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Why Do Students Use GenAI? Integrating the ARCS Motivation Model and UTAUT to Explain Students' Behavioral Intention and Academic Use Behavior

Didah Nurhamidah
Universitas Negeri Jakarta, Indonesia
UIN Syarif Hidayatullah Jakarta, Indonesia
ORCID: 0000-0001-7843-7833

Lutfi Syauki Faznur
Universitas Muhammadiyah Jakarta, Indonesia
ORCID: 0009-0009-8431-4464

Nuryani Nuryani
UIN Syarif Hidayatullah Jakarta, Indonesia
ORCID: 0000-0002-6824-594X

Teguh Arie Sandy
Ahli Media Consultant, Malang, Indonesia
ORCID: 0000-0003-3246-7310

Syihaabul Hudaa
Institut Teknologi dan Bisnis Ahmad Dahlan Jakarta, Indonesia
ORCID: 0000-0003-2206-6791

ABSTRACT

Generative artificial intelligence (GenAI) is becoming embedded in higher education, but adoption research often separates technology acceptance from students' motivational experience. This study integrates the ARCS Motivation Model and UTAUT to examine behavioral intention and academic GenAI use behavior among Indonesian higher education students. Data were obtained from 308 valid survey responses and analyzed using SmartPLS 4 with 5,000 bootstrap samples. Confidence ($\beta = .261$, $p < .001$), social influence ($\beta = .263$, $p = .002$), and facilitating conditions ($\beta = .282$, $p < .001$) were positively associated with behavioral intention. Behavioral intention ($\beta = .347$, $p < .001$) and facilitating conditions ($\beta = .520$, $p < .001$) were positively associated with user behavior. The model explained 65.7% of behavioral intention and 65.9% of user behavior. PLSpredict indicated positive predictive relevance for both endogenous constructs.

Keywords: academic use behavior, ARCS motivation model, behavioral intention, generative artificial intelligence, PLS-SEM, students, UTAUT

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INTRODUCTION

Generative artificial intelligence has moved from an experimental technology to a routine academic resource in a remarkably short period. Students can now request explanations, generate alternative examples, structure essays, revise language, prepare presentation content, and evaluate draft answers through conversational systems that respond instantly. This breadth distinguishes GenAI from earlier educational technologies, because the same interface can function as tutor, writing assistant, brainstorming partner, feedback provider, and answer generator. Recent reviews describe substantial opportunities for personalization, accessibility, feedback, and productivity, but they also document risks involving accuracy, bias, privacy, dependence, academic integrity, and the displacement of productive struggle (Chiu, 2022; Kasneci, 2023; Lo, 2023; Miao & Holmes, 2023).

Student adoption is therefore not a simple question of whether a tool is available. Academic use emerges from the interaction between perceived utility, ease, social expectations, access to supporting resources, and the quality of the learning experience itself. Large surveys indicate that students often value GenAI for writing, idea generation, explanation, and research support, while remaining concerned about fabricated information and the legitimacy of AI-assisted work (Baek et al., 2024; Chan & Hu, 2023). Systematic reviews likewise show that student responses vary across disciplines, institutional policies, prior experience, and the task being completed (Qian, 2025; Wu et al., 2025). A model that treats all use as a single undifferentiated act risks obscuring these differences.

Most empirical adoption studies rely on the Technology Acceptance Model, UTAUT, or UTAUT2. These frameworks have established that performance expectancy, effort expectancy, social influence, facilitating conditions, habit, hedonic motivation, and trust can explain students' willingness to adopt AI-supported technologies (Acosta-Enriquez et al., 2024; Budhathoki et al., 2024; Lai et al., 2024; Strzelecki, 2024; Zhao et al., 2025). UTAUT is particularly useful because it distinguishes intention from actual use and gives facilitating conditions a direct role in enabling behavior (Sandy et al., 2026; Venkatesh et al., 2003). Nevertheless, acceptance models primarily describe beliefs about technology. They provide a less developed account of why the learning experience attracts attention, feels personally relevant, strengthens confidence, or produces satisfaction.

