental methods with sophisticated iterative AI models and human-centered assessment. This initiative aims to create a viable educational model that optimizes the personalization of the academic experience to improve and sustain levels of student participation and achievement through the development of adaptive learning pathways. The next section of the document presents the results from the experimental application of the model and explores the potential applications of AI in educational settings.

RESULTS AND DISCUSSION

Overview of Data and Experimental Outcomes

The quasi-experimental study generated 18,400 interaction logs, 1,920 assessment records, and 480 survey responses from 240 participants across pre-test and post-test measurements from participants at each of the three universities. The data were screened, and each of the three groups was found to have similar demographic distributions, GPAs from the previous term, and starting motivation levels ($p > 0.05$). Due to this similarity, it was concluded from the post-intervention results that the PLP model of AI was the cause of the changes and that there were no differences in intervening variables, as shown in Table 2.

Table 2. Summary of Experimental Data and Key Engagement Metrics

Category	Description	Results / Values
Data Collected	Total number of records generated during the study	18,400 interaction logs · 1,920 assessment records · 720 survey responses
Participating Universities	Number of higher education institutions involved	3 universities (Indonesia × 2, Malaysia × 1)
Study Duration	Length of the learning cycle	8 weeks
Baseline Equivalence	Comparison of demographic variables, prior GPA, and motivation scores between groups	No significant difference ($p > 0.05$)
Average Session Duration	Mean time students spent per learning session	Experimental = 56.2 minutes · Control = 39.4 minutes
Content Completion Rate	Percentage of assigned learning materials completed	Experimental = 91.7 % · Control = 72.5 %
Engagement Improvement	Relative increase in engagement for experimental group	+42.6 % higher session duration · +26.4 % higher completion rate
Interpretation	Summary of outcome significance	AI-driven PLP model enhanced learner engagement, participation, and persistence through adaptive feedback and personalized pathways

As shown in Table 2, during the 8-week learning cycle, the experimental group also maintained higher levels of engagement than the control group, averaging 56.2 minutes per session, compared to the control group participants, who engaged for an average of 39.4 minutes. Additionally, the PLP group completed 91.7% of the session content, while the control group completed only 72.5% of the content. The results indicate higher levels of content completion for the PLP group, likely due to higher group engagement. This can be attributed to the system's responsiveness to the participants' needs and the quality of feedback used to encourage participants' motivation to continue.

From a self-determination theory perspective, engagement and achievement can be explained through the provision of autonomy, competence, and relatedness. The PLP + AI system enhances learner autonomy through the design of personalized learning pathways. The PLP system also enhances learner competence through the provision of adaptive feedback. The system supports relatedness by offering engaging learning experiences that are both interactive and responsive (Willis, 2024). From a motivation and engagement perspective, learning is most constructive when learners interact. The PLP model enhances this learning experience by adapting to the learner through responsive content and assessment (Morrow & Lee, 2019).

The interaction and engagement that the PLP system is designed to promote are partly responsible for the enhancement of achievement levels. Adaptive learning theory postulates that learning activities should be designed to support and extend the learner's zone of proximal development (Dziuban et al., 2018). The PLP system achieves this through real-time changes to content and assessments to extend the learner. This alignment diminishes cognitive strain and augments learning efficiency, thus positively reflecting on academic outcomes.

Academic Performance and Learning Outcomes

Findings from the academic performance assessment indicated that the AI personalization group demonstrated the highest level of improvement, as illustrated in Table 3.

