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The Influence of AI Personalization, Feedback, and Usage on Student Engagement: A PLS-SEM Study on the Mediating Role of Technology Engagement in Indonesian Higher Education

Ahmad Abdullah Aswad[1*], Tegar Angbirah Parerungan[2], Elma Nurjannah[3], Muh. Akbar[4]
[1,2,3,4] *Universitas Negeri Makassar, Indonesia*

Corresponding e-mail : bajadeh123@gmail.com

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ABSTRACT

The rapid integration of Artificial Intelligence (AI) in higher education has the potential to transform learning, yet access to technology does not guarantee active student participation2. Concrete evidence regarding the specific impact of AI features on psychological engagement remains limited. This study aims to examine the structural relationship between AI features (Usage, Personalization, and Feedback) and Student Engagement, specifically investigating the mediating role of Technology Engagement3. Methods: This study employed a quantitative approach with a non-experimental cross-sectional design4. Data were collected from 71 undergraduate students in Eastern Indonesia, predominantly from information technology majors5. The structural model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4 software to test direct and indirect effects6. Results: The analysis revealed that the model possesses substantial predictive power, explaining 74.4% of the variance in Technology Engagement (R^2=0.744) and 66.4% in Student Engagement (R^2=0.664). AI Personalization & Adaptivity emerged as the most dominant predictor, significantly influencing Technology Engagement (β =0.516, p < 0.001) and Student Engagement directly (β=0.310, p =0.010). Conversely, AI Usage and Feedback showed no significant direct effects on Student Engagement but demonstrated significant positive indirect effects through Full Mediation of Technology Engagement99. Conclusion: The findings confirm that Technology Engagement acts as a critical "gatekeeper" mechanism. The intensity of AI usage and automatic feedback alone is insufficient to drive academic engagement unless students first establish a strong sense of control and psychological engagement with the technology. Thus, educational strategies should prioritize adaptive personalization over mere instrumental use.

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INTRODUCTION

The massive integration of AI features, such as adaptive personalization and data-driven analytics, has fundamentally transformed the global higher education ecosystem [1]. This shift extends beyond delivery methods to reconstruct student-technology interaction dynamics, directly impacting the quality of academic engagement [2]. While global strategies aim to accelerate learning quality, their effectiveness relies heavily on how users psychologically adopt the technology [3]. Consequently, AI integration must be evaluated not merely as a technical trend, but as a pedagogical phenomenon influencing student learning behavior [4].

In Indonesia, AI adoption is intensifying to support an adaptive "Smart Learning" ecosystem, yet access alone does not ensure success [5]. Reports suggest that students often utilize AI instrumentally for instant task completion rather than building meaningful cognitive attachment to the learning process [6]. This phenomenon creates a critical gap between AI's ideal potential as an intelligent partner and the reality of its shallow utilization in the field [7]. Therefore, there is an urgent need to examine how psychological mechanisms, specifically technology engagement, bridge the use of AI features with actual student engagement.

This study is grounded in Technology Engagement Theory, which defines engagement as the quality of user experience across affective, cognitive, and behavioral dimensions [8]. In digital learning, effectiveness is determined not by usage frequency, but by the depth of user engagement and control over the technology [9]. Consequently, mere access to AI tools does not guarantee educational success without active psychological involvement. This theory serves as the conceptual foundation for analyzing Technology Engagement as a critical mediator between AI features and student outcomes.

Empirically, research confirms that AI personalization features enhance intrinsic motivation by tailoring materials to individual needs [10]. Similarly, real-time feedback has been shown to contribute effectively to self-efficacy and academic engagement [11]. However, conflicting literature notes that high usage intensity does not correlate linearly with engagement if unaccompanied by psychological attachment [12]. This discrepancy highlights the necessity of an overlooked mediating variable, Technology Engagement, to fully explain the variance in student engagement.

Although AI in education is widely studied, most research focuses on direct effects, neglecting the simultaneous interaction of dimensions like Usage, Personalization, and Feedback in an integrated model [13] [6]. Additionally, there is a distinct scarcity of literature positioning Technology Engagement as a mediating variable to explain the "black box" psychological mechanisms of AI's influence. Furthermore, empirical validation of this structural relationship within the specific context of developing countries, such as Indonesia, remains limited. This study addresses these methodological and contextual gaps by applying Structural Equation Modeling (SEM-PLS) to validate the proposed mediation model.