The ARCS motivation model provides this complementary educational perspective. Attention concerns the capacity of an instructional experience to stimulate and sustain curiosity. Relevance reflects alignment with learners' goals, needs, prior knowledge, and future aspirations. Confidence captures expectations of control and success. Satisfaction concerns the positive consequences and sense of accomplishment that follow learning. The model has been applied across digital, blended, game-based, and technology-mediated settings, and a recent systematic review confirms its continuing value as an instructional-design framework, theoretical lens, and motivational measurement tool (Fang et al., 2024). In GenAI-supported learning, these dimensions are especially salient because prompts, responses, feedback, and adaptation shape motivation during the interaction itself.

Integrating ARCS and UTAUT addresses an important theoretical gap. UTAUT explains whether students regard GenAI as useful, manageable, socially endorsed, and practically accessible. ARCS explains whether interaction with GenAI is engaging, meaningful, confidence-building, and satisfying. These mechanisms may overlap empirically, but they are not conceptually identical. For example, a student may find GenAI easy to operate without finding its responses relevant to a learning goal. Conversely, an explanation may be highly relevant and motivating even when access is constrained by device limitations

or unreliable connectivity. Combining the frameworks permits a direct comparison of motivational and acceptance-related predictors within one structural model.

Many studies measure adoption through general intention or a single global frequency item. Such measures cannot reveal whether students primarily use GenAI to brainstorm, plan, seek information, request explanations, obtain direct answers, create written content, revise text, solve problems, or evaluate work. These activities differ in cognitive demand and pedagogical value. Editing a self-produced draft may support reflection, whereas requesting a complete answer before attempting a task may reduce independent problem solving. Recent scholarship therefore calls for more behaviorally specific analyses that connect acceptance to authentic academic practices rather than treating use as a homogeneous outcome (Bittle & El-Gayar, 2025; Qian, 2025; Wu et al., 2025).

The theoretical contribution of integrating ARCS and UTAUT lies in comparing motivational and technology-acceptance explanations within the same structural model. UTAUT emphasizes functional beliefs, social expectations, and enabling resources. ARCS emphasizes the quality of the learner's motivational experience. Recent 2026 evidence makes this integration particularly timely because researchers are increasingly examining motivation, actual use, and the intention-behavior relationship rather than treating GenAI adoption as a single outcome (Parveen et al., 2026; Tian et al., 2026).

This study responds to both gaps by integrating the four ARCS dimensions and four UTAUT dimensions in a model of behavioral intention and academic GenAI use. Academic use behavior is represented through nine activity categories: brainstorming, planning, information seeking, explanation seeking, direct answer seeking, writing and content creation, editing and revision, learning and problem-solving support, and evaluation and feedback. This structure enables the study to identify the strongest predictors of intention, compare the role of intention and facilitating conditions in reported use, and describe the academic activities in which GenAI is most prominent.

The study asks three questions. First, which ARCS and UTAUT variables are most strongly associated with students' behavioral intention to use GenAI? Second, to what extent are behavioral intention and facilitating conditions associated with academic use behavior? Third, which GenAI-supported academic activities are most strongly reported by students? The study contributes by connecting motivation design and technology acceptance, separating intention from behavior, and making the behavioral outcome more transparent. It also offers practical evidence for institutions seeking to promote productive uses rather than merely increasing adoption.

THEORETICAL BACKGROUND AND HYPOTHESES

Academic GenAI Use as a Multidimensional Behavior

Academic GenAI use is better understood as a profile of activities than as a binary condition. Students may use the same system for concept clarification, content creation, language revision, feedback, or direct answer acquisition. These activities share a technological platform but differ in purpose, learner agency, and cognitive engagement. Student-perception studies consistently identify idea generation, writing support, personalized explanation, and rapid feedback as prominent benefits, while also warning that direct answer generation may encourage dependence or obscure authorship (Chan & Hu, 2023; Cotton et al., 2024; Farrokhnia et al., 2024; Sampah et al., 2026).

The nine academic-use categories used in this study capture the principal stages of academic work. Brainstorming and planning concern idea generation and task organization. Information and explanation seeking concern knowledge access and concept clarification. Writing and content creation, editing and revision, and evaluation and feedback concern the production and refinement of academic artifacts. Learning and problem-solving support concerns scaffolded reasoning and practice. Direct answer seeking represents a distinct pattern because high use may indicate convenience but not necessarily deep learning. This differentiation supports a more critical interpretation of a high overall use score.

