AI-supported Personalized Learning, Student Engagement, and Perceived Learning Outcomes in Hanoi Universities: A SEM Mediation Analysis

Tran Thi Hong [1], Nguyen Minh Tuan [1], and Nguyen Nghi Thanh [2,*]

[1] Faculty of Social Sciences and Humanities, Thai Nguyen University of Sciences, Thai Nguyen Province, Vietnam
[2] Faculty of Interdisciplinary Sciences, Academy of Public Administration and Governance, Vietnam
Email: hong792014@gmail.com (T.T.H.); tuannm@tnus.edu.vn (N.M.T.); thanhnn7899@gmail.com (N.N.T.)
*Corresponding author
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***Abstract*—This study examines the associations among Artificial Intelligence (AI)-supported personalized learning, student engagement, and perceived learning outcomes among undergraduate students at universities in Hanoi, Vietnam. Drawing on student engagement theory and AI-in-education research, the study operationalizes AI-supported personalization as a shared perceived functional construct comprising data-informed adaptation through adaptive recommendations, timely feedback, learning analytics, conversational scaffolding, automated diagnosis, and flexible learning pathways. It does not estimate differential associations across particular AI tools or functions. Survey data were collected in 2025 from 300 undergraduate students with experience using AI-supported or AI-assisted digital learning tools. Structural equation modeling was used to assess measurement quality, estimate theoretically specified paths, and examine the indirect association through student engagement. The results indicate positive associations between AI-supported personalized learning and student engagement, between AI-supported personalized learning and perceived learning outcomes, and between student engagement and perceived learning outcomes. The analysis identified a significant indirect association through student engagement together with a remaining direct association, a pattern consistent with partial mediation in the specified cross-sectional model. The outcome construct reflects students' self-reported perceptions rather than grades, test scores, or other objective indicators of academic achievement. Accordingly, the findings represent cross-sectional evidence from Hanoi universities and should not be interpreted as causal or nationally representative. The study contributes by clarifying engagement as a plausible pedagogical mechanism associated with AI-specific personalization functions and by identifying implications for responsible AI integration in Vietnamese higher education.**

***Keywords*—artificial intelligence in education, personalized learning, student engagement, perceived learning outcomes, Hanoi universities**

I. Introduction

Artificial Intelligence (AI) is reshaping higher education by changing how universities design learning activities, provide feedback, monitor progress, and support students. Recent reviews show that AI tools in higher education are increasingly used for personalized feedback and recommendations, intelligent tutoring, learning analytics, assessment support, and generative learning assistance [1–3]. These developments make AI-supported personalized learning a timely topic for empirical investigation because its educational value depends not only on technical capacity but also on design quality, learner interaction, and pedagogical integration.

Personalized learning is important because university students differ in prior knowledge, motivation, learning pace, academic readiness, digital competence, and self-regulation. AI-supported systems can respond to these differences by analyzing learner data, recommending materials, adapting learning pathways, providing timely feedback, and identifying students who need additional support [4–6]. Accordingly, AI should be understood not only as a technological innovation but also as a pedagogical resource that can support more responsive and learner-centered education.

However, the adoption of AI does not by itself imply better learning outcomes. Associations between AI-supported personalization and learning are likely to depend on how students interact with AI-enabled systems and whether they perceive these systems as relevant to meaningful learning activity. Student engagement, commonly understood through behavioral, emotional, and cognitive dimensions, is therefore a plausible explanatory mechanism linking learning environments with academic experiences [7–9]. Without active engagement, AI tools may be underused, misused, or disconnected from students' actual learning processes.

Universities in Hanoi provide a relevant setting for examining this issue within Vietnamese higher education. Vietnam has adopted a national AI strategy through 2030 and a sectoral scheme for strengthening the integration of digital technologies into education and training during the 2022–2025 period, guided by a long-term strategic vision extending to 2030 [10, 11]. Hanoi is a major higher education hub where universities are increasingly exposed to digital platforms, AI-assisted applications, online learning systems, and data-informed academic support. However, AI integration across institutions remains uneven, and many practices are still developing in relation to curriculum design, lecturer capacity, student readiness, and responsible AI use [12, 13]. This raises an associational research question: to what extent is students' perceived experience of AI-supported personalized learning related to their engagement and self-reported learning outcomes in Hanoi universities?

Although research on AI in education has expanded rapidly, four gaps remain. First, many studies emphasize AI affordances, adoption, or ethical implications, while fewer studies explain the learning mechanisms through which AI-supported personalization is associated with student outcomes [1, 3, 14]. Second, construct boundaries remain

insufficiently precise: a shared perception of AI-enabled personalization functions should be distinguished from tool-specific associations that require comparative designs across chatbots, generative AI assistants, adaptive platforms, automated feedback systems, and learning analytics applications. Third, empirical evidence from emerging higher education systems remains limited compared with evidence from technologically advanced systems [12, 15]. Fourth, student engagement is often examined as an outcome of digital learning rather than as an intervening association that may help explain why AI-supported personalization is related to perceived learning outcomes [16–18].