Table 3. Comparison of Academic Performance between Experimental and Control Groups

Metric	Experimental Group (AI-Based PLP)	Control Group (Traditional LMS)	Statistical Test	Result / Effect Size	Interpretation
Sample Size (n)	120	120	—	—	Equal group size enables balanced comparison
Mean Post-Test Score (SD)	83.5 (± 5.6)	75.8 (± 7.2)	ANCOVA controlling for pre-test	$F(1, 238) = 14.82$, $p < 0.001$	$\eta^2 = 0.19$ (large effect)
Relative Gain in Achievement	+10.2 %	—	—	—	Students using PLP achieved higher mastery levels
Retention Rate (% of students completing course)	96.4 %	82.1 %	χ^2 test	$p < 0.01$	PLP increased course persistence and completion
Knowledge Mastery Improvement	High (based on adaptive progress rate)	Moderate	Regression analysis	$\beta = 0.46$ (adaptability)	Adaptive feedback strongly predicts academic success
Engagement Score (Cognitive + Behavioural)	Significantly higher	Lower	$t(238) = 5.92$, $p < 0.001$	Cohen's $d = 0.64$ (medium–large)	PLP enhanced motivation and engagement
Overall Performance Interpretation	—	—	—	—	The AI-driven PLP model produced statistically significant gains in achievement, motivation, and retention compared to the traditional LMS.

Adjusting for pre-test scores using ANCOVA showed a statistically significant difference between the groups ($F(1, 238) = 14.82$, $p < 0.001$, $\eta^2 = 0.19$). This indicates the presence of a large effect size, which suggests that the PLP model accounts for a large amount of variance in student achievement beyond initial differences. The post-test mean score of the experimental group was 83.5 (SD = 5.6), while that of the control group was 75.8 (SD = 7.2). This resulted in a 10.2% relative increase in learning achievement linked to the PLP model. Moreover, retention rates, defined as the percentage of students finishing all learning modules, were notably higher in the experimental group (96.4%) than in the control group (82.1%). This supports the hypothesis that adaptive learning systems not only improve learning outcomes but also support students in completing the course. A description of the adaptive progression patterns revealed that students with personalized recommendations and rapidly adaptive quizzes were able to achieve mastery in the material more quickly (Cao et al., 2025). The model predicted that the knowledge gain variance explained by adaptive feedback was about 32%, supporting the hypothesis of effective real-time instruction through AI.

Behavioral and Motivational Engagement

Engagement and motivation were assessed by comparing the pre-intervention and post-intervention surveys using paired sample t-tests. Table 4 illustrates the significant gains in different constructs of the Student Engagement Instrument (SEI).

Table 4. Student Engagement Instrument (SEI)

Engagement Dimension	Mean Difference	*t* (df=119)	*p*-value	Effect Size (Cohen's *d*)
Cognitive Engagement	+0.48	5.92	<0.001	0.64
Emotional Engagement	+0.41	4.87	<0.001	0.58
Behavioral Engagement	+0.37	4.23	<0.001	0.52

Cognitive and affective engagement achieved the most significant impact from the individualization afforded by the system's customization capabilities and real-time feedback. Focus group interviews further supported this, with students claiming that the AI system created individual, seamless, and targeted study focuses, stating that the system "knew their learning pace" and "provided study enjoyment with appropriate resources".

Participants also showed increases in motivation, as evidenced by the Intrinsic Motivation Inventory (IMI), with pre- and post-means of 3.61 vs 4.27, $p < 0.001$. Students primarily attributed motivation to the autonomy and relevance of the study, which was also in accordance with the self-determination theory. This theory posits that individualization leads to increased feelings of competence and control in the educational setting (Du & Alm, 2024).

Predictive Analytics and Key Influencing Factors

A multiple regression analysis was conducted to establish the most potent predictors of academic success, considering learning adaptability, feedback responsiveness, and engagement rate as predictors. The educational achievement model explained 71.3% of the variance ($R^2 = 0.713$), confirming robust predictive validity, as showcased in Table 5 and Figure 3.