ARCS Motivation Dimensions

Attention is the entry point of motivated learning. GenAI can attract attention through conversational interaction, immediate responses, variation in examples, and the possibility of iterative questioning. When students experience the tool as novel and responsive, they may become more willing to continue using it. Yet attention alone can be superficial; novelty may fade, and excessive stimulation can fragment concentration. The expected relationship is positive because sustained curiosity should strengthen willingness to use the tool for future learning tasks (Fang et al., 2024; Keller, 1987; Parveen et al., 2026).

H1: Attention is positively associated with students' behavioral intention to use GenAI for academic learning.

Relevance refers to the perceived fit between GenAI support and a learner's needs, goals, prior knowledge, and academic tasks. Personalized explanations, examples adjusted to the user's level, and task-specific feedback can make learning support feel immediately applicable. Research on GenAI in education repeatedly identifies personalization and contextualized assistance as central benefits (Chiu, 2022; Gašević et al., 2023; Miao & Holmes, 2023; OECD, 2026). When responses align with students' objectives, the technology should be perceived as worth integrating into their routines.

H2: Relevance is positively associated with students' behavioral intention to use GenAI for academic learning.

Confidence concerns students' belief that they can operate GenAI purposefully, judge the quality of its output, and complete demanding tasks with appropriate support. This dimension is more demanding than basic ease of use because it includes strategic prompting, verification, control, and avoidance of overdependence. GenAI literacy research emphasizes that effective use requires users to evaluate outputs rather than accept them uncritically (Dilinika, 2026; Miao & Holmes, 2023; Qian, 2025). Students who feel capable of directing and checking the technology should show stronger intention to use it.

H3: Confidence is positively associated with students' behavioral intention to use GenAI for academic learning.

Satisfaction represents the positive evaluation that follows interaction. Students may feel satisfied when GenAI reduces confusion, improves a draft, helps them complete a task, or provides timely feedback. Positive outcomes can reinforce future use, particularly when the tool contributes to a sense of progress or achievement. Experimental evidence indicates that well-designed AI feedback can improve revision and positive learning emotions, supporting the expectation that satisfying experiences promote continued use (Meyer et al., 2024).

H4: Satisfaction is positively associated with students' behavioral intention to use GenAI for academic learning.

UTAUT Dimensions

Performance expectancy is the belief that using a technology will improve task performance. In academic settings, this includes saving time, improving understanding, enhancing writing quality, and supporting problem solving. It is frequently among the strongest predictors in technology-adoption research, including recent studies of ChatGPT and AI in higher education (Budhathoki et al., 2024; Habibi et al., 2024; Strzelecki, 2024). Students who expect clear learning and productivity gains should report

stronger intention.

H5: Performance expectancy is positively associated with students' behavioral intention to use GenAI for academic learning.

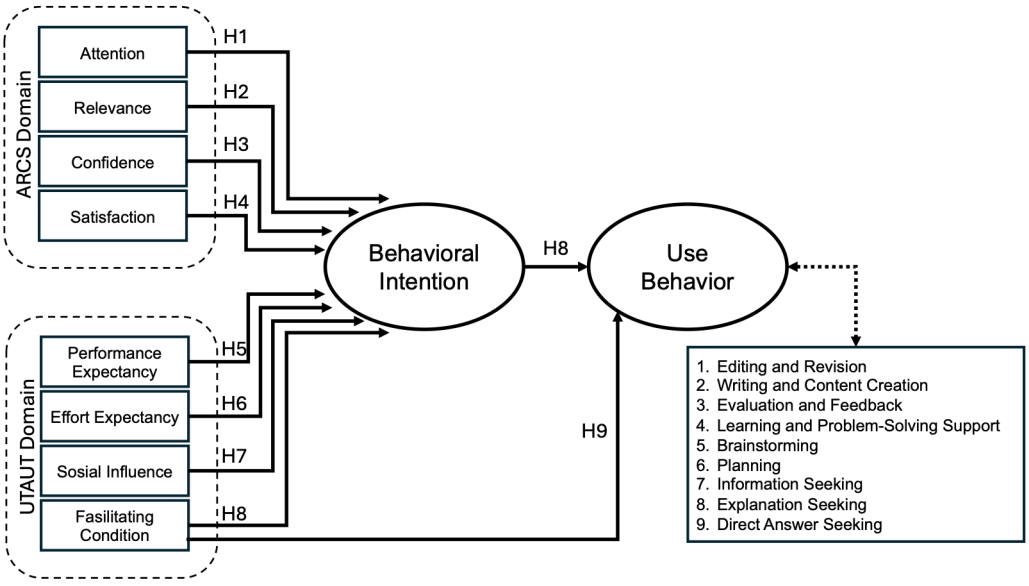
Effort expectancy concerns the perceived ease of learning and using GenAI. Conversational interfaces reduce technical barriers because students can communicate in natural language. Nevertheless, obtaining high-quality outputs still requires prompt formulation, iterative refinement, and verification. Studies of ChatGPT acceptance commonly report a positive role for perceived ease, although its effect may weaken when students already possess substantial digital experience or when usefulness dominates the decision (Acosta-Enriquez et al., 2024; Lai et al., 2024; Strzelecki, 2024).