To address these gaps, this study examines the associations among AI-supported personalized learning, student engagement, and perceived learning outcomes among undergraduate students at universities in Hanoi, Vietnam, during 2025. It estimates whether student engagement statistically accounts for an indirect association between AI-supported personalization and perceived learning outcomes. The analysis treats AI-supported personalization as a shared perceived functional construct and does not compare specific AI tool categories. By doing so, the study shifts attention from AI adoption as a technological trend to AI-specific personalization functions that may be associated with learning perceptions through behavioral, emotional, and cognitive engagement. Because the data are cross-sectional and self-reported, the study does not establish temporal sequence, causal effects, or objective academic achievement.

II. Literature Review and Hypothesis Development

A. AI-supported Personalized Learning in Higher Education

AI-supported personalized learning refers to students' perceived experience of AI technologies that adapt learning content, pace, feedback, assessment, and support to individual learning needs. In this study, the construct captures shared perceived AI-enabled functions rather than a particular platform, brand, or tool category. These functions include adaptive learning systems that recommend resources, intelligent tutoring systems that provide step-by-step guidance, learning analytics dashboards that visualize progress, automated feedback tools that diagnose errors, AI chatbots that provide conversational scaffolding, and generative AI assistants that support explanations, practice tasks, and revision [2, 3, 19]. The construct therefore represents the common functional experience of personalization across tools; it neither compares tool categories nor attributes the estimated associations to any single AI application. Tool-specific differences remain outside the scope of the present model.

Prior research suggests that perceived AI-supported personalization may be associated with perceived learning benefits when learners experience closer matching of resources to ability, clearer identification of knowledge gaps, relevant recommendations, and timely feedback [3, 4, 20]. Its distinctive theoretical basis is data-informed adaptation: learner actions, questions, error patterns, time on task, and progress indicators can be used to update feedback, recommendations, and learning pathways. However, the present study does not test whether these functions themselves produce learning gains. Instead, it examines whether student engagement forms a statistically supported explanatory pathway between the shared perceived personalization construct and perceived learning outcomes [21, 22].

B. Student Engagement as a Learning Mechanism

Student engagement is generally understood to encompass three interrelated dimensions: behavioral, emotional, and cognitive. The behavioral dimension reflects students' active involvement and participation in learning-related tasks, task completion, attendance, interaction with learning resources, and active involvement in academic tasks. The emotional dimension reflects students' affective responses to learning, expressed through interest, enjoyment, motivation, satisfaction, and a feeling of connection to the academic community. The cognitive dimension represents the intellectual effort invested in learning, including focused attention, regulation of one's own learning, deliberate use of appropriate strategies, and thoughtful analysis of course materials [7–9].

In AI-supported learning environments, engagement is theoretically relevant because students must interpret feedback, act on recommendations, interact with digital platforms, and regulate their learning. AI-specific functions such as real-time feedback, adaptive task selection, personalized explanations, learning analytics, and conversational scaffolding may be associated with engagement when students perceive them as relevant and usable [17, 18, 21]. Conversely, systems perceived as difficult, inaccurate, opaque, irrelevant, or ethically problematic may coincide with lower engagement [23, 24].

C. Perceived Learning Outcomes in AI-supported Personalized Learning

Perceived learning outcomes refer in this study to students' subjective assessments of their understanding, capacity to complete academic tasks, problem-solving ability, learning confidence, self-directed learning, and overall learning performance. The construct does not represent verified changes in knowledge or skills and is not equivalent to grades, test scores, assignment quality, course completion, or platform-based performance data. This boundary is essential because self-reported perceptions may be educationally informative while differing from objectively measured achievement.

Prior research indicates that AI-supported personalized learning environments can be associated with more favorable learning experiences when they provide level-appropriate materials, timely feedback, progress information, and support for independent learning [3, 25, 26]. Generative AI and intelligent tutoring tools may be linked to perceived learning benefits through explanations, practice tasks, writing support, and course-content review [22, 23, 27]. These associations depend on how students use AI support and should not be interpreted as evidence that AI use necessarily produces deeper understanding or objective achievement.

D. Hypothesis Development

Greater exposure to AI-enabled individualized learning is anticipated to correspond with higher levels of student engagement. Personalized recommendations, adaptive

exercises, automated feedback, and AI-based academic guidance are intended to make learning activities more relevant and responsive to students' needs. Students who perceive a closer match between learning resources, their pace, and their difficulties may also report more active participation, stronger support, and greater cognitive effort [4, 9, 17]. Therefore, the first hypothesis is proposed:

H1: AI-supported personalized learning is positively associated with student engagement.