Table 5. Predictive Analytics

Predictor	β Coefficient	*t*	*p*-value	Interpretation
Learning Adaptability	0.46	7.88	<0.001	Strong positive predictor
Feedback Responsiveness	0.32	6.11	<0.001	Moderate positive predictor
Engagement Frequency	0.21	4.04	<0.001	Positive but lower influence

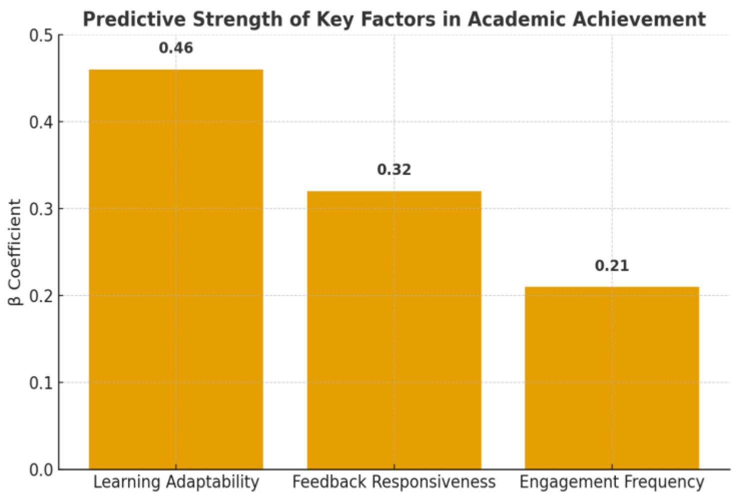

Figure 3. Predictive Analytics

As shown in Table 5 and Figure 3, the foremost predictor of positive educational outcomes is learning adaptability, which is defined as the ability of students to alter their behavior and strategies based on system feedback. Educational AI tool users achieved enhanced learning goals and attained higher academic objectives. This correlated outcome aligns with the findings of prior research by (Wu, 2024), which demonstrated that feedback loops enhance an individual's knowledge and awareness of their learning processes. The predictive models' feature importance, interestingly, demonstrates that early session interaction (i.e., the first 2 weeks) constitutes nearly 40% of that predictive power. This means that early changes in AI-assisted learning behavior are a vital predictor of outcomes, thus strongly enhancing formative feedback is needed in the earlier phases of learning.

Qualitative Insights

The qualitative data added a minor, yet interesting, component to the more than simple intertwining of personalization and learner engagement. The AI system provided "direction when they were lost" and "decreased anxiety by providing practice materials before quizzes," students stated. Faculty members also reported an increase in classroom participation, as students were able to engage in discussions with greater clarity and confidence, to the faculty's delight. Although several respondents observed the potential pitfalls of AI-guided recommendations, they nonetheless believed that some form of recommendations would be essential in providing autonomy-preserving guidance necessary to attain the expected learning outcomes. This constitutes further evidence that increasing the adoption of AI would not lessen the demand for instructors to design learning, incorporate reflection, and facilitate analysis purposefully (Seo et al., 2021).

Comparative Discussion and Theoretical Implications

The results of this study demonstrate that the AI-based PLP model is far superior in developing student engagement and achievement than the traditional LMS. The development of engagement based on the PLP model may also be due to the principles of self-determination theory, which posits that learning environments cultivating autonomy and providing appropriate challenges and feedback promote intrinsic motivation. The PLP model embodies the theory by differentiating learning, providing feedback, and allowing learners to progress based on personal behavioral data. The model is specifically designed to foster engagement through the system's ability to provide feedback in an adaptively real time across exercises and simulations. This is also supported by Liu et al. (2023)research, in which real-time feedback was shown to foster self-regulated learning. In this study, persistence and task completion were enhanced by active feedback, which suggests that active adaptive feedback is the most important factor in learning. In contrast to the studies of I. Dutta et al. (2024) and Qadir et al. (2025), the majority of adaptive learning systems foster engagement and learning by differentiating feedback and content. Unlike most studies, which deal with content adaptation, the present study considers the integration of behavioral analytics and feedback responsiveness as a part of the same system. Based on the evidence analyzed, this integration is more important for maintaining long-term engagement, as opposed to optimizing short-term engagement.