H6: Effort expectancy is positively associated with students' behavioral intention to use GenAI for academic learning.

Social influence reflects the extent to which teachers, peers, institutions, and significant others encourage or legitimize technology use. GenAI adoption is strongly shaped by local norms because students must interpret whether AI assistance is accepted, discouraged, or permitted only for specific tasks. Clear instructor guidance can reduce uncertainty and establish responsible patterns, while peer use can normalize experimentation (Budhathoki et al., 2024; Doty & Lipien, 2024).

H7: Social influence is positively associated with students' behavioral intention to use GenAI for academic learning.

Figure 1
Proposed conceptual model



Facilitating conditions concern the devices, connectivity, access, skills, guidance, and assistance required to use GenAI. In the original UTAUT logic, these conditions directly enable use behavior, because intention cannot be translated into action when resources are absent (Parveen et al., 2026; Venkatesh et al.,

2003). In educational contexts, facilitating conditions may also shape intention by making future use appear feasible and institutionally supported. Recent adoption studies emphasize infrastructure, AI literacy, institutional policy, and support as practical conditions for responsible integration (Miao & Holmes, 2023; OECD, 2026; Zhao et al., 2025).

H8: Facilitating conditions are positively associated with students' behavioral intention to use GenAI for academic learning.
H9: Behavioral intention is positively associated with students' academic GenAI use behavior.
H10: Facilitating conditions are positively associated with students' academic GenAI use behavior.

The proposed model treats behavioral intention as the proximal motivational mechanism that translates beliefs and learning experiences into action. Facilitating conditions retain a direct path to use behavior because access and support can enable or constrain actual use independently of intention. Figure 1 presents the complete framework.

METHOD

Research Design and Participants

This study used a quantitative cross-sectional survey design to examine the relationships among motivational experiences, technology-acceptance beliefs, behavioral intention, and academic GenAI user behavior among Indonesian higher education students. Participants were recruited through the Indonesian student-oriented Facebook group "Keluh Kesah Ngampus (KKN)" (https://www.facebook.com/groups/827089962420981). The survey invitation was posted in the group, and students who were interested could voluntarily complete the questionnaire. No respondent was forced or directly pressured to participate.

Because the study did not use a complete sampling frame of Indonesian higher education students, the recruitment procedure is best described as voluntary response sampling through an online student community. The study therefore does not claim probability sampling or random sampling. The final dataset included 308 valid responses from Indonesian higher education students.

Before distributing the questionnaire, ethical clearance was granted from the National Body of Research and Innovation of the Republic of Indonesia (BRIN), a recognized national ethical committee. The study was conducted by PT. Ahli Media Consultant, which was institutionally registered with the National Research and Innovation Agency of the Republic of Indonesia (BRIN) under registration number D02607050. Participation in the survey was voluntary. Respondents were informed that they could decide whether to complete the questionnaire, and no coercion was used during recruitment. Because no separate study-specific ethics approval number was available in the submitted materials, the manuscript does not claim formal ethical clearance from BRIN.

To assess sample-size adequacy, a statistical power analysis was conducted using G*Power. The analysis used F tests with the linear multiple regression fixed-model procedure for R^2 deviation from zero, with eight predictors, an assumed effect size of $f^2 = .15$, $\alpha = .05$, and desired statistical power of .95. The analysis indicated a minimum sample requirement of 160 respondents. The final analytical sample of 308 valid responses therefore exceeded the minimum sample requirement indicated by the specified power-analysis assumptions.