More extensive use of AI-enabled individualized learning is anticipated to correspond with stronger student-reported learning gains. Students who perceive adaptive materials as better matched to their readiness and timely feedback as useful for monitoring errors may also report more favorable learning perceptions. Flexible pathways may likewise be associated with perceived support for self-paced learning and targeted improvement [3, 26, 28]. Therefore:

H2: AI-supported personalized learning is positively associated with perceived learning outcomes.

Greater learner engagement is anticipated to correspond with more favorable perceptions of academic achievement. Students who are actively involved in their studies tend to contribute consistently to instructional activities, fulfill coursework requirements, engage purposefully with course content, request constructive feedback, and maintain their effort when encountering challenges. Prior research has shown that student engagement is closely associated with academic achievement, persistence, and learning satisfaction [9, 29, 30]. Therefore:

H3: Higher levels of student engagement are linked to more favorable perceptions of learning achievement.

Finally, student engagement is expected to account for an indirect association between AI-supported personalized learning and perceived learning outcomes. AI-supported personalization may provide conditions that students perceive as relevant and responsive, while students reporting stronger behavioral, emotional, and cognitive engagement may also report more favorable learning outcomes. Engagement is therefore modeled as a theoretically specified intervening construct rather than as a temporally or causally established mechanism [16–18]. Therefore:

H4: AI-enabled personalized learning is indirectly associated with students' perceived learning gains through their level of engagement.

E. Conceptual Framework

The proposed framework specifies AI-supported personalized learning as the exogenous predictor construct, student engagement as the intervening construct, and perceived learning outcomes as the endogenous construct. AI-supported personalization represents a shared perception of AI-enabled functions and not a comparison of specific tool types. Fig. 1 depicts three directional Structural Equation Modeling (SEM) paths: H1 from AI-supported personalized learning to student engagement, H2 from AI-supported personalized learning to perceived learning outcomes, and H3 from student engagement to perceived learning outcomes. H4 is represented as the indirect association through student engagement. The paths indicate covariance-based, theoretically specified associations in a cross-sectional SEM model; they do not demonstrate temporal sequence or causal direction. In practice, the constructs may be reciprocally related: engaged students may generate richer behavioral data that AI systems can use to refine recommendations, feedback, and learning pathways. Testing such recursive adaptation requires longitudinal or experimental evidence.

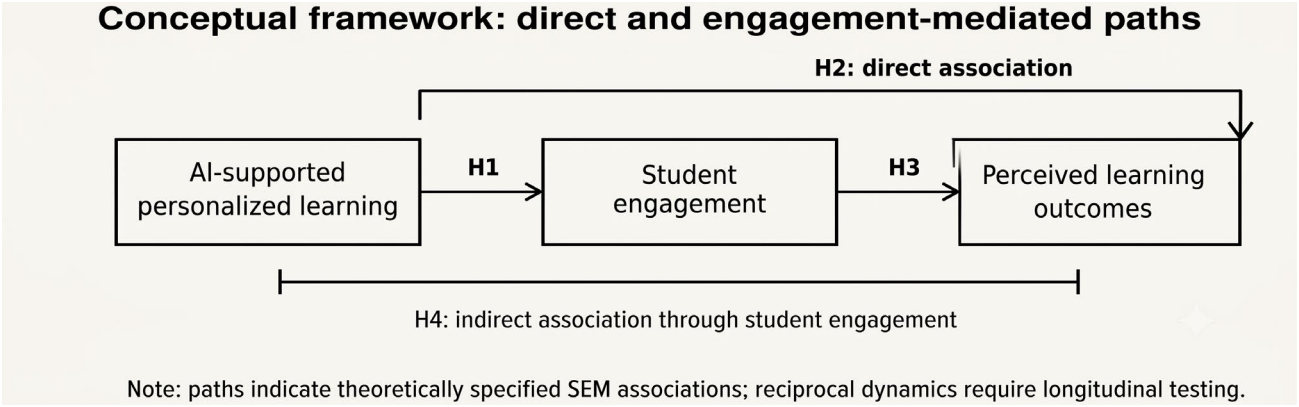

Fig. 1. Conceptual framework showing H1–H4.

III. Materials and Methods

A. Research Design and Context

Using data gathered at a single point in time, the research adopted a quantitative survey approach to assess the interrelationships among AI-enabled individualized learning, learner engagement, and self-reported learning achievement. The research area was universities in Hanoi, Vietnam, and the research period was 2025. The quantitative approach supported the evaluation of theory-based hypotheses and the estimation of direct and mediated pathways linking the latent variables. Nevertheless, the one-wave nature of the data limits causal inference. Accordingly, the SEM estimates indicate relationships consistent with the proposed theoretical framework but do not establish temporal ordering or causality among the constructs.

The empirical setting was Hanoi-based universities within Vietnam's broader higher education digital transformation agenda. Universities in Hanoi are increasingly adopting digital learning platforms, AI-assisted applications, learning management systems, and data-informed learning support [11, 12]. This context is relevant because AI integration is expanding but remains uneven across institutions. The study therefore focuses on students' experience of AI-supported or AI-related personalized

learning in universities located in Hanoi.