The urgency of this research lies in its dual contribution. Theoretically, it advances EdTech literature by establishing Technology Engagement as the critical intermediary mechanism explaining the differential effectiveness of AI features. Practically, the findings offer strategic guidance for designing AI-based curricula that prioritize psychological engagement over mere technological access [5]. This approach directly aligns with the national agenda for pedagogical and student-centered AI integration.

Research Question (Based on problem statements in introduction (gap analysis):

The main objective of this study is to analyze the structural relationship between AI features (AI Use in Learning, Personalization & Adaptivity, Feedback & Analytics), Technology Engagement as a mediator, and Student Engagement [3] as an outcome variable. Specifically, the research objectives are formulated as follows:

1. To examine the effect of AI features (AI Use in Learning, Personalization & Adaptivity, Feedback & Analytics) on the formation of student Technology Engagement.
2. To analyze the direct effect of AI features on the level of Student Engagement.
3. To prove the mediating role of Technology Engagement in the relationship mechanism between AI features and Student Engagement.
4. Identify the dimensions of AI features that have the most dominant contribution (largest effect size) in increasing student engagement.
5. Formulate practical implication recommendations for optimizing AI implementation in higher education.

METHOD

Research Design

This study uses a quantitative approach with a non-experimental cross-sectional study design. This method was chosen to examine the structural relationship between variables at a single point in time, allowing researchers to efficiently capture population dynamics without direct intervention [14]; [15]. Based on the proposed conceptual framework, this study analyzes the influence of AI Use in Learning, AI Personalization & Adaptivity, and AI Feedback & Analytics on Student Engagement, with Technology Engagement as a mediating variable. This approach is considered appropriate for validating the proposed mediated model to explain the simultaneous influence mechanism between variables [16]; [17].

Participant

Participants in this study included active undergraduate students at various universities in Eastern Indonesia, selected using non-probability purposive sampling techniques to broaden geographical representation in educational technology literature. Inclusion criteria were strictly set for students who had intensive experience in utilizing Generative AI tools to support academic activities, ranging from idea searching to assignment correction, with a minimum frequency of use of once per week. To minimize bias and comprehensively capture variations in Technology Engagement, participant recruitment included various disciplinary backgrounds, ranging from Science and Technology (STEM) to Social Sciences and Humanities, enabling comparative analysis of technology adoption patterns across curricula.

Population and the methods of sampling Instrumentation

A total of 71 undergraduate students participated in this study (N=71). The demographic profile was dominated by males (57.7%) and those aged between 17 and 19 years (59.2%). In terms of academic progress, most respondents were in their second year or Semester 3 (67.6%) and belonged to the class of 2024 (69.0%). Regarding disciplinary background, the sample was dominated by STEM (Science, Technology, Engineering, and Mathematics) fields, particularly in Information and Computer Technology study programs (81.7%). In addition, the data shows a high level of digital readiness and AI adoption. Almost all respondents (98.6%) have personal devices for digital learning. In terms of intensity of use, the majority (63.9%) reported using AI-based technology every day, while 29.2% used it 3–5 times a week, indicating that participants are active users in the AI ecosystem.

Instrument

This research instrument was created to measure five main variables in the conceptual model. There are a total of 19 statement items that were taken and revised from previous studies to remain relevant to the context of this study. The distribution of measurement items for each variable is shown in Table 1 below.

Table 1. Research Instruments

No	Variable	Statement
1.	AI Use in Learning (AIUL)	1-4
2.	AI Personalization & Adaptivity (AIPA)	5-7

No	Variable	Statement
3.	AI Feedback & Analytics (AIFB)	8-11
4.	Technology Engagement (TE)	12-15
5.	Student Engagement (SE)	16-19

Each item in the questionnaire is measured using a 4-point Likert scale. This scale is constructed with a rating range from 1 ("Strongly Disagree") to 4 ("Strongly Agree"). The use of an even-numbered scale was deliberately chosen to eliminate the "Neutral" or mid-point option. This forced-choice approach aims to minimize central tendency bias (the tendency of respondents to choose safe answers in the middle) and social desirability bias, thereby producing more definitive data in measuring respondents' attitudes [18]; [19]; [20].