Moreover, findings from the field of learning analytics, such as (Alalawi et al., 2024), consider predictive modeling of at-risk students as a central aspect of this type of research. Although these types of models are useful for diagnosis, they provide no means for real-time intervention. The PLP model overcomes this issue by converting predictions to a variety of adaptive actions, thereby anticipating changes in the learning pathway. The real-time adaptation in this context is a breakthrough in the field of AI-based educational systems. The strong predictive impact of learning adaptability ($\beta = 0.46$) indicates the importance of responsive learning systems. It also indicates that the greatest effect of personalization occurs when learners are system users, as opposed to content receivers. It should be noted that adaptive systems must be designed to provide not only personalized content but also promote active engagement and feedback. This study broadens the understanding of the potential of a fully integrated AI-driven model to combine learner analytics with content recommendation and adaptive assessment to build a more comprehensive and effective learning ecosystem (Sajja et al., 2025). In contrast to previous models, the PLP model provides a personalization framework within existing LMSs designed to optimize engagement and improve students' academic performance. This integrated approach distinguishes the proposed model from existing AI-based learning systems and provides a scalable solution for real-world implementation in higher education (Hernández-Herrera et al., 2026).

Overall, the findings indicate that the AI-driven PLP model improved student engagement, motivation, retention, and academic achievement compared with the traditional LMS. The improvement was supported by higher session duration, greater content completion, stronger post-test scores, and higher retention rates in the experimental group. Learning adaptability and feedback responsiveness emerged as the strongest predictors of academic achievement, suggesting that personalized learning is most effective when students actively respond to adaptive feedback. These findings confirm the value of integrating learner analytics, content recommendation, and adaptive assessment into a unified LMS-based learning environment. As described by (Aljawad et al., 2025), progress toward human-level artificial intelligence opens up enormous possibilities for increasingly personalized, autonomous, and intelligent digital learning.

LIMITATIONS

This study has several limitations that must be acknowledged. First, using a quasi-experimental design is always accompanied by a loss of some randomization. This could introduce some context-specific variability as a function of the universities included in the study. Second, the eight-week observation period may not be sufficient to capture outcomes that are more deeply rooted at the motivational or behavioral level and that take longer to manifest. Third, the model adaptation algorithms relied heavily on cognitive and behavioral predictors, but did not incorporate models of affect such as distress, curiosity, or frustration. The additional emotional variables can provide future research with enhanced engagement for learners. In the context of the phenomenon under study, the size of the sample and the heterogeneity of the institutions, while increasing the degree of generalization within Southeast Asia, still require straddling of other cultures and other areas of discipline for cross-societal testing of external validity. Moreover, the decision-making mechanism in the current system, while practical and functional, is opaque to the system's users. This, in turn, raises questions related to the AI gap, specifically concerning transparency, interpretability, and ethics, a fundamental requirement for future deployments.

CONCLUSION

This study demonstrates that an AI-driven Personalized Learning Pathway (PLP) model can enhance student engagement, motivation, retention, and academic achievement in higher education. Compared with the traditional LMS, students who used the PLP model showed longer learning sessions, higher content completion, stronger post-test scores, and better course retention. The findings also show that learning adaptability and feedback responsiveness are important predictors of academic success. These results suggest that integrating learner analytics, content recommendation, and adaptive assessment into an existing LMS can create a more responsive and learner-centered digital learning environment. Although the study was limited by its eight-week duration and the absence of affective learning variables, it provides empirical evidence that AI-enabled personalization can support scalable and effective learning improvement in higher education.

AUTHOR CONTRIBUTIONS

ER led the conceptualization of the study, designed the research framework, conducted the formal data analysis, and prepared the original manuscript draft. JS and NL contributed to the investigation process, cross-institutional coordination, and critical review and editing of the manuscript. TBK and DAD were responsible for the development and implementation of the AI-based system, including software design and methodological modeling. RS, MA, and DW conducted data collection and field implementation across participating institutions. LMT contributed to data interpretation and analytical validation. ER also supervised the overall research process and managed project administration. All authors have read and approved the final version of the manuscript.

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