B. Participants and Sampling

The target population consisted of undergraduate students enrolled in universities in Hanoi, Vietnam, during 2025. Undergraduate students were selected because they are direct users of digital and AI-supported learning tools and can report how they experience these tools in relation to their engagement and perceived learning outcomes. Respondents were eligible if they had used at least one AI-supported or AI-assisted learning tool in their university learning activities, such as adaptive learning platforms, AI chatbots, generative AI applications, automated feedback systems, personalized learning functions, or learning management systems with AI-related support.

A purposive sampling strategy was used to ensure that participants had relevant experience with AI-supported learning. The final sample included 300 valid responses from undergraduate students at universities in Hanoi. This sample size is adequate for SEM because it provides sufficient cases for assessing measurement reliability, model fit, direct paths, and mediation effects. However, because the sampling design was non-probability based and geographically focused on Hanoi, the findings should be interpreted as evidence from a relevant urban university context rather than as nationally representative evidence for all Vietnamese higher education institutions.

To clarify the scope of AI experience, respondents were asked to report exposure to one or more AI-related learning categories: generative AI assistants, adaptive learning platforms, AI chatbots, automated feedback systems, learning analytics dashboards, personalized recommendation functions, or AI-enhanced learning management systems. The analysis did not compare these categories or estimate category-specific associations; instead, it assessed the shared perception that AI-enabled functions provided personalized support in university learning activities.

C. Measurement Instruments

Data were gathered through a standardized survey instrument designed to assess AI-supported personalized learning, student engagement, and perceived learning outcomes. Participants evaluated each statement using a five-category agreement scale, with scores extending from 1 ("strongly disagree") to 5 ("strongly agree"). A separate section recorded respondents' characteristics, covering gender, age, academic year, disciplinary area, institutional type, and how often they used AI tools.

AI-supported personalized learning was measured as a shared perceived functional construct using six items reflecting adaptive content, personalized recommendations, timely feedback, flexible learning pathways, diagnostic support, and a personalized learning experience. It was therefore defined by students' perceptions of AI-enabled functions rather than by a single product or tool type. Student engagement was measured using seven items covering behavioral, emotional, and cognitive engagement. Perceived learning outcomes were measured using six explicitly self-referential items capturing students' perceived understanding, academic-task capability, problem-solving ability, learning confidence, self-direction, and overall learning performance. These items were not intended to measure verified academic achievement or actual skill gains.

The items were adapted from prior research on AI-supported learning, personalized learning, student engagement, and technology-enhanced learning outcomes [4, 7, 9, 28, 31] and refined for the context of universities in Hanoi. Content validity was examined through expert review by four specialists in higher education, educational technology, and research methodology. Because the survey was administered to Vietnamese undergraduate students, item wording was checked for conceptual equivalence, clarity, and contextual relevance. Pilot feedback was used to revise ambiguous wording and improve the questionnaire sequence. To maintain construct clarity, the learning-outcome items were worded as perceptions and reviewed to avoid implying objective improvement. The final measurement items are presented in Appendix A.

D. Ethical Approval and Informed Consent

Data were collected in 2025 through a structured survey administered to eligible undergraduate students at universities in Hanoi. The survey began with a screening question confirming respondents' experience with AI-supported or AI-assisted learning tools. Only participants who satisfied the eligibility requirement were retained. Prior to full-scale data collection, the questionnaire was trialed with a limited group of students to assess whether the items were understandable, easy to read, and likely to elicit consistent responses. Their comments informed the refinement of unclear expressions and the reordering of questions to create a more coherent survey flow.

This research was conducted according to Decision No. 80/CV-HVCTQG issued by the National Academy of Public Administration and Management on April 16, 2025. Before completing the survey, students received an explanation of its scholarly purpose and were advised that taking part was entirely optional. The instrument requested no information that could reveal an individual respondent's identity. Participants were also informed that their answers would remain anonymous, be handled confidentially, and be analyzed exclusively for research.

E. Data Analysis Strategy

Data analysis was conducted in several stages. First, the dataset was screened for missing values, duplicate submissions, patterned answers, and ineligible responses. Descriptive statistics were used to summarize the respondent profile and AI-use frequency. Second, the consistency of the indicators within each construct was evaluated through Cronbach's alpha and composite reliability. For both measures, coefficients exceeding 0.70 were taken to indicate adequate internal coherence under commonly applied SEM criteria [32].