Procedures

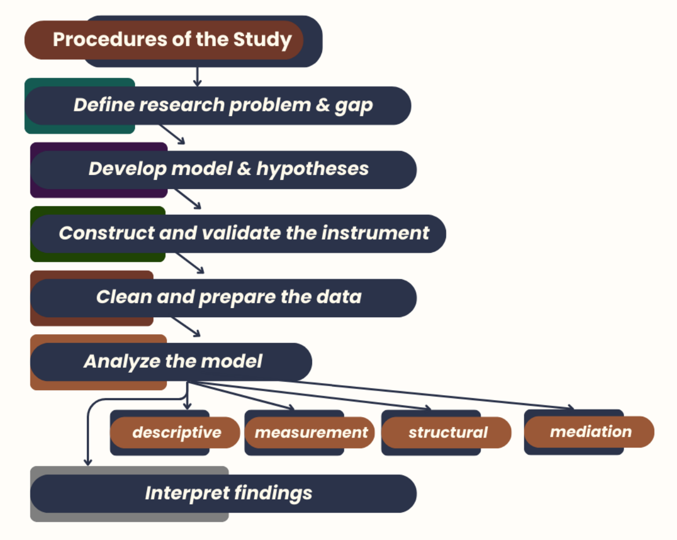

Figure 1. Procedure Steps

A systematic procedural flow was used in this study. It began with problem definition, conceptual model development, and hypothesis formulation based on an in-depth literature review. This study adapted instruments from previous studies [21]; [7] which had been confirmed to have passed content validity testing (IOC ≥ 0.67) and obtained ethical approval. The focus of the next stage was the construction and validation of instruments. Once the instruments were completed, the process continued to the data collection and preparation stage (clean and ready), using a cross-sectional design with purposive sampling techniques through an online survey of students who actively use AI. After the data was completed, the model analysis stage was carried out in stages, beginning with descriptive analysis to describe the data distribution and demographic profiles. Then, inferential analysis is performed using structural equation modeling based on partial least squares (SEM-PLS), which includes evaluation of the measurement model (outer model). SEM-PLS analysis requires reliability and convergent validity (factor loadings greater than 0.70; AVE greater than 0.50).

Analysis plan (Descriptive and Inferential Statistical Test)

Data analysis in this study was conducted using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach with the help of SmartPLS version 4 software. The PLS-SEM technique was chosen based on its robustness in handling complex path models and its flexibility with relatively limited sample sizes without strict assumptions of data normality. This approach allows for the simultaneous testing of predictive relationships between latent constructs, where Technology Engagement is positioned as a mediator variable, AI features (AI Use, Personalization, Feedback) as independent exogenous variables, and Student Engagement as a dependent endogenous variable. Model evaluation was conducted in two rigorous stages. First, the PLS algorithm is used to assess the measurement model to verify the validity and reliability of the instruments. Convergent validity was assessed using external load values (≥ 0.708) and extracted average variance (AVE greater than 0.5), while internal consistency was assessed using composite reliability and Cronbach's alpha with a threshold above 0.704. To ensure that there were clear differences between latent variables, the Fornell-Larcker criteria and Heterotrait-Monotrait Ratio (HTMT) were used to examine discriminant validity. The threshold was less than 0.90.

Then, structural model assessment was used to test the research hypothesis. The coefficient of determination (R^2) and predictive relevance (Q^2) were used to measure the predictive power of the model. In addition, the significance of direct effects and indirect effects was tested using the Bootstrapping procedure with 5,000 subsamples at a 95% confidence level. This study uses an integrated framework developed by [16] to accurately identify mediation effects. This framework divides the types of mediation into Full Mediation or Partial Mediation (Complementary/Competitive) based on the statistical significance of direct and indirect effects, as used in the latest technology mediation studies.

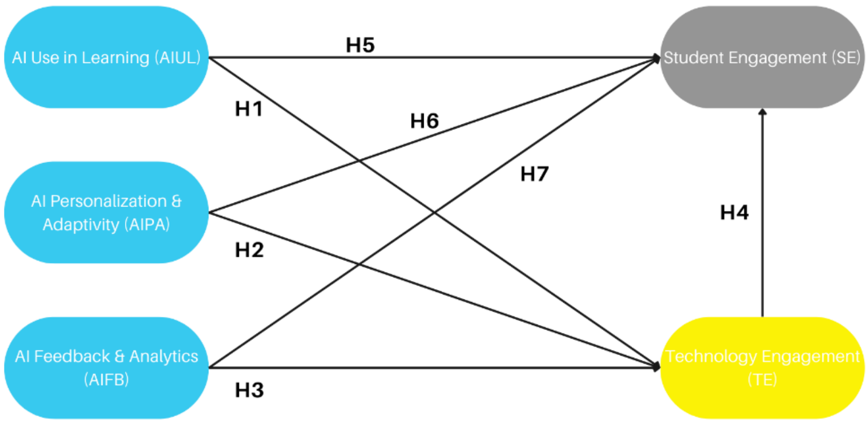

Figure 2. The Model Proposed in This Study

H1: AI Use in Learning has a positive and significant effect on Technology Engagement.
H2: AI Personalization & Adaptivity has a positive and significant effect on Technology Engagement.
H3: AI Feedback & Analytics has a positive and significant effect on Technology Engagement.
H4: Technology Engagement has a positive and significant effect on Student Engagement.
H5: AI Use in Learning has a positive and significant effect on Student Engagement.
H6: AI Personalization & Adaptivity has a positive and significant effect on Student Engagement.
H7: AI Feedback & Analytics has a positive and significant effect on Student Engagement.

RESULTS AND DISCUSSION

Results

Demographic Profile of Respondents

The study involved 71 undergraduate students, primarily from STEM disciplines (81.7%), with the majority aged 17–19 years (59.2%). The measurement model evaluation confirmed robust validity and reliability. All item loadings exceeded the 0.708 threshold, ranging from 0.743 to 0.898. Internal consistency was established with Cronbach's Alpha and Composite Reliability values above 0.70 for all constructs. Convergent validity was supported by Average Variance Extracted (AVE) values exceeding 0.50, while discriminant validity was confirmed via the Fornell-Larcker criterion, where the square root of AVE for each construct surpassed its correlations with other latent variables.

Table 2. Respondent Demographic Profile

No.	Category	Description	Percentage (%)
1.	Gender	Male	57.7%
		Female	42.3%
2.	Age	17 – 19 Years	59.2%
		20 – 23 Years	40.8%
3.	Semester	Semester 1	7.0%
		Semester 3	67.6%
		Semester 5	7.0%
		Semester 7	18.3%
4.	Major	STEM	81.7%
		Non-STEM	18.3%
5.	AI Usage Frequency	Dailies	63.9%
		3-5 times/week	29.2%
		1-2 times/week	6.9%

Measurement Model Evaluation

Model measurement evaluation was conducted to assess the validity and reliability of latent constructs. Figure 3 shows the estimation results of the PLS algorithm (Outer Model), which indicates the loading factor value for each indicator.