Table 1 shows that 209 respondents (67.9%) were bachelor's students, 93 (30.2%) were master's students, and 6 (1.9%) were doctoral students. The sample comprised 228 men (74.0%) and 80 women (26.0%). The largest age groups were 21–23 years (45.8%) and 18–20 years (43.5%). GenAI use frequency was distributed across all five categories, with 70 respondents (22.7%) reporting use 3–5 times per week and another 70 (22.7%) reporting almost daily use.

Weekly use duration also varied. The largest category was 3–5 hours per week (24.0%), followed

by 30–59 minutes (21.4%) and 1–2 hours (20.8%). Experience with GenAI was likewise distributed across categories, with 72 respondents (23.4%) reporting 1–3 months and another 72 (23.4%) reporting 4–6 months of use.

Table 1
Respondent characteristics (N = 308)

Characteristic	n	%
Education level		
Bachelor	209	67.9
Master	93	30.2
Doctoral	6	1.9
Gender		
Male	228	74.0
Female	80	26.0
Age		
18–20 years	134	43.5
21–23 years	141	45.8
24–26 years	22	7.1
27–30 years	7	2.3
>31 years	4	1.3
Use frequency		
Less than once a month	54	17.5
1–3 times a month	60	19.5
1–2 times a week	54	17.5
3–5 times a week	70	22.7
Almost every day	70	22.7
Weekly use duration		
<30 minutes	54	17.5
30–59 minutes	66	21.4
1–2 hours	64	20.8
3–5 hours	74	24.0
>5 hours	50	16.2
Length of GenAI experience		
<1 month	50	16.2
1–3 months	72	23.4
4–6 months	72	23.4
7–12 months	60	19.5
>12 months	54	17.5

Measures and Instrument Development

The measurement instrument was self-developed based on the conceptual definitions of the ARCS Motivation Model and UTAUT and informed by relevant empirical literature on educational technology and GenAI adoption. The instrument was designed specifically for the academic GenAI context rather than directly adopting a single previously validated questionnaire. The latent variables comprised Attention, Relevance, Confidence, Satisfaction, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Behavioral Intention, and User Behavior.

All items were measured using a five-point Likert scale ranging from from 1 (strongly disagree) to 5 (strongly agree) (Cohen, 1960; Creswell & Creswell, 2023). The original item statements were written in Indonesian, and English renderings are presented in the measurement documentation for reporting

purposes. The instrument translated the conceptual meaning of each theoretical construct into statements relevant to students' academic use of GenAI.

Academic GenAI use behavior was represented by nine activity indicators: brainstorming, planning, information seeking, explanation seeking, direct answer seeking, writing and content creation, editing and revision, learning and problem-solving support, and evaluation and feedback. The activity profile was included to reveal how students used GenAI rather than merely whether they used it. The estimated SmartPLS model specified these indicators reflectively. Because the nine activities are conceptually heterogeneous, future validation should compare this specification with a formative alternative. Full item wording, theoretical sources, scale anchors, and measurement specifications are reported in Appendix A.

The item wording translated the substantive meaning of ARCS and UTAUT into the context of GenAI-supported academic learning. ARCS indicators focused on attention, goal alignment, strategic control, and satisfaction during interaction. UTAUT indicators measured perceived academic benefits, ease of interaction, social support, and the availability of devices, internet access, digital skills, institutional guidance, and assistance. The instrument therefore required assessment of reliability, convergent validity, discriminant validity, and collinearity before structural relationships could be interpreted.

Data Analysis

Partial least squares structural equation modeling was conducted using SmartPLS 4 (Hair et al., 2021; Ringle et al., 2023, 2024). The analysis followed a sequential procedure comprising measurement-model assessment, discriminant-validity assessment, structural-model assessment, hypothesis testing, and predictive assessment. Construct-level reliability and convergent validity were evaluated using Cronbach's alpha, rho_A, composite reliability, and average variance extracted (AVE). Discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT). Structural collinearity was assessed using inner VIF, and the structural model was evaluated using standardized path coefficients, R^2, adjusted R^2, and f^2.

Statistical inference used bootstrapping with 5,000 subsamples, percentile confidence intervals, two-tailed tests, and a significance level of .05. A directional hypothesis was considered supported only when the coefficient sign was consistent with the proposed direction and the bootstrap inference indicated statistical significance. Confidence intervals were considered alongside p values when making hypothesis decisions. Predictive assessment was conducted using PLSpredict at the latent-variable level. Q^2predict values, prediction errors, and comparisons with benchmark models were examined (Hair et al., 2021; Sarstedt et al., 2022).