Third, convergent validity was evaluated using standardized factor loadings and Average Variance Extracted (AVE). Standardized loadings above 0.70 and AVE values above 0.50 were interpreted as evidence of convergent validity. Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT) [33]. Fourth, Confirmatory Factor Analysis (CFA) and SEM fit were evaluated using common fit indices, including Chi-square/df, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of

Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR), following recent CFA model-fit guidance [34]. Finally, the indirect association through student engagement was estimated using bootstrapping and Confidence Intervals (CI). In this cross-sectional design, the term mediation refers to statistical decomposition of direct and indirect paths and not to a demonstrated temporal process. Because the study used cross-sectional self-reported data, common method bias was addressed through procedural remedies during questionnaire design and administration, including anonymous participation, neutral wording, separation of predictor and outcome items across questionnaire sections, and assurance that there were no right or wrong answers. The possibility of residual common method variance is acknowledged in the limitations because objective achievement data, platform logs, and marker-variable data were not included.

IV. Results and Discussion

A. Descriptive Statistics and Sample Characteristics

A total of 300 valid responses were included in the analysis. The sample consisted of undergraduate students from universities in Hanoi, Vietnam, who had experience using AI-supported or AI-assisted digital learning tools. Table 1 summarizes the respondent profile.

Table 1. Demographic characteristics of respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	126	42.0
	Female	165	55.0
	Prefer not to say	9	3.0
Age	Under 20	75	25.0
	20–22	174	58.0
	23–25	42	14.0
	Over 25	9	3.0
Year of study	First year	61	20.3
	Second year	105	35.0
	Third year	74	24.7
	Fourth year	52	17.3
	Other	8	2.7
Field of study	Engineering & Technology	79	26.3
	Business & Management	74	24.7
	Social Sciences	57	19.0
	Education	48	16.0
	Health Sciences	33	11.0
	Other	9	3.0
University type	Public	219	73.0
	Private	81	27.0
Frequency of AI use	Rarely	43	14.3
	Sometimes	110	36.7
	Often	103	34.3
	Very often	44	14.7

The demographic profile indicates that the sample included students from different years of study, fields, and institutional types. Most respondents reported using AI tools at least sometimes, suggesting that the sample had sufficient exposure to evaluate AI-supported personalized learning. However, the sample was dominated by students from public universities, which should be considered when interpreting the findings.

B. Measurement Model Assessment

Reliability and validity tests were conducted before structural model testing. Table 2 shows that all constructs exceeded the recommended thresholds for Cronbach's alpha, composite reliability, and AVE.

Table 2. Reliability and convergent validity results

Construct	Items	Cronbach's alpha	CR	AVE
AI-supported personalized learning	6	0.884	0.912	0.633
Student engagement	7	0.895	0.917	0.613
Perceived learning outcomes	6	0.875	0.906	0.616

All Cronbach's alpha values were above 0.70, indicating acceptable internal consistency. Composite reliability values were also above 0.70, and AVE values exceeded 0.50, supporting convergent validity. The CFA results showed acceptable model fit (Table 3). Standardized factor loadings were all above 0.70 (Table 4), indicating that the observed items adequately represented their latent constructs.

Table 3. Measurement model fit indices

Fit index	Recommended threshold	Result
chi-square/df	<3.00	2.14
CFI	>0.90	0.956
TLI	>0.90	0.948
RMSEA	<0.08	0.062
SRMR	<0.08	0.041

Table 4. Standardized factor loadings

Construct	Item	Loading
AI-supported personalized learning	AIPL1	0.781
	AIPL2	0.806
	AIPL3	0.793
	AIPL4	0.817
	AIPL5	0.772
	AIPL6	0.804
Student engagement	SE1	0.761
	SE2	0.784
	SE3	0.803
	SE4	0.792
	SE5	0.771
	SE6	0.815
	SE7	0.755
Perceived learning outcomes	LO1	0.779
	LO2	0.804
	LO3	0.787
	LO4	0.812
	LO5	0.766
	LO6	0.801

Discriminant validity was further supported because the square roots of AVE for the three constructs were 0.796 for AI-supported personalized learning, 0.783 for student engagement, and 0.785 for perceived learning outcomes, and HTMT diagnostics were below the commonly recommended 0.85 criterion. Together, the reliability, convergent validity, factor-loading, and discriminant-validity assessment indicate that the measurement model was adequate for structural model testing. The three latent constructs were therefore considered theoretically distinct and empirically suitable for subsequent SEM analysis.

Common method bias was also considered because all variables were collected through the same self-report questionnaire. Procedural safeguards were implemented before data collection, but the study interprets the findings cautiously because questionnaire-based cross-sectional designs cannot fully eliminate common method variance.

C. Structural Model Assessment

After confirming the adequacy of the measurement model,

SEM was conducted to test the hypothesized relationships among AI-supported personalized learning, student engagement, and perceived learning outcomes. The structural model demonstrated acceptable fit, as shown in Table 5.

The standardized path coefficients (Table 6) indicate that AI-supported personalized learning was positively and significantly associated with student engagement (beta = 0.62, $p < 0.001$). AI-supported personalized learning also showed a positive direct association with perceived learning outcomes (beta = 0.31, $p < 0.001$) (Table 7). Student engagement was positively and significantly associated with perceived learning outcomes (beta = 0.49, $p < 0.001$).