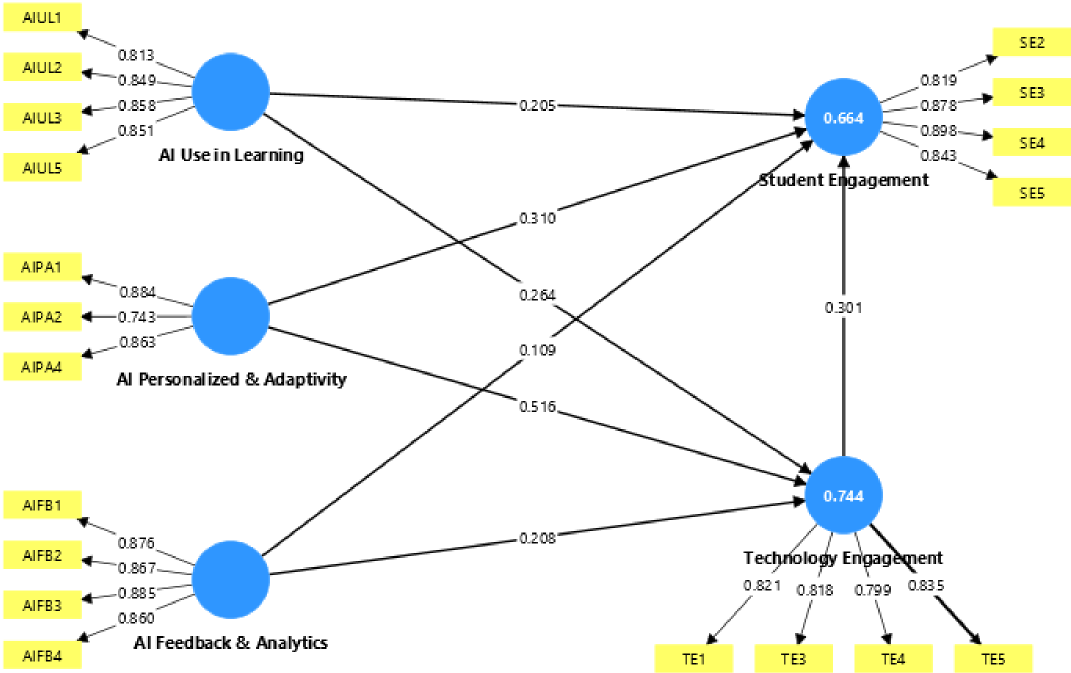

Figure 3. Outer Model

Convergent Validity

Convergent validity and instrument reliability were evaluated based on the parameters of Outer Loading, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). The results of the analysis in Table 4 show that all indicators have a loading factor > 0.708 and an AVE value > 0.50. In addition, Cronbach's Alpha and CR values above 0.70 confirm good internal consistency.

Table 3. Convergent Validity and Reliability Test Results

Construct	Item	Outer Loading	Cronbach's Alpha	Composite Reliability (rho_a)	AVE
AI Feedback & Analytics	AIFB1	0.876	0.895	0.899	0.761
	AIFB2	0.867			
	AIFB3	0.885			
	AIFB4	0.860			
AI Personalization & Adaptivity	AIPA1	0.884	0.775	0.784	0.693
	AIPA2	0.743			
	AIPA4	0.863			

Construct	Item	Outer Loading	Cronbach's Alpha	Composite Reliability (rho_a)	AVE
AI Use in Learning	AIUL1	0.813	0.865	0.879	0.710
	AIUL2	0.849			
	AIUL3	0.858			
	AIUL5	0.851			
Student Engagement	SE2	0.819	0.883	0.887	0.740
	SE3	0.878			
	SE4	0.898			
	SE5	0.843			
Technology Engagement	TE1	0.821	0.835	0.836	0.670
	TE3	0.818			
	TE4	0.799			
	TE5	0.835			

Table 4 demonstrates that all measurement items achieved convergent validity, with outer loadings exceeding the 0.708 threshold. Furthermore, all constructs met reliability requirements (Cronbach's Alpha and CR > 0.70) and convergent validity criteria (AVE > 0.50).

Discriminant Validity

Discriminant validity is assessed to determine the extent to which constructs are empirically distinct from other constructs. The goal is to ensure that each latent variable measures a different phenomenon. There should be no conceptual overlap, or concept overlap, which could bias the results of structural analysis. The conservative Fornell-Larcker criteria stipulate that the square root of the Average Variance Extracted (AVE), or the value on the thick diagonal, must be greater than the highest correlation value of the construct with other constructs in the model (or the off-diagonal value). The statistical logic underlying this criterion is that a construct should be able to explain the variance of its own indicators better than the variance of other constructs.

All constructs consistently meet these criteria, as shown by the analysis results presented in Table 5. The Technology Engagement construct shows an AVE square root value of 0.818. This number indicates the highest correlation with another variable, AI Personalization (0.802). Although these two variables have a fairly strong correlation, which is reasonable given that AI personalization often involves technology, the difference in values indicates that respondents still consider the two concepts to be distinct entities. A similar pattern was found for the other variables; consistently, the correlation values below the diagonal are greater. These results indicate that the research instrument has adequate discriminant validity and that the model does not have significant multicollinearity issues. Therefore, hypothesis testing can be conducted safely [16].

Table 4. Discriminant Validity (Fornell-Larcker Criterion)

	AIFB	AIPA	AIUL	SE	TE
AIFB	0.872				
AIPA	0.724	0.832			
AIUL	0.632	0.512	0.843		
SE	0.689	0.736	0.632	0.860	
TE	0.749	0.802	0.660	0.767	0.818

The discriminant validity evaluation shows satisfactory results, as indicated by the matrix in Table 5. On the main diagonal (bolded), the AVE square root values range from 0.818 to 0.872. These values are higher than the inter-construct correlation coefficients in the same row and column, known as off-diagonals. For example, the Engagement Technology construct has an AVE square root value of 0.818. This indicates the highest correlation with another variable, Personalization AI (0.802). Although these two variables are highly correlated, the difference in values indicates that they are still considered statistically distinct entities. This shows that each latent variable has the capacity to explain the variance of its own indicators better than the variance of other variables. Thus, this research instrument has strong discriminant validity and the structural model is safe from multicollinearity interference between latent variables.

Structural Model Evaluation

After confirming the validity and reliability of the instruments, the evaluation continued with the structural model to test the research hypotheses. This assessment included examining collinearity issues, the significance of path coefficients, the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2).

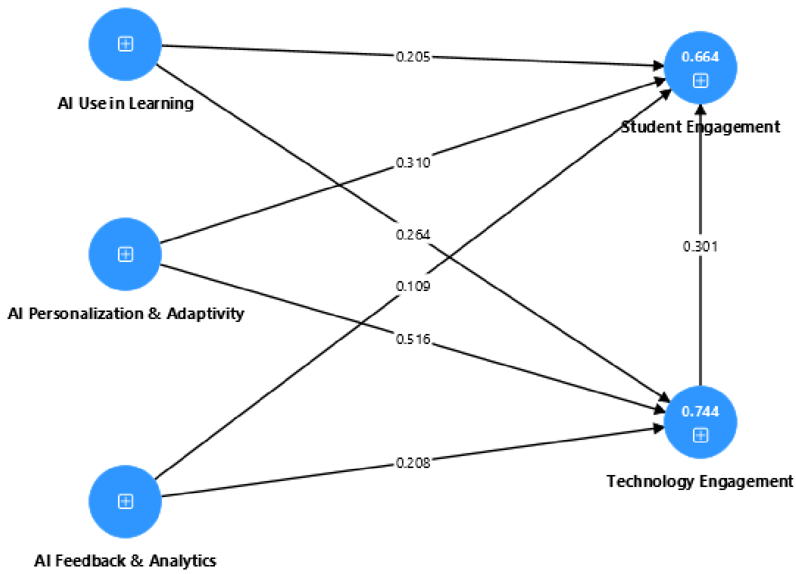

Figure 4. Inner Model

Collinearity Assessment (VIF)

Before interpreting structural relationships, lateral collinearity between predictor variables was examined using the Variance Inflation Factor (VIF) value. The analysis results show that all VIF values in the inner model are below the threshold of 5.0 (VIF < 3.0 is recommended), with the highest value being (2.676). This confirms that there are no multicollinearity issues that could bias the path estimation results.

Path Coefficients (Direct Effects)

Hypothesis testing was conducted using the bootstrapping procedure with 5,000 subsamples to assess the significance of the path coefficient β. The hypothesis acceptance criteria were based on t-statistics values > 1.96 and p-values < 0.05. The results of the analysis in Table 6 show varying relationship patterns. The AI Personalization & Adaptivity variable proved to be the most dominant predictor, having a significant positive influence on both Technology Engagement (β =0.516, p =0.000) and Student Engagement (β =0.310, p =0.010). Conversely, interesting findings were seen in the AI Feedback and AI Use in Learning variables. These two variables did not have a significant direct effect on Student Engagement (p > 0.05), even though both had a significant effect on Technology Engagement. This indicates that the impact of AI use and feedback on student engagement is likely to occur through a mediator, rather than directly.

Table 5. Hypothesis Test Results (Direct Effects)

Hypothesis	Original Sample (β)	t-Statistics	P-Values	Decision
H1	0.208	2.050	0.020	Significant
H2	0.109	0.863	0.194	Not significant
H3	0.516	4.491	0.000	Significant
H4	0.310	2.323	0.010	Significant
H5	0.264	2.328	0.010	Significant
H6	0.205	1.635	0.051	Not significant
H7	0.301	2.022	0.022	Significant

The structural model was assessed using a bootstrapping procedure with 5,000 subsamples to test the significance of path coefficients (Table 6). The analysis reveals that AI Personalization & Adaptivity serves as the dominant predictor, exerting a significant positive influence on both Technology Engagement (β = 0.516, p < 0.001) and Student Engagement (β = 0.310, p = 0.010). Conversely, while AI Use in Learning (β = 0.208, p = 0.020) and AI Feedback & Analytics significantly influenced Technology Engagement, neither demonstrated a significant direct effect on Student Engagement (p > 0.05). Finally, Technology Engagement was found to have a significant positive impact on Student Engagement (β = 0.301, p = 0.022).

Mediation Analysis

Mediation analysis was conducted to examine the role of Technology Engagement as an intermediary mechanism linking AI features with Student Engagement. This test was performed by reviewing the Specific Indirect Effects values and comparing them with the significance of the direct effects. The results of the analysis in Table 8 confirm that Technology Engagement significantly mediates all three relationship paths, but with different characteristics. Specifically, the AI Personalization & Adaptivity variable has the largest indirect effect (β=0.156). Given that the direct effect of this variable was also proven to be significant in previous tests, this mediating role is categorized as Partial Mediation (Complementary). This means that AI personalization can increase student engagement both directly and through increased technology engagement. Conversely, the phenomenon of Full Mediation was found in the AI Use in Learning and AI Feedback & Analytics variables. This conclusion is based on the finding that the direct influence of these two variables on Student Engagement is not significant ($p > 0.05$), but their indirect influence through Technology Engagement is proven to be positive. These findings indicate that simply the intensity of AI use or the acceptance of feedback does not necessarily make students feel engaged, unless these activities first succeed in triggering their engagement with technology.

Table 6. Mediation Test Results (Indirect Effect)

Mediation Pathway	**Specific Indirect Effect (β)**	**Total Effect**	**Type of Mediation**	**Interpretation**
AIPA → TE → SE	0.156	0.466	Partial Mediation	Personalization increases engagement directly and indirectly via technology.
AIUL → TE → SE	0.079	0.285	Full Mediation	The use of AI is only effective in increasing student engagement if it is mediated by Technology Engagement.
AIFB → TE → SE	0.063	0.171	Full Mediation	AI feedback requires strong technological interaction to have an impact on student engagement.

First, the mediation path AI Personalization → Technology Engagement → Student Engagement has the highest indirect effect coefficient, with a beta of 0.156. This mechanism is categorized as Partial Mediation (Complementary) due to its significant direct path. These results indicate that AI personalization is a very strong predictor; through content relevance, it can directly increase student engagement and enhance its effect through better technology interaction. This variable is the most influential in the overall model with a total effect of 0.466. Second, more important results were found regarding the variables of AI usage and AI response. Although they do not have a significant direct influence, both variables have positive indirect effects ($\beta = 0.07$ and $\beta = 0.063$), so they are categorized as Full Mediation. Empirically, these figures indicate that technological engagement functions as a "gatekeeper." If students do not yet feel engaged, proficient, and in control of the technology, the use of AI and feedback features will not be able to increase student engagement. In other words, technological interaction is an important extension for AI use and feedback.

Discussion

This study aimed to deconstruct the "black box" mechanism linking AI features to student engagement. The empirical findings challenge the techno-centric assumption that the mere availability of intelligent tools automatically fosters academic participation. By positioning Technology Engagement as a central mediator, this study reveals that students' psychological interaction with the tool acts as a necessary filter for the effectiveness of AI features. The results confirm that simply providing advanced AI tools is insufficient; the user's sense of engagement with the technology itself determines whether these tools facilitate learning or merely serve as shortcuts.

The analysis identifies AI Personalization & Adaptivity as the most dominant predictor, exhibiting both direct and indirect effects. Theoretically, this finding strongly supports Self-Determination Theory (SDT), particularly regarding the need for autonomy and competence. Unlike static learning tools, adaptive AI systems tailor the difficulty and pace of material to individual needs, which helps prevent cognitive overload and boredom. As noted by [10], adaptive technology enables a customized learning experience that significantly encourages intrinsic motivation. Additionally, [12] found that intelligent optimization models help students allocate cognitive resources more efficiently, directly impacting active participation. This reinforces the view of [22] that system adaptability rather than mere tool availability is the main driver of personalized learning success.

A critical and unexpected finding is the Full Mediation observed in AI Feedback and AI Usage. Contrary to studies by [11] and [21], which reported direct benefits of feedback on engagement, this study found that automated feedback alone has no significant direct impact. This discrepancy can be explained by the phenomenon of "Instrumental Use". Students often view AI feedback merely as technical correction data rather than pedagogical support. As [6] argue, without psychological assistance, students use AI as a "shortcut" to complete technical tasks, rendering the technology ineffective for deep learning. Furthermore, [10] emphasize that AI cannot yet replace human social support; without a sense of Technology Engagement where students feel competent and enthusiastic feedback is perceived only as technical information, failing to motivate learning. This aligns with [23] who emphasize that technical skills alone are insufficient without "digital readiness" to transform interactions into positive outcomes. Thus, Technology Engagement functions as a "gatekeeper": usage intensity and feedback only translate into student engagement if the student first establishes a psychological bond with the technology.

These findings resolve inconsistencies in recent literature regarding AI adoption. While some scholars argue that increased digital interaction linearly improves learning, our results support the more critical view of [12] and [24],who warn that "high usage" is not synonymous with "high engagement." The study empirically proves that without digital literacy and psychological attachment, the effectiveness of AI features diminishes. Consequently, the "Full Mediation" status of AI Usage and Feedback serves as a warning against the uncritical integration of AI in curricula that ignores the user's psychological readiness.

Implications

Theoretical Implications This study makes a significant contribution to EdTech literature by clarifying the psychological mechanisms behind AI effectiveness. First, the finding of Full Mediation for AI Usage and Feedback fills a critical gap, challenging the assumption that access automatically increases engagement. It expands Technology Engagement Theory by proving that psychological interaction is an absolute prerequisite for the successful integration of digital tools. Second, the dominance of the Personalization feature (Partial Mediation) reinforces the relevance of Adaptive Learning Theory in modern higher education, confirming that system adaptability not just tool availability is the primary driver of intrinsic motivation in digital ecosystems.

Practical Implications Practically, this research provides an evidence-based framework for policymakers and educators. The results suggest that curricula should strictly prioritize adaptive personalization features over mass-usage mandates. Educational institutions must shift focus from simply acquiring sophisticated tools to designing interaction strategies that foster students' sense of competence and autonomy. Educators should ensure that AI adoption is accompanied by pedagogical approaches that build students' "digital readiness," preventing the technology from becoming a mere instrumental shortcut.

Research Contribution

This study makes a significant theoretical and practical contribution to the development of educational technology literature. Theoretically, this study offers novelty by validating the role of Technology Engagement as a mediating mechanism of “gatekeepers” that has often been overlooked in previous studies on AI adoption. The findings regarding full mediation on the variables of AI Use and Feedback empirically challenge the common assumption that mere access to or frequency of technology use automatically increases academic engagement. This study clarifies that psychological interaction with technology is an absolute prerequisite for the effectiveness of AI tools. In addition, the confirmation of the dominance of the Personalization feature (Partial Mediation) reinforces the relevance of Adaptive Learning theory, showing that system adaptability is the main driver of students' intrinsic motivation in the digital ecosystem. Practically, this research provides an evidence-based framework for higher education institutions to design AI integration strategies that no longer focus solely on the sophistication of the tools, but rather on interaction designs that foster students' sense of competence and autonomy with technology.

Limitations and Suggestions

Although these findings offer valuable insights, this study relies on cross-sectional data, which limits the ability to infer definitive causal relationships between AI features and student engagement. Furthermore, the focus on a specific educational context with a sample size dominated by technology-based disciplines (STEM) may limit the generalizability of the results to non-technical fields.

Future research should employ longitudinal designs to track the temporal dynamics of techEcology engagement over time. Expanding the sample size to include non-technical disciplines and diverse institutional backgrounds is highly recommended to test the robustness of the findings across heterogeneous populations. Additionally, a mixed-methods approach would be beneficial to explore the contextual factors influencing human-AI interactions and how such collaboration can be optimized to support critical thinking skills.

CONCLUSIONS

This study successfully elucidates the psychological mechanisms governing the influence of AI features on student engagement. By validating a structural model where Technology Engagement serves as a pivotal mediator, empirical results confirm that the integration of AI in higher education is not a monolithic solution. The primary insight reveals a dichotomy in AI features: while Personalization drives engagement through a dual pathway (direct and indirect), Usage Intensity and Feedback rely entirely on the "gatekeeper" role of Technology Engagement (Full Mediation) to be effective. This underscores that mere access to technology does not guarantee meaningful psychological engagement.

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