

STUDENTS' ATTITUDES TOWARD GENERATIVE AI AS A MEDIATING PATHWAY TO PERCEIVED GENERATIVE AI SUPPORT FOR SELF-REGULATED LEARNING IN HIGHER EDUCATION

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ABSTRACT

Generative artificial intelligence (GAI) is increasingly integrated into higher education, creating opportunities for flexible and personalised learning while raising questions about AI-supported learning. This study examines whether students' attitudes toward GAI mediate the relationships between perceived ease of use (PEU), perceived usefulness (PU), and perceived Generative AI support for self-regulated learning (GAI-SRL). A cross-sectional survey was conducted with 264 undergraduate students at a public university in Indonesia. Data were analysed using partial least squares structural equation modelling (PLS-SEM). PEU and PU were positively associated with attitudes toward GAI, while attitudes were positively associated with perceived GAI support for self-regulated learning. PEU and PU also showed significant direct relationships with GAI-SRL, and their indirect relationships through attitudes were significant, indicating partial statistical mediation. These findings suggest that students' attitudes toward GAI constitute an intermediate statistical pathway linking technology-related perceptions with perceived GAI support for self-regulated learning. The study extends technology acceptance research by positioning attitudes toward GAI within a learning-oriented framework and highlights responsible, learner-centred use of GAI while preserving students' learning agency.

KEYWORDS

Generative artificial intelligence, higher education, perceived AI support, responsibility, self-regulated learning, technology acceptance

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Highlights

- Attitudes toward GAI form an intermediate pathway to perceived AI support for SRL.
- Attitudes partially mediate PEU and PU relationships with perceived AI support for SRL.
- Responsible AI use should preserve students' learning agency.

INTRODUCTION

Generative Artificial Intelligence (GAI) is rapidly becoming part of higher education, changing how students access information, obtain feedback, and approach academic tasks. Applications such as ChatGPT, Gemini, and Claude can provide explanations, generate examples, offer alternative solutions, and support students throughout the learning process. These capabilities have expanded the role of AI from a supplementary digital resource to a more active component

of contemporary learning environments (Madrid Akpovo, 2025; Chatzopoulos, 2026; Kim and Thille, 2026). Recent research further highlights the potential of GAI to support personalised learning, academic productivity, problem solving, and flexible access to learning resources (Chang et al., 2023; Tariq, 2025; Hou et al., 2026). At the same time, the growing use of GAI has raised concerns about over-reliance, uncritical acceptance of AI-generated information, and the potential weakening of learner autonomy when AI

is used without adequate reflection (Choi et al., 2024; Zhai, Wibowo and Li, 2024; Zhang et al., 2024).

However, the educational value of GAI does not depend solely on what the technology can provide. It also depends on how students perceive and use it during learning. Students must decide when AI assistance is appropriate, how much support to seek, and whether AI-generated information should be accepted, questioned, or verified. These decisions involve more than technical competence; they reflect students' beliefs and attitudes toward the role of AI in their learning (Svenningsson et al., 2022; Yanto et al., 2023; Acosta-Enriquez et al., 2024). Students with similarly favourable perceptions of GAI may therefore engage with the technology in fundamentally different ways. Some may use AI strategically to clarify concepts, compare explanations, and support independent learning, whereas others may rely on AI primarily to complete academic tasks with limited reflection or evaluation (Mahniza et al., 2024; Tariq, 2025; Rahimi and Faskhodi, 2026). This distinction suggests that students' attitudes toward GAI may have a broader educational role than simply predicting technology acceptance or intention to use.

The Technology Acceptance Model (TAM) explains how perceived usefulness (PU) and perceived ease of use (PEU) shape users' evaluations of technology. TAM has also been applied to Generative AI in higher education, where these perceptions have been linked to attitudes, acceptance, and intention to use AI (Hwang, Lee and Lee, 2025; Lee, Ramasamy and Subbarao, 2025). Consistent with this framework, studies have reported that students who perceive GAI as useful and easy to use tend to develop more favourable attitudes and stronger intentions to incorporate AI into academic activities (Karan and Chakma, 2025; Mustofa et al., 2025; Ozili, 2025). Research has also identified related factors, including trust and perceived competence, as relevant to students' acceptance and engagement with AI-supported technologies (Dahri et al., 2024; Park, Lee and Do, 2025; Shahzad, Xu and Asif, 2025). These studies have substantially advanced understanding of why students accept and adopt AI-based technologies.

Technology acceptance, however, does not fully explain how students engage with GAI after adopting it. Educational use also depends on how learners direct, evaluate, and integrate AI assistance into their learning processes. Recent research has therefore highlighted learner agency, critical evaluation, metacognition, and responsible engagement in AI-supported learning (Chauncey and McKenna, 2023; Kim et al., 2025; Ge, 2026). Students' attitudes may consequently provide an important psychological pathway through which perceptions of AI are associated with students' perceived support for learning regulation.

Self-regulated learning (SRL) offers a complementary perspective because it focuses on how learners set goals, plan, monitor progress, use strategies, and reflect on learning (Zimmerman, 2013; Nilson and Zimmerman, 2023). These processes are particularly relevant to higher education, where students are expected to manage learning with increasing autonomy (Schunk and Zimmerman, 2012). GAI can provide explanations, feedback, alternative strategies, and on-demand assistance that may support these processes (Guan, Li and Gu, 2024; Sardi et al., 2025a; Zhang and Chen, 2026).

Recent studies have similarly reported that AI-supported learning can facilitate metacognitive and self-regulatory processes when

students remain actively involved in directing their learning (Molenaar, 2022; Joo, Han and Park, 2026; Melanou and Beege, 2026). However, access to GAI does not necessarily mean that students perceive it as supporting their self-regulated learning. Students still need to evaluate and decide how AI-generated information should be used, particularly because excessive reliance may reduce opportunities for independent reasoning and cognitive engagement (Wang, 2024; Bueno-Vesga et al., 2026). Thus, learners remain the principal agents of regulation, while GAI functions as a resource whose educational value depends partly on how students approach and use it.

These observations reveal a conceptual intersection between technology acceptance and SRL that remains insufficiently explained. TAM helps explain why students perceive and accept GAI, whereas SRL explains how students regulate their learning. Less clear is how students' attitudes toward GAI connect these two perspectives once AI becomes part of the learning process. Existing research has established relationships between perceived usefulness, perceived ease of use, and technology acceptance (Runge, Hebibi and Lazarides, 2025; Wang, Li and Zou, 2025), while research on AI-supported learning has increasingly examined how GAI can assist self-regulatory and metacognitive processes (Fitriati and Willian, 2025; EL Hosayny, Razkane and Yeou, 2026). However, limited research has examined whether students' attitudes toward GAI mediate the relationships between perceived ease of use, perceived usefulness, and perceived Generative AI support for self-regulated learning. This gap leaves the role of students' attitudes insufficiently understood at the intersection between technology-related perceptions and AI-supported learning regulation.

The present study addresses this gap by examining students' attitudes toward GAI as a mediator between technology-related perceptions and perceived GAI support for self-regulated learning. Students' attitudes are conceptualised as an evaluative orientation toward the use of GAI for academic learning, whereas GAI-SRL captures students' perceptions of how GAI supports learning-regulation processes. Because the study uses cross-sectional data, the proposed relationships are examined as statistical associations rather than temporal or causal processes.

The study extends technology acceptance research by examining attitudes toward GAI in a learning-oriented context rather than focusing only on acceptance or behavioural intention. It also connects PEU and PU with perceived GAI support for self-regulated learning within a single mediation model. The findings provide implications for AI-supported learning, particularly regarding student agency, critical evaluation, and responsible use of GAI. The remainder of the paper presents the methods, results, discussion, limitations, and conclusion.

MATERIALS AND METHODS

Research Design

This study employed a cross-sectional quantitative survey design to examine the structural relationships among perceived ease of use (PEU), perceived usefulness (PU), students' attitudes toward Generative Artificial Intelligence (ATT), and perceived Generative AI support for self-regulated learning (GAI-SRL). The analysis examined whether attitudes

toward GAI statistically mediate the relationships between technology-related perceptions and perceived GAI support for self-regulated learning (Creswell, 2012).

The conceptual model integrates the Technology Acceptance Model (TAM) and Self-Regulated Learning (SRL) theory. PEU and PU were specified as exogenous constructs, ATT as the mediating construct, and GAI-SRL as the endogenous construct. In contrast to interpreting SRL as a direct measure of students' self-regulated learning ability, GAI-SRL captures students' perceptions of how Generative AI supports specific learning-regulation processes.

Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to estimate the measurement and structural models and to examine the direct and indirect statistical relationships among the constructs. PLS-SEM was selected because the analytical objective combined estimation of the hypothesised structural relationships with an emphasis on explained variance and predictive assessment of the endogenous constructs. Because the study used cross-sectional data, the estimated relationships and mediation effects were interpreted as statistical associations within the proposed conceptual model rather than as evidence of temporal or causal effects.

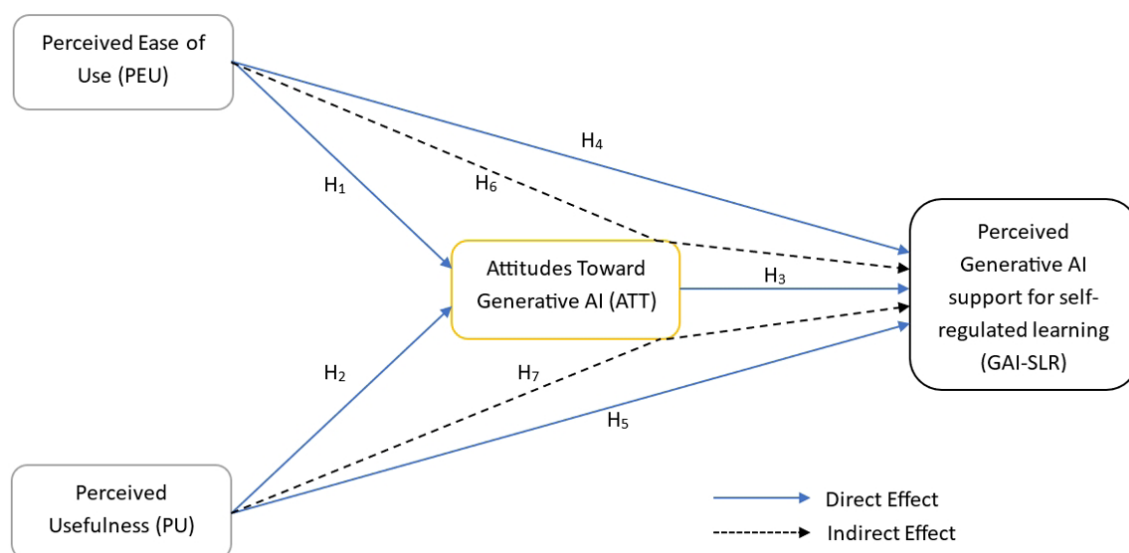


Figure 1: Proposed Conceptual Model of Students' Attitudes Toward Generative AI and Perceived Generative AI Support for Self-Regulated Learning

Proposed Conceptual Model and Hypotheses

The conceptual model proposed in this study is derived from the integration of the Technology Acceptance Model (TAM) and Self-Regulated Learning (SRL) theory. As discussed in the Introduction, TAM provides a robust explanation of how learners develop favourable attitudes toward emerging technologies through their perceptions of usefulness and ease of use. In contrast, SRL theory explains how learners regulate their cognitive, motivational, and behavioural processes to achieve meaningful learning outcomes. Building upon these complementary perspectives, the present study proposes that students' attitudes toward Generative Artificial Intelligence (GAI) conceptually connect technology-related perceptions with self-regulated learning.

Figure 1 illustrates the proposed conceptual model. Within the model, perceived ease of use (PEU) and perceived usefulness (PU) function as exogenous constructs representing students' evaluations of the functional characteristics of Generative AI. Students' attitudes toward GAI (ATT) are positioned as the central mediating construct, reflecting learners' evaluative orientation toward the use of AI in academic learning. Perceived Generative AI Support for Self-Regulated Learning (GAI-SRL) serves as the endogenous construct, representing students' perceptions of how Generative AI supports learning-regulation processes such as goal setting, planning, monitoring, evaluation, strategy formulation, and learning engagement.

Consistent with TAM, students who perceive Generative AI as useful and easy to use are expected to develop more favourable attitudes toward AI-supported learning. These positive attitudes are subsequently expected to be associated with stronger perceptions of Generative AI support for self-regulated learning. In addition to these indirect relationships, the conceptual model also posits that perceived usefulness and perceived ease of use are directly associated with perceived Generative AI support for self-regulated learning. This specification recognises that students' technology-related perceptions may contribute to learning regulation both independently and through their attitudes toward AI. Consequently, the proposed mediation model enables examination of whether students' attitudes provide empirical support for the conceptual perspective advanced in this study.

Based on this conceptual model, the following hypotheses were formulated:

- **H1:** Perceived Ease of Use (PEU) is positively associated with students' attitudes toward Generative AI (ATT).
- **H2:** Perceived Usefulness (PU) is positively associated with students' attitudes toward Generative AI (ATT).
- **H3:** Students' attitudes toward Generative AI (ATT) are positively associated with perceived Generative AI support for self-regulated learning (GAI-SRL).
- **H4:** Perceived Ease of Use (PEU) is positively associated with perceived Generative AI support for self-regulated learning (GAI-SRL).

- **H5:** Perceived Usefulness (PU) is positively associated with perceived Generative AI support for self-regulated learning (GAI-SRL).
- **H6:** Students' attitudes toward Generative AI (ATT) mediate the relationship between Perceived Ease of Use (PEU) and perceived Generative AI support for self-regulated learning (GAI-SRL).
- **H7:** Students' attitudes toward Generative AI (ATT) mediate the relationship between Perceived Usefulness (PU) and perceived Generative AI support for self-regulated learning (GAI-SRL).

Participants and Sampling Procedure

This study was conducted at a public university in Indonesia. The target population comprised undergraduate students who had prior experience using Generative Artificial Intelligence applications, such as ChatGPT, Gemini, or comparable AI-based tools, for academic learning purposes. Participants were recruited using purposive sampling based on predefined eligibility criteria. Participants were required to (1) be currently enrolled as undergraduate students, (2) have used Generative AI for academic learning purposes during the current academic year, and (3) voluntarily agree to participate in the study. Restricting participation to students with prior experience using Generative AI ensured that respondents were able to evaluate AI-supported learning based on actual educational experience rather than hypothetical expectations.

Data were collected through an online questionnaire during the first semester of the 2025/2026 academic year. A total of 278 questionnaires were returned. During the predefined eligibility screening procedure, 9 responses were excluded because the personal information provided could not be verified as indicating active undergraduate student status. A further 5 responses were excluded because the respondents reported very limited use of Generative AI for academic learning and therefore did not meet the study's predefined eligibility criterion concerning prior experience with Generative AI. Thus, 14 responses were excluded and 264 valid responses were retained for the final analysis.

The final sample consisted of 112 male students (42.4%) and 152 female students (57.6%), with a mean age of 20.8 years ($SD = 1.34$). Participation was voluntary, and before completing the questionnaire, respondents were informed about the purpose of the study and provided electronic informed consent. Respondents' names and student identification numbers (NIM) were collected solely for the purpose of verifying active undergraduate student status. These identifying data were not included in the analytical dataset and were deleted before statistical analysis. Accordingly, the statistical analyses were conducted using de-identified data, while responses were treated confidentially.

Instrument Development and Measurement

The research instrument was developed using a theory-informed adaptation and contextualisation approach. The measurement items were selected from established empirical studies and adapted to the context of Generative AI use for academic learning in higher education. The adaptation was guided by the conceptual definitions of the constructs and the requirements of the proposed structural model.

The questionnaire was administered primarily in Indonesian, which was the language used by the respondents. An English equivalent was provided in parentheses for each item in the research documentation and manuscript to facilitate correspondence with the international research literature. The English versions were not used as a separate measurement form.

The adaptation sources were mapped to the constructs as follows: Perceived Ease of Use (PEU; PEU1–PEU5) and Perceived Usefulness (PU; PU1–PU5) were primarily informed by Yanto et al. (2023), Students' Attitudes toward Generative AI (ATT; ATT1–ATT5) were informed by Svenningsson et al. (2022), and Perceived Generative AI Support for Self-Regulated Learning (GAI-SRL; SRL1–SRL7) was informed by Mahniza et al. (2024). The source items were contextualised so that references to technology or learning activities specifically referred to students' academic use of Generative AI.

The adaptation process involved contextual wording adjustments intended to improve clarity, readability, and relevance for Indonesian undergraduate students while preserving the intended conceptual meaning of the source items. The adapted questionnaire was subsequently reviewed by five experts with expertise in educational technology, instructional design, learning psychology, educational measurement, and higher education pedagogy. The experts evaluated the relevance, representativeness, clarity, and contextual appropriateness of the items, and their comments were used to refine wording before the main data collection.

A formal independent back-translation procedure was not conducted because the questionnaire was administered in Indonesian and the English versions were provided only as corresponding English renderings. Likewise, no separate formal cognitive-interview study was conducted before the main survey. Item clarity and contextual suitability were instead examined through the expert-review process. These item structures are reflected in the measurement indicators reported in Table 1.

The Perceived Ease of Use (PEU) construct consisted of five indicators measuring students' perceptions of the usability, accessibility, and comprehensibility of Generative AI in academic learning. These indicators assessed the extent to which students perceived AI systems as easy to learn, straightforward to operate, and usable without requiring specialised technical skills. Likewise, the Perceived Usefulness (PU) construct comprised five indicators representing students' evaluations of the educational benefits of Generative AI, including its contribution to learning effectiveness, efficiency, knowledge acquisition, independent learning, time management, and understanding of complex learning materials. Together, these two constructs represent students' technology-related perceptions, consistent with the Technology Acceptance Model.

The Students' Attitudes toward Generative AI (ATT) construct was operationalised as students' overall evaluative orientation toward the use of Generative AI for academic learning. The construct encompasses complementary cognitive, affective, confidence-related, and responsibility-oriented aspects of students' orientation toward GAI. ATT1 and ATT2 primarily represent students' openness and positive evaluation of GAI as a learning tool. ATT4 reflects confidence in using

Construct	Indicators	Adaptation source
PEU	PEU1. AI technology is easy to use	Yanto et al. (2023)
	PEU2. AI technology is easy to access	
	PEU3. AI technology interfaces are user-friendly and intuitive	
	PEU4. AI technology is easy to understand	
	PEU5. Using AI technology does not require specific skills	
PU	PU1. AI technology helps to improve my knowledge	Yanto et al. (2023)
	PU2. AI technology helps improve learning efficiency and effectiveness	
	PU3. AI technology helps me to be self-reliant	
	PU4. AI technology helps save time	
	PU5. AI helps me understand complex and in-depth learning materials	
ATT	ATT1. I have an open and accepting attitude towards AI for use in learning	Svenningsson et al. (2022)
	ATT2. I have a positive perception of AI as a learning tool	
	ATT3. I take responsibility for verifying AI-generated content before using it	
	ATT4. I am more confident when using AI technology in learning	
	ATT5. I enjoyed using AI technology as a learning tool	
GAI-SRL	SRL1. Generative AI assists in setting clear and achievable learning goals	Mahniza et al. (2024)
	SRL2. Generative AI supports the development of effective learning plans	
	SRL3. Generative AI helps evaluate and reflect on the studied materials	
	SRL4. Generative AI enables consistent monitoring of learning progress	
	SRL5. Generative AI guides the formulation of personalised learning strategies	
	SRL6. Generative AI boosts motivation and willingness to engage in learning activities	
	SRL7. Generative AI makes the learning process more enjoyable and engaging	

Table 1: Constructs, Indicators, and Adaptation Sources (Source: Authors' adaptation based on Yanto et al. (2023), Svenningsson et al. (2022), and Mahniza et al. (2024))

GAI for learning, while ATT5 captures the affective dimension of enjoyment. ATT3 reflects a responsibility-oriented disposition toward verifying AI-generated information before using it academically. This indicator was therefore interpreted as an attitudinal orientation toward responsible AI use rather than as a direct behavioural measure. The five indicators were modelled reflectively as manifestations of an overall evaluative orientation toward GAI. Although they cover complementary facets of attitude, their conceptual coherence and empirical results supported their treatment as a single reflective construct. The broader conceptualisation of ATT remains a limitation to be examined in future research.

The Perceived Generative AI Support for Self-Regulated Learning (GAI-SRL) construct was operationalised to capture students' perceptions of how Generative AI assists, supports, or enables their learning-regulation processes. The seven indicators address goal setting, learning planning, evaluation and reflection, monitoring of learning progress, formulation of personalised learning strategies, motivational engagement, and learning engagement. Accordingly, GAI-SRL does not represent a direct measure of students' self-regulated learning ability. Rather, it represents students' perceived contribution of Generative AI to processes associated with self-regulated learning. This distinction is important because the present study examines students' perceptions of AI-supported learning rather than objectively measuring changes in their self-regulatory competence. All measurement items were assessed using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Content Validity and Expert Review

To strengthen the methodological rigour of the measurement instrument, content validity was assessed through expert judgement using the Content Validity Index (CVI). This procedure was conducted before the main data collection to evaluate whether the adapted measurement items adequately represented their intended constructs and were appropriate for the context of Generative AI-supported learning in higher education.

A panel of five experts was purposively invited to participate in the validation process. The panel represented complementary areas of expertise, including educational technology, instructional design, learning psychology, educational measurement, and higher education pedagogy. Before the evaluation, each expert received the questionnaire, operational definitions of the constructs, and the proposed conceptual model.

Experts independently evaluated the relevance of each indicator using a four-point rating scale ranging from 1 (not relevant) to 4 (highly relevant). I-CVI values were calculated as the proportion of experts assigning a relevance rating of 3 or 4, and S-CVI/Ave was calculated as the average of the item-level CVIs. Given the small size of the five-expert panel, I-CVI values were interpreted cautiously. Following Polit, Beck, and Owen (2007), I-CVI values of approximately 0.78 or higher may be regarded as evidence of good content validity, with the observed values in the present study ranging from 0.80 to 1.00. The S-CVI/Ave values ranged from 0.92 to 0.96 across the four constructs (Table 2).

Latent Construct	Number of Items	Range of I-CVI	S-CVI/Ave
Perceived Ease of Use (PEU)	5	0.80 – 1.00	0.92
Perceived Usefulness (PU)	5	0.80 – 1.00	0.94
Attitudes toward GAI (ATT)	5	0.80 – 1.00	0.96
Perceived GAI Support for Self-Regulated Learning (GAI-SRL)	7	0.80 – 1.00	0.93

Table 2: Content Validity Index (CVI) Results by Latent Construct (Source: Authors' own analysis based on expert judgement)

Data Analysis Procedure

Data analysis was conducted using SmartPLS 3.0 following a two-stage PLS-SEM procedure. The first stage involved assessment of the measurement model, followed by evaluation of the structural model and mediation relationships. Given the cross-sectional research design, all estimated relationships were interpreted as statistical associations rather than causal effects (Hair et al., 2019).

The measurement model was assessed in terms of internal consistency reliability, convergent validity, and discriminant validity. Internal consistency reliability was evaluated using Cronbach's Alpha (CA) and Composite Reliability (CR). Convergent validity was assessed using indicator outer loadings and Average Variance Extracted (AVE). Discriminant validity was examined using the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT).

The structural model was evaluated using path coefficients, coefficient of determination (R^2), collinearity assessment, effect sizes (f^2), predictive relevance (Q^2), and out-of-sample predictive assessment using PLSpredict. Effect size f^2 was used to assess the contribution of each exogenous construct to the explained variance of the endogenous construct. Predictive relevance was examined using the blindfolding procedure, with positive Q^2 values interpreted as evidence of predictive relevance. PLSpredict was additionally used to assess out-of-sample predictive performance using the resulting Q^2 predict values.

Mediation effects were assessed through indirect effects estimated using bootstrapping with 5,000 resamples. The indirect effects of PEU and PU on GAI-SRL through ATT were examined using the bootstrapped estimates and confidence intervals. Consistent with the cross-sectional design, statistically significant indirect effects were interpreted

as evidence of statistical mediation within the proposed model rather than evidence of a temporal or causal mechanism.

Procedural Considerations for Common-Method Variance

Because the predictor, mediator, and endogenous constructs were measured using self-report items within the same online questionnaire and at the same measurement occasion, the potential for common-method variance was considered. Several procedural safeguards were applied, including voluntary participation, electronic informed consent, confidentiality of responses, and de-identification of the analytical dataset.

Names and student identification numbers were collected only to verify active student status and were deleted before statistical analysis. The analytical dataset therefore did not contain direct personal identifiers.

The outer and inner VIF values reported in the structural model were used to assess statistical collinearity and were not treated as a formal test of common-method bias. Therefore, the VIF results should not be interpreted as demonstrating the absence of common-method variance. Given the single-source, self-report measurement approach, the possibility of common-method variance cannot be completely excluded and is considered in the interpretation of the findings.

RESULTS

Measurement Model Assessment

The measurement model demonstrated satisfactory reliability and validity across PEU, PU, ATT, and GAI-SRL. Indicator collinearity, internal consistency, convergent validity, and discriminant validity were within the specified criteria. As shown in Table 3, outer VIF values ranged from 2.849 to 4.135, indicating no excessive indicator collinearity.

Indicator	VIF	Indicator	VIF
PEU1	2.941	ATT1	3.568
PEU2	2.964	ATT2	3.410
PEU3	3.486	ATT3	4.135
PEU4	3.075	ATT4	2.849
PEU5	3.347	ATT5	3.288
PU1	3.346	SRL1	2.967
PU2	3.597	SRL2	3.506
PU3	3.610	SRL3	3.571
PU4	3.699	SRL4	3.339
PU5	3.642	SRL5	3.540
		SRL6	3.783
		SRL7	3.444

Table 3: Outer VIF Values Analysis (Source: own data processing)

Multicollinearity was also assessed at the structural-model level using inner VIF values. As shown in Table 4, all inner VIF values ranged from 1.191 to 1.330, indicating that collinearity among the predictor constructs was also within acceptable limits. The VIF analyses were conducted to assess statistical

collinearity and should not be interpreted as a formal test of common-method bias. Because all constructs were measured through the same self-report questionnaire, the potential for common-method variance is addressed separately as a methodological limitation of the study.

Construct	ATT	GAI-SRL
PEU	1.191	1.316
PU	1.191	1.330
ATT	–	1.279

Table 4: Inner VIF Values Analysis (Source: own data processing)

Internal Consistency Reliability and Convergent Validity

Following the assessment of indicator multicollinearity, internal consistency reliability and convergent validity were evaluated. Internal consistency reliability was examined using Cronbach's Alpha, rho_A, and Composite Reliability (CR), while convergent validity was assessed using indicator outer loadings and Average Variance Extracted (AVE).

As shown in Table 5, outer loadings ranged from 0.860 to 0.917, while Cronbach's Alpha, rho_A, and Composite Reliability ranged from 0.933 to 0.953, 0.936 to 0.953, and 0.949 to 0.961, respectively. AVE values ranged from 0.778 to 0.815. All values exceeded the specified thresholds,

supporting indicator reliability, internal consistency, and convergent validity.

Discriminant Validity

Discriminant validity was assessed to determine whether the four latent constructs represented empirically distinguishable dimensions within the proposed model. The assessment used the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT). As presented in Table 6, the square root of the AVE for each construct exceeded its correlations with the other constructs. The square roots of AVE were 0.888 for ATT, 0.897 for PU, 0.903 for PEU, and 0.882 for GAI-SRL. These results satisfy the Fornell–Larcker criterion and indicate satisfactory discriminant validity.

Construct	Indicator Loading	Cronbach's Alpha (> 0.7)	rho_A (> 0.7)	CR (> 0.7)	AVE (> 0.5)	Convergent Validity
PEU	0.896–0.906	0.943	0.944	0.956	0.815	Valid
PU	0.876–0.917	0.939	0.939	0.953	0.804	Valid
ATT	0.879–0.901	0.933	0.936	0.949	0.789	Valid
GAI-SRL	0.860–0.899	0.953	0.953	0.961	0.778	Valid

Table 5: Reliability and Convergent Validity of the Measurement Model (Source: own data processing)

Constructs	ATT	PU	PEU	GAI-SRL
ATT	0.888			
PU	0.429	0.897		
PEU	0.389	0.401	0.903	
GAI-SRL	0.418	0.456	0.459	0.882

Table 6: Discriminant Validity Assessment Using the Fornell–Larcker Criterion (Source: own data processing)

The HTMT criterion was subsequently examined to provide additional evidence of construct distinctiveness. As shown in Table 7, all HTMT values were below 0.90, with values

ranging from 0.436 to 0.492. Together, the Fornell–Larcker and HTMT results supported discriminant validity among the four constructs.

Constructs	ATT	PU	PEU	GAI-SRL
ATT	—			
PU	0.473	—		
PEU	0.436	0.458	—	
GAI-SRL	0.462	0.489	0.492	—

Table 7: Heterotrait–Monotrait Ratio (HTMT) (Source: own data processing)

Structural Model Assessment

Following confirmation of the adequacy of the measurement model, the structural model was evaluated to examine the hypothesised relationships among PEU, PU, ATT, and GAI-SRL. The assessment considered direct path

coefficients, statistical significance, coefficient of determination (R^2), effect sizes (f^2), predictive relevance (Q^2), and out-of-sample predictive performance using PLSpredict. The mediating role of ATT was subsequently examined through bootstrapped indirect effects. Because

the study employed a cross-sectional design, the structural results are interpreted as statistical associations within the proposed conceptual model. In particular, statistically significant indirect effects are interpreted as evidence of statistical mediation rather than as evidence of a temporal or causal mechanism.

Direct Effects

The structural relationships were evaluated using the bootstrapped path coefficients, standard errors, t-values, p-values, and 95% confidence intervals. As presented in Table 8, all five hypothesised direct relationships were positive and statistically significant, with all 95% confidence intervals excluding zero.

Hypothesis	Path	β	SE	t	p	95% CI	Decision
H ₁	PEU → ATT	0.259	0.053	4.902	< 0.001	[0.152, 0.357]	Supported
H ₂	PU → ATT	0.325	0.051	6.353	< 0.001	[0.221, 0.420]	Supported
H ₃	ATT → GAI-SRL	0.199	0.059	3.339	0.001	[0.077, 0.315]	Supported
H ₄	PEU → GAI-SRL	0.278	0.056	4.954	< 0.001	[0.160, 0.379]	Supported
H ₅	PU → GAI-SRL	0.259	0.053	4.845	< 0.001	[0.150, 0.360]	Supported

Table 8: Direct Effects and Hypothesis Testing (Source: own data processing)

Perceived ease of use was positively associated with attitudes toward GAI ($\beta = 0.259$, $SE = 0.053$, $t = 4.902$, $p < 0.001$, 95% CI [0.152, 0.357]), supporting H1. Perceived usefulness showed a stronger positive association with ATT ($\beta = 0.325$, $SE = 0.051$, $t = 6.353$, $p < 0.001$, 95% CI [0.221, 0.420]), supporting H2. ATT was positively associated with perceived GAI support for self-regulated learning (GAI-SRL) ($\beta = 0.199$, $SE = 0.059$, $t = 3.339$, $p = 0.001$, 95% CI [0.077, 0.315]), supporting H3. PEU also demonstrated a positive association with GAI-SRL ($\beta = 0.278$, $SE = 0.056$, $t = 4.954$, $p < 0.001$, 95% CI [0.160, 0.379]), supporting H4. Similarly, PU was positively associated with GAI-SRL ($\beta = 0.259$, $SE = 0.053$, $t = 4.845$, $p < 0.001$, 95% CI [0.150, 0.360]), supporting H5. Overall, the results support all five hypothesised direct relationships. Given the cross-sectional design, these coefficients indicate associations within the proposed model and should not be interpreted as causal effects.

Explanatory Power of the Model

The explanatory power of the structural model was assessed using the coefficient of determination (R^2). The R^2 values represent the proportion of variance in each endogenous construct explained by its predictor constructs. As presented in Table 9, the model explained 24.0% of the variance in ATT ($R^2 = 0.240$) and 32.9% of the variance in perceived GAI support for self-regulated learning (GAI-SRL) ($R^2 = 0.329$). Thus, the proposed model accounted for a larger proportion of variance in GAI-SRL than in ATT.

These values indicate that PEU and PU jointly explain part of the observed variation in students' attitudes toward GAI, while PEU, PU, and ATT collectively explain part of the variation in students' perceived GAI support for self-regulated learning. The R^2 values should be interpreted as explanatory evidence within the present model rather than as evidence of causal influence.

Endogenous Construct	R^2	Interpretation
ATT	0.240	24.0% of variance explained
GAI-SRL	0.329	32.9% of variance explained

Table 9: Coefficient of Determination (R^2) (Source: own data processing)

Effect Size (f^2)

Effect sizes (f^2) were examined to assess the contribution of each predictor to the explained variance of the corresponding endogenous construct. As presented in Table 10, all structural relationships showed small individual effect sizes.

The largest effect was observed for PEU on ATT ($f^2 = 0.117$), followed by PU on GAI-SRL ($f^2 = 0.090$), PEU on GAI-SRL ($f^2 = 0.075$), PU on ATT ($f^2 = 0.074$), and ATT on GAI-SRL ($f^2 = 0.045$). Although the corresponding structural paths were statistically significant, their individual contributions to the explained variance were relatively modest.

Structural Relationship	f^2	Interpretation
PEU → ATT	0.117	Small
PU → ATT	0.074	Small
PEU → GAI-SRL	0.075	Small
PU → GAI-SRL	0.090	Small
ATT → GAI-SRL	0.045	Small

Table 10: Effect Size (f^2) of the Structural Relationships (Source: own data processing)

Predictive Relevance (Q^2)

Blindfolding produced positive Q^2 values for ATT (0.186) and GAI-SRL (0.251), indicating predictive relevance for

both endogenous constructs (Table 11). The higher value for GAI-SRL indicates stronger predictive relevance within the estimated model.

Endogenous Construct	Q^2	Predictive Relevance
ATT	0.186	Yes
GAI-SRL	0.251	Yes

Table 11: Predictive Relevance (Q^2) of the Endogenous Constructs (Source: own data processing)

Out-of-Sample Predictive Assessment

PLSpredict showed positive Q^2_{predict} values for all indicators of ATT and GAI-SRL (Table 12). Values ranged from 0.087 to 0.185 for ATT and from 0.134 to 0.223 for GAI-SRL.

Because the present analysis does not report a comparison of

prediction errors with a linear-model benchmark, the positive Q^2_{predict} values are reported descriptively as evidence that the PLS predictions outperform the naïve benchmark used in the Q^2_{predict} calculation. No claim is made regarding low, medium, or high predictive power without comparison of prediction-error metrics against the linear-model benchmark.

Construct	Indicator	Q^2_{predict}
ATT	ATT1	0.176
ATT	ATT2	0.157
ATT	ATT3	0.140
ATT	ATT4	0.087
ATT	ATT5	0.185
GAI-SRL	SRL1	0.206
GAI-SRL	SRL2	0.210
GAI-SRL	SRL3	0.223
GAI-SRL	SRL4	0.176
GAI-SRL	SRL5	0.201
GAI-SRL	SRL6	0.200
GAI-SRL	SRL7	0.134

Table 12: PLSpredict Results (Source: own data processing)

Mediating Role of Students' Attitudes toward Generative AI

The mediating role of students' attitudes toward Generative AI was examined using bootstrapped specific indirect effects. As shown in Table 13, the indirect relationship between PEU and perceived GAI support for self-regulated learning through ATT was positive and statistically significant ($\beta = 0.051$, $SE = 0.017$, $t = 2.954$, $p = 0.003$, 95% $CI [0.021, 0.090]$). Because the corresponding direct relationship between PEU and GAI-SRL remained positive and statistically significant ($\beta = 0.278$, $p < 0.001$), the result indicates partial statistical mediation, supporting H6.

The indirect relationship between PU and GAI-SRL through ATT was also positive and statistically significant ($\beta = 0.065$, $SE = 0.023$, $t = 2.837$, $p = 0.005$, 95% $CI [0.025, 0.117]$). Because the direct relationship between PU and GAI-SRL remained significant ($\beta = 0.259$, $p < 0.001$), H7 was supported and the mediation was partial.

Both indirect effects were statistically significant, with confidence intervals excluding zero. Given the cross-sectional design, these mediation results indicate statistical mediation within the proposed model but do not establish temporal ordering or causality.

Hypothesis	Indirect Path	β	SE	t	p	95% CI	Direct (β)	Mediation Decision
H ₆	PEU → ATT → GAI-SRL	0.051	0.017	2.954	0.003	[0.021, 0.090]	0.278	Partial mediation
H ₇	PU → ATT → GAI-SRL	0.065	0.023	2.837	0.005	[0.025, 0.117]	0.259	Partial mediation

Table 13: Specific Indirect Effects and Statistical Mediation (Source: own data processing)

DISCUSSION

Interpretation of the Structural Relationships

The structural coefficients provide further insight into the relative strength of the relationships within the model. PU had the strongest association with ATT, whereas PEU showed the slightly stronger direct association with GAI-SRL. The indirect association through ATT was somewhat stronger for PU than for PEU. This pattern indicates that perceived usefulness may be particularly relevant to students' evaluations of GAI, while ease of use has a somewhat stronger direct association with perceived AI support for self-regulated learning.

The model explained 24.0% of the variance in ATT and 32.9% in GAI-SRL. However, all individual f^2 values were small (0.045–0.117), indicating that the observed relationships represent modest contributions within a broader set of factors. Thus, although the structural relationships were statistically significant, the contribution of each individual predictor was relatively modest. This finding supports a cautious interpretation in which perceived AI-supported self-regulated learning is likely associated with multiple factors beyond the constructs included in the present model.

PEU and PU in AI-Supported Self-Regulated Learning

The significant direct relationships of PEU and PU with GAI-SRL indicate that students' perceptions of the usability and educational value of GAI are statistically associated with how strongly they perceive AI as supporting their learning-regulation processes. PEU showed a positive association with GAI-SRL ($\beta = 0.278$), while PU also demonstrated a positive association ($\beta = 0.259$). These findings are consistent with the broader logic of the Technology Acceptance Model, in which perceived usefulness and perceived ease of use are important determinants of users' evaluations of technology. In the present learning-oriented model, however, these perceptions are examined in relation to students' perceived AI support for learning regulation rather than technology adoption alone.

The slightly stronger relationship between PEU and GAI-SRL suggests that usability may be particularly relevant when students incorporate GAI into learning activities. When AI tools are perceived as easy to access, understand, and operate, students may perceive fewer barriers to obtaining explanations, feedback, examples, or other forms of learning assistance. These functions may support processes associated with planning, monitoring, reflection, and strategy formulation. Previous research has similarly highlighted the potential of Generative AI to provide accessible explanations, personalised assistance, feedback, and flexible learning support (Banihashem et al., 2024; Kizilcec et al., 2024; Ge, 2026).

PU also demonstrated a significant positive association with GAI-SRL. Students who see clear educational value in GAI may also view it as useful for learning-related processes. Its value may lie in clarifying difficult concepts, generating alternative explanations, providing immediate assistance, and supporting academic tasks. These affordances may be relevant to self-regulated learning processes because students can potentially use them when deciding what to learn, how to approach a task, and how to evaluate their understanding (Xiaolei and Teng, 2024; Kim and Thille, 2026; Melanou and Beege, 2026).

The findings do not show that making GAI easier to use or more useful will improve students' self-regulated learning ability. They instead indicate an association between technology-related perceptions and perceived AI support for learning regulation. Because GAI-SRL captures perceived assistance rather than objectively observed regulatory competence, the findings should be understood as evidence concerning students' perceptions of AI-supported learning processes.

Students' Attitudes toward Generative AI as a Mediating Pathway

The mediation results indicate that ATT mediates the relationships between technology-related perceptions and perceived GAI support for self-regulated learning. The indirect relationship between PEU and GAI-SRL through ATT was significant ($\beta = 0.051$, $p = 0.003$), while the indirect relationship between PU and GAI-SRL through ATT was also significant ($\beta = 0.065$, $p = 0.005$). Because the corresponding direct relationships remained significant, both relationships represent partial statistical mediation.

The stronger indirect relationship observed for PU suggests that perceived usefulness may have a somewhat greater association with GAI-SRL when operating through students' attitudes toward GAI. This pattern is theoretically plausible because perceptions of educational usefulness may contribute to favourable evaluations of the technology, which are subsequently associated with stronger perceptions of AI-supported learning regulation. Nevertheless, the cross-sectional design does not establish that usefulness perceptions temporally precede attitudes or that attitudes subsequently cause changes in learning regulation. The mediation findings therefore represent statistical associations consistent with the proposed conceptual pathway rather than evidence of a causal process.

ATT represented a broad evaluative orientation toward GAI, including positive evaluation, confidence, enjoyment, and responsibility-oriented evaluation of AI-generated information. The positive association between ATT and GAI-SRL therefore suggests that students' overall orientation toward GAI is relevant to how they perceive AI support for learning-regulation processes. The responsibility-oriented component is particularly important in the context of Generative AI. Students may obtain explanations, suggestions, or information from AI systems without necessarily evaluating their accuracy or appropriateness. Previous research has emphasised the importance of critical evaluation, verification, and responsible engagement when Generative AI is used for educational purposes (Chauncey and McKenna, 2023; Asio, 2024; Tang et al., 2024; Akbay et al., 2025). A favourable attitude toward GAI should therefore not be equated with simple willingness to use the technology. It may also involve how students evaluate the role and appropriate use of AI within their learning processes.

Theoretical Contribution

Theoretically, the findings extend the application of the Technology Acceptance Model by connecting technology-related perceptions with a learning-oriented outcome. Previous applications of TAM to Generative AI have primarily focused on acceptance, intention to use, and technology-related evaluations (Dahri et al., 2024; Hwang et al., 2025; Mustofa et al., 2025). The findings extend the Technology Acceptance Model by linking technology-related perceptions with a learning-oriented outcome: perceived GAI support for self-regulated learning. Rather than treating acceptance as the endpoint, the model examines how attitudes toward GAI relate to students' perceptions of AI-supported learning processes. The partial mediation results indicate that ATT accounts for part, but not all, of the relationships between PEU, PU, and GAI-SRL. This extension should be interpreted as a conceptual and statistical contribution rather than evidence of a causal regulatory process.

Pedagogical and Institutional Implications

The results point to several considerations for AI-supported learning in higher education. The significant direct and indirect

relationships suggest that effective integration of Generative AI should address not only students' access to AI tools and perceptions of their usefulness, but also the ways in which students evaluate and incorporate AI into their learning processes. In particular, the partial mediation pattern suggests that favourable attitudes toward GAI are relevant to perceived AI support for self-regulated learning, although they do not represent the only pathway.

Instructors can ask students to establish learning goals before using GAI, formulate purposeful prompts, compare AI-generated responses with course materials, and explain how they verified the information. These activities keep students responsible for planning, monitoring, evaluating, and making learning decisions. This approach is consistent with the view of AI as a metacognitive and learning scaffold rather than an autonomous learning agent (Xia et al., 2023; Chiu, 2024; Weng et al., 2024). Such practices may help students use GAI as a support for learning rather than as a substitute for cognitive engagement (Li et al., 2025; Sardi et al., 2025b; Bueno-Vesga et al., 2026; Ding and Song, 2026).

At the institutional level, guidance can address transparency, verification, attribution, and appropriate AI use in learning and assessment. Faculty development should support instructors in translating these principles into learning activities and assessment practices.

Limitations and Directions for Future Research

Several limitations should be considered when interpreting the findings. First, the data came from a single higher education institution in Indonesia. Institutional and disciplinary contexts, as well as prior GAI experience, may shape students' perceptions and attitudes. Replication across institutions and disciplines is therefore needed to assess the transferability of the model.

Second, the cross-sectional design limits temporal and causal interpretation. Although mediation analysis identified significant indirect relationships, the data do not establish that PEU or PU precede ATT or that ATT subsequently changes learning regulation. Longitudinal and experimental studies are needed to examine these temporal relationships.

Third, the study relied on self-reported questionnaire data collected through a single online questionnaire. Although this approach is appropriate for examining perceptions and attitudes, it may not fully capture students' actual use of Generative AI or their observable learning-regulation processes. In particular, GAI-SRL reflects students' perceived support from Generative AI rather than direct evidence of self-regulated learning competence or observed behaviour. Future studies could combine questionnaires with AI-use logs, learning analytics, task-based assessments, observations, or interviews to capture actual AI use and learning-regulation processes.

Fourth, the use of a single self-report measurement occasion creates the potential for common-method variance. Procedural safeguards, including voluntary participation, informed consent, confidentiality, and de-identification of the analytical dataset, were applied; however, these procedures cannot completely eliminate common-method variance. The VIF

values were used to assess statistical collinearity, not as a formal test of common-method bias. Future research could reduce this concern through temporal separation of measurements, multiple data sources, behavioural indicators, or methodologically heterogeneous measures.

Finally, the model includes only four constructs and therefore does not capture all factors that may shape perceived AI support for self-regulated learning. AI literacy, prior experience, trust, perceived reliability, ethical awareness, task characteristics, and actual patterns of AI use may also be relevant. Future studies could incorporate these variables and use longitudinal, multi-institutional, and multimethod designs to examine how students' perceptions and attitudes develop over time.

CONCLUSION

This study examined the relationships among perceived ease of use, perceived usefulness, students' attitudes toward Generative AI, and perceived Generative AI support for self-regulated learning. PEU and PU were positively associated with ATT and GAI-SRL, while ATT was positively associated with GAI-SRL. Significant indirect relationships through ATT, together with significant direct relationships, indicated partial statistical mediation. The findings extend technology acceptance research by placing attitudes toward GAI within a learning-oriented framework focused on perceived AI support for self-regulated learning. They also highlight the importance of purposeful AI use, verification of AI-generated information, and continued student responsibility for learning decisions. Given the cross-sectional, self-report design and single-institution sample, the findings should be interpreted as statistical associations rather than causal effects. Future longitudinal, experimental, and multimethod research can further examine how these relationships develop over time.

ETHICAL AND INSTITUTIONAL CONSIDERATIONS

Formal approval from a separate institutional ethics committee or Institutional Review Board (IRB) was not obtained because a separate ethics review was not required under the institutional procedure applicable to this educational survey at the time of data collection. The study instead followed the institutional research-permission procedure of Universitas Negeri Padang, and written institutional permission to conduct the research was obtained through the applicable institutional procedure. Participation was voluntary, and respondents were informed about the purpose of the study before providing electronic informed consent. Respondents' names and student identification numbers (NIM) were collected solely to verify active undergraduate student status. These identifying data were not included in the analytical dataset and were deleted before statistical analysis. The analytical dataset was therefore de-identified, and the responses were treated confidentially.

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