Table 5. Structural model fit indices

Fit index	Recommended threshold	Result	Evaluation
chi-square/df	<3.00	2.21	Acceptable
CFI	>0.90	0.953	Good
TLI	>0.90	0.946	Good
RMSEA	<0.08	0.064	Acceptable
SRMR	<0.08	0.043	Good

Table 6. Structural path results

Hypothesis	Path	beta	t-value	p-value	Result
H1	AI-supported personalized learning → Student engagement	0.62	11.48	<0.001	Supported
H2	AI-supported personalized learning → Perceived learning outcomes	0.31	5.76	<0.001	Supported
H3	Student engagement → Perceived learning outcomes	0.49	8.92	<0.001	Supported

Table 7. Mediation analysis results

Mediation path	Direct effect	Indirect effect	Total effect	95% CI	p-value	Conclusion
AI-supported personalized learning → Student engagement → Perceived learning outcomes	0.31	0.30	0.61	[0.22, 0.39]	<0.001	Partial mediation

The model explained 38.4% of the variance in student engagement and 52.7% of the variance in perceived learning outcomes. These values indicate that AI-supported personalized learning and student engagement jointly provide a meaningful explanation of perceived learning outcomes among the surveyed undergraduate students at universities in Hanoi.

D. Mediation Analysis

Bootstrapping was used to estimate the indirect association through student engagement. The indirect coefficient (Table 7) was significant (beta = 0.30, 95% CI [0.22, 0.39], $p < 0.001$), and the direct association remained significant. This pattern is consistent with partial mediation in the specified SEM but represents an associational decomposition, not a demonstrated temporal process, because the data are cross-sectional.

The mediation analysis indicates that the observed relationship between AI-supported personalized learning and perceived learning outcomes includes both a direct association and an indirect association through student engagement. Students reporting stronger perceptions of AI-specific personalization also tended to report higher engagement, which covaried with more favorable perceived learning outcomes. This pattern is consistent with partial mediation in the specified model but does not establish that AI-supported personalization temporally or causally increases engagement or learning.

E. Discussion

This study examined how the shared perceived functional construct of AI-supported personalized learning is associated with student engagement and perceived learning outcomes among undergraduate students at universities in Hanoi, Vietnam (Table 8). The positive path indicates that students who report stronger perceptions of adaptive recommendations, learning-path adjustments, timely feedback, conversational scaffolding, learning analytics, and diagnostic support also tend to report stronger behavioral, emotional, and cognitive engagement. This is not a tool-specific effect: the model does not determine whether chatbots, generative AI assistants, adaptive platforms, or analytics dashboards differ in their associations with engagement. The result is consistent with recent reviews showing that AI-specific functions may be associated with engagement when integrated into meaningful learning designs rather than used as isolated technological add-ons [3, 17]. However, the cross-sectional data cannot establish that AI-supported personalization causes engagement.

Table 8. Hypothesis testing summary

Hypothesis	Relationship	beta	p-value	Result
H1	AI-supported personalized learning → Student engagement	0.62	<0.001	Supported
H2	AI-supported personalized learning → Perceived learning outcomes	0.31	<0.001	Supported
H3	Student engagement → Perceived learning outcomes	0.49	<0.001	Supported
H4	AI-supported personalized learning → Student engagement → Perceived learning outcomes	0.30	<0.001	Supported

The positive direct association between AI-supported personalized learning and perceived learning outcomes indicates that students reporting more adaptive, responsive, and supportive AI experiences also report more favorable self-assessments of course understanding, academic-task capability, problem-solving ability, learning confidence, self-direction, and overall learning performance. These are perceived outcomes; the result does not demonstrate actual improvement in grades, test performance, assignment quality, or other objective indicators. The pattern is consistent with evidence on adaptive learning systems, intelligent tutoring tools, and generative AI-assisted feedback [3, 26, 27], while remaining bounded by the study's self-report design.

Student engagement was also positively associated with perceived learning outcomes. Thus, students reporting greater participation, motivation, and cognitive effort tended to report more favorable learning perceptions. This pattern positions engagement as an important correlate within the model rather than as a proven cause of learning success. It is

consistent with broader engagement research reporting associations with achievement, persistence, and learning satisfaction [7, 9, 29].

The statistically significant indirect path through student engagement is the study's central explanatory result. The pattern is consistent with engagement as a plausible pedagogical pathway linking perceived AI-specific personalization functions with perceived learning outcomes. Substantively, adaptive recommendations, timely feedback, learning analytics, automated diagnosis, conversational scaffolding, and flexible pathways may coincide with stronger learning perceptions when students also report active participation, motivation, and cognitive effort. However, the cross-sectional model does not show that personalization first changes engagement and then produces learning gains; longitudinal or experimental evidence is needed to establish such a sequence [16–18].