RESULTS

Respondent Profile and Academic-Use Pattern

Students reported relatively frequent use of GenAI across all nine academic activities. Evaluation and feedback received the highest mean score (M = 4.523, SD = 0.595), followed by learning and problem-solving support (M = 4.481, SD = 0.622) and editing and revision (M = 4.471, SD = 0.544). Planning and writing and content creation also received high mean scores, while information seeking and brainstorming occupied the middle positions. Explanation seeking and direct answer seeking had the lowest mean scores, although both remained above 4.00. Overall, the pattern indicates that students reported using GenAI most frequently for evaluating, developing, and refining academic work rather than primarily seeking direct answers.

Table 2
Descriptive ranking of academic GenAI use activities

Rank	Academic GenAI Use Activity	Mean	SD	Indicator
1	Evaluation and Feedback	4.523	0.595	BU9
2	Learning and Problem-Solving Support	4.481	0.622	BU8
3	Editing and Revision	4.471	0.544	BU7
4	Planning	4.412	0.672	BU2
5	Writing and Content Creation	4.393	0.654	BU6
6	Information Seeking	4.360	0.706	BU3
7	Brainstorming	4.347	0.640	BU1
8	Explanation Seeking	4.299	0.792	BU4
9	Direct Answer Seeking	4.244	0.788	BU5

As shown in Table 2, evaluation and feedback recorded the highest mean score, followed by learning and problem-solving support and editing and revision. These results indicate that students commonly used GenAI across activities involving evaluation, problem solving, and refinement of academic work. Direct answer seeking recorded the lowest mean, but its relatively high score indicates that answer-oriented use remained part of students' reported academic practices. The relatively larger standard deviations for explanation seeking and direct answer seeking also indicate greater variation among respondents in these activities.

Measurement Model Assessment

Table 3 presents construct-level reliability and convergent validity. Cronbach's alpha ranged from .771 to .881, rho_A from .792 to .886, composite reliability from .832 to .914, and AVE from .521 to .680. All constructs therefore exceeded the conventional AVE reference of .50, while the reliability coefficients indicated adequate internal consistency.

Table 3
Reflective measurement model assessment

Construct	Cronbach's α	rho_A	CR	AVE
Attention	0.770	0.792	0.832	0.590
Behavioral Intention	0.881	0.886	0.914	0.680
Confidence	0.877	0.884	0.902	0.536
Effort Expectancy	0.855	0.866	0.888	0.521
Facilitating Condition	0.801	0.851	0.855	0.552
Performance Expectancy	0.822	0.861	0.868	0.568
Relevance	0.874	0.877	0.901	0.535
Satisfaction	0.775	0.803	0.834	0.524
Social Influence	0.851	0.857	0.885	0.592
User Behavior	0.878	0.883	0.902	0.526

Discriminant Validity

Table 4 reports HTMT values for the latent variables. The values ranged from .644 to .844, and all observed pairwise values remained below the conservative reference of .85. The highest value was .844 for Facilitating Condition and Behavioral Intention, followed by .837 for Facilitating Condition and Effort Expectancy and .831 for User Behavior and Effort Expectancy. These results provide construct-level evidence that the latent variables remained empirically distinguishable in the estimated model.

Table 4

Heterotrait-monotrait ratio of correlations

Construct	AT	BI	CO	EE	FC	PE	RE	SA	SI	UB
AT										
BI	0.761									
CO	0.746	0.788								
EE	0.825	0.787	0.806							
FC	0.807	0.844	0.773	0.767						
PE	0.712	0.644	0.694	0.703	0.827					
RE	0.723	0.707	0.793	0.760	0.773	0.752				
SA	0.808	0.661	0.795	0.753	0.829	0.806	0.722			
SI	0.804	0.817	0.806	0.738	0.769	0.747	0.723	0.792		
UB	0.827	0.818	0.810	0.831	0.793	0.676	0.742	0.701	0.834	

Structural Relationships and Hypothesis Testing

Table 5 presents the structural coefficients, inner VIF values, effect sizes, confidence intervals, and hypothesis decisions. Inner VIF values ranged from 2.168 to 2.878 for predictors of Behavioral Intention and were 2.223 for both predictors of User Behavior. These values were below the common tolerance reference of 5 and also below the more conservative preference of 3, indicating that the structural paths could be interpreted without the high collinearity observed in the earlier model.

Table 5

Structural paths and hypothesis tests

H	Structural Path	Inner VIF	β	SD	t	p	95% CI	f^2	Decision
H1	Attention -> Behavioral Intention	2.780	0.013	0.079	0.163	0.871	[-0.134, 0.176]	0.000	Not supported
H2	Relevance -> Behavioral Intention	2.168	0.077	0.069	1.118	0.264	[-0.054, 0.217]	0.005	Not supported
H3	Confidence -> Behavioral Intention	2.355	0.261	0.075	3.469	< .001	[0.114, 0.411]	0.059	Supported
H4	Satisfaction -> Behavioral Intention	2.663	-0.027	0.064	0.423	0.672	[-0.153, 0.097]	0.001	Not supported
H5	Performance Expectancy -> Behavioral Intention	2.637	-0.022	0.068	0.319	0.749	[-0.143, 0.127]	0.001	Not supported
H6	Effort Expectancy -> Behavioral Intention	2.571	0.053	0.072	0.735	0.462	[-0.084, 0.199]	0.002	Not supported
H7	Social Influence -> Behavioral Intention	2.327	0.263	0.087	3.043	0.002	[0.083, 0.426]	0.047	Supported
H8	Facilitating Condition -> Behavioral Intention	2.878	0.282	0.072	3.930	< .001	[0.132, 0.416]	0.060	Supported
H9	Behavioral Intention -> User Behavior	2.223	0.347	0.064	5.418	< .001	[0.227, 0.479]	0.159	Supported
H10	Facilitating Condition -> User Behavior	2.223	0.520	0.063	8.302	< .001	[0.390, 0.634]	0.356	Supported

Confidence, social influence, and facilitating condition were positively associated with Behavioral

Intention. Confidence had β = .261 (p < .001, 95% CI [.112, .407], f^2 = .059), social influence had β = .263 (p = .002, 95% CI [.083, .426], f^2 = .047), and facilitating condition had β = .282 (p < .001, 95% CI [.132, .416], f^2 = .060). Attention, relevance, satisfaction, performance expectancy, and effort expectancy were not statistically significant. The negative coefficients for performance expectancy (β = −.022) and satisfaction (β = −.027) were small and not statistically significant, so they do not provide evidence of substantive negative relationships.

Behavioral Intention was positively associated with User Behavior (β = .347, p < .001, 95% CI [.227, .479], f^2 = .159). Facilitating Condition had the strongest direct association with User Behavior (β = .520, p < .001, 95% CI [.390, .634], f^2 = .356). This pattern indicates that the enabling conditions surrounding GenAI use had a stronger direct association with reported user behavior than behavioral intention alone.

Explanatory Power and Model Fit

As reported in Table 6, the model explained 65.7% of the variance in Behavioral Intention (R^2 = .657; adjusted R^2 = .647) and 65.9% of the variance in User Behavior (R^2 = .659; adjusted R^2 = .656). The corresponding Q^2predict values were .616 for Behavioral Intention and .641 for User Behavior, indicating positive latent-variable predictive relevance in the PLSpredict assessment. These predictive results should be interpreted as evidence from the specified prediction procedure rather than as proof of out-of-sample predictive performance beyond the reported PLSpredict assessment.

Supplementary fit diagnostics were SRMR = 0.088 for the saturated model and 0.089 for the estimated model. NFI values were 0.538 and 0.536, respectively. These indices are treated as supplementary diagnostics rather than as decisive evidence of model quality.

Table 6

Explanatory power and predictive relevance

Endogenous Construct	R^2	Adjusted R^2	Q^2predict
Behavioral Intention	0.657	0.647	0.616
User Behavior	0.659	0.656	0.641

Specific Indirect Effects

Table 7 reports specific indirect relationships through Behavioral Intention. Confidence showed a significant positive indirect relationship with User Behavior (β = .091, p = .008, 95% CI [.034, .166]). Facilitating Condition also showed a significant positive indirect relationship through Behavioral Intention (β = .098, p = .001, 95% CI [.044