At the same time, reverse and reciprocal explanations remain plausible. Students who are already more engaged may be more likely to seek AI tools, interact with them frequently, and evaluate AI-supported learning positively. In adaptive environments, their activity may generate richer behavioral data that systems can use to refine recommendations, feedback, and learning pathways. The present study cannot determine the direction or timing of this process; future research should use longitudinal, experimental, cross-lagged panel, or learning analytics-based designs to examine reciprocal adaptation over time.

The Hanoi university context strengthens the relevance and boundary conditions of these findings. Vietnam's national policy agenda has emphasized AI development and educational digital transformation, but recent analysis indicates that implementation requires infrastructure, equity, digital pedagogy, administration, strategic planning, and stakeholder coordination [10–12]. Evidence from universities in Hanoi therefore shows how national digital transformation priorities are reflected in student learning experience at one major urban higher education hub, but it should not be generalized automatically to all Vietnamese higher education institutions.

F. Theoretical and Practical Implications

1) Theoretical implications

The study contributes to AI-in-education literature in three ways. First, it clarifies the distinctive mechanism and boundary of AI-supported personalization. The contribution does not rest on a broad claim that technology-enhanced learning is associated with better outcomes. Instead, it specifies a shared perceived functional construct grounded in data-informed adaptation through recommendations, feedback, analytics, automated diagnosis, conversational scaffolding, and learning-path adjustment. These AI-specific functions distinguish the construct from general teacher support, flipped learning, or ordinary digital platforms. Because tool types were not compared, the contribution concerns the common functional experience of AI personalization rather than differential tool-specific associations [1, 3].

Second, the study extends student engagement theory by positioning engagement as a statistically supported intervening association between perceived AI-supported learning conditions and perceived learning outcomes. This framing connects AI-in-education research with engagement theory and helps explain why students who report more personalized AI experiences may also report stronger perceived benefits [17, 18]. Given the cross-sectional design, engagement should be interpreted as a plausible explanatory mechanism in the specified model, not as a temporally verified causal mediator. It may also participate in a reciprocal process by generating behavioral data that inform subsequent personalization.

Third, the study adds empirical evidence from universities in Hanoi, Vietnam, a context that remains less represented in international AI-in-education research. The findings suggest that theoretical models of AI-supported personalized learning should be tested in diverse institutional and national contexts rather than generalized only from technologically advanced higher education systems [12, 15].

2) Practical implications

For universities, the findings support a design-oriented implication rather than a causal claim: AI adoption should be evaluated by whether students perceive specific functions—adaptive resources, timely feedback, learning analytics, diagnostic support, conversational scaffolding, and flexible pathways—as relevant and usable. Universities should not assume that adopting any AI tool will yield equivalent learning benefits, because this study did not compare tool categories. Accessibility, transparency, curriculum alignment, and human oversight remain essential [1, 3].

For lecturers, the observed associations suggest that AI-supported functions should be embedded in pedagogical design rather than deployed as isolated technologies. Lecturers can use feedback, recommendations, and analytics to create opportunities for participation, reflection, problem solving, and self-regulated learning while retaining professional judgment and human interaction. These are design implications from an associational study, not evidence that a particular AI tool will cause higher engagement [14, 21, 24].

For students, universities should provide guidance on responsible and effective AI use. Students need support in using AI to deepen engagement with course content, plan learning, interpret feedback, and complete academic tasks responsibly. Because this study measured perceived rather than objective outcomes, institutions should evaluate grades, test performance, assignment quality, and platform behavior separately. Guidance should also address academic integrity, overreliance on AI, data privacy, and critical evaluation of AI-generated content [23, 24, 35].

For policymakers, the study highlights the need for institutional and national guidelines on ethical and pedagogically sound AI use in higher education. Policy support should address infrastructure, lecturer training, data governance, academic integrity, and equity. This is important to prevent AI-supported learning from widening gaps between institutions or student groups with different levels of digital access [11, 12, 24].

G. Limitations and Future Research

This study has several limitations. First, it used a

cross-sectional survey design, which limits the ability to establish temporal or causal order. It is possible that students who are already more engaged are more likely to use AI tools or to perceive AI-supported learning more positively. Future studies should use longitudinal, experimental, cross-lagged panel, or learning analytics-based designs to examine how AI-supported personalization and engagement influence each other over time.

Second, the study relied on self-reported measures, and the dependent variable was perceived learning outcomes rather than objective academic achievement. The revised items explicitly ask for students' perceptions of understanding, academic-task capability, problem-solving ability, confidence, self-direction, and overall learning performance. Even with this wording, perceived improvement may differ from actual improvement. Future research should combine surveys with grades, test scores, assignment quality, course completion, platform logs, learning analytics, or performance-based assessments. This would permit direct comparison between subjective learning perceptions and objective indicators [1, 3].

Third, the study used purposive sampling and focused on undergraduate students at universities in Hanoi. Therefore, the findings should be interpreted as evidence from a major urban university context rather than as nationally representative evidence for Vietnamese higher education. Future studies should use larger and more diverse samples, compare public and private universities, and examine differences across provinces, regions, disciplines, and student groups.

Fourth, the study models student engagement as a single intervening construct and AI-supported personalized learning as a broad shared perceived functional construct. Consequently, the estimates cannot be attributed to specific tools or functions, and no conclusion can be drawn about whether generative AI, adaptive platforms, chatbots, automated feedback, learning analytics, or AI-enhanced learning management systems have different associations with engagement or learning perceptions. Future studies should use comparative, multigroup, experimental, or feature-level designs to examine these distinctions. They may also extend the model by adding digital literacy, AI readiness, trust in AI, academic self-efficacy, lecturer support, perceived usefulness, or ethical concerns as mediators or moderators [17, 22, 28].

Fifth, measuring all constructs through a single survey instrument leaves open the possibility of common method variance. Although the study applied procedural controls—including anonymous participation, neutrally worded items, and the placement of predictor and outcome measures in separate questionnaire sections—future research should employ marker variables, integrate multiple data sources, and incorporate objective performance measures or behavioral records from learning platforms.

V. Conclusion

This study investigated the associations among AI-supported personalized learning, student engagement, and perceived learning outcomes among undergraduate students at universities in Hanoi, Vietnam. Using survey data collected in 2025 from 300 undergraduate students and SEM, the analysis estimated three direct paths and an indirect path through student engagement. The model was designed to examine theory-consistent associations, not causal effects.

The findings indicate positive associations between AI-supported personalized learning and student engagement, between AI-supported personalized learning and perceived learning outcomes, and between student engagement and perceived learning outcomes. The indirect association through student engagement was statistically significant while the direct association remained significant, a pattern consistent with partial mediation in the specified cross-sectional model. These results show that students who perceive stronger AI-enabled personalization also tend to report higher engagement and more favorable learning perceptions. They do not demonstrate that AI functions caused engagement or objective academic improvement.

The study contributes to AI-in-education research by identifying student engagement as a plausible pedagogical mechanism and by specifying the AI-related functions that make the personalization construct theoretically distinct from general digital learning support. The contribution concerns a shared perceived functional construct rather than differential associations of specific tool types. The conclusions remain bounded by the cross-sectional self-report design, purposive sample from Hanoi universities, and use of perceived rather than objective learning outcomes. For universities in Hanoi and comparable Vietnamese higher education contexts, the observed associations support attention to lecturer capacity, student guidance, ethical use policies, human oversight, and learning designs that prioritize engagement, alongside separate evaluation of objective academic performance.

Appendix A: Questionnaire Items

All items were measured on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The learning-outcome items assess respondents' subjective perceptions of learning. They do not measure grades, test scores, assignment quality, verified skill gains, or other objective achievement indicators. The measurement items used in the questionnaire are presented in Table A1 below.

Table A1. Measurement items

Code	Measurement item
AIPL1	AI-supported learning tools provide learning materials that match my learning needs.
AIPL2	AI-supported platforms recommend learning resources that are relevant to my progress.
AIPL3	AI tools help me receive timely feedback on my learning progress.
AIPL4	AI-supported platforms allow me to learn at my own pace.
AIPL5	AI tools help identify areas where I need additional academic support.
AIPL6	AI-supported learning makes my learning experience more personalized.
SE1	I actively participate in AI-supported learning activities.
SE2	I regularly interact with AI-supported learning tools or platforms.
SE3	I feel motivated when using AI-supported learning tools.
SE4	I find AI-supported learning activities interesting.
SE5	I concentrate on learning tasks when using AI-supported platforms.
SE6	I make an effort to understand materials provided through AI-supported learning tools.
SE7	AI-supported learning encourages me to regulate my own learning.
LO1	I perceive a clearer understanding of course content when using AI-supported learning.
LO2	I perceive greater ability to complete academic tasks when using AI tools.

LO3	I perceive stronger problem-solving ability when using AI-supported learning.
LO4	I perceive greater confidence in learning when using AI-supported learning.
LO5	I perceive myself as more self-directed when using AI tools for learning.
LO6	Overall, I perceive favorable learning performance with AI-supported personalization.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to ethical and confidentiality restrictions.

Disclosure of AI Use

ChatGPT was used only to support language editing, structural refinement, formatting, and manuscript clarity. The authors reviewed, verified, and approved all AI-assisted changes and take full responsibility for the accuracy, originality, integrity, and final content of the manuscript. No AI tool was used as an author or to replace scholarly judgment.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Tran Thi Hong contributed to conceptualization, investigation, data curation, and writing the original draft. Nguyen Minh Tuan contributed to methodology, validation, formal analysis, and manuscript review and editing. Nguyen Nghi Thanh contributed to supervision, project administration, theoretical framing, and critical revision of the manuscript. All authors read and approved the final version of the manuscript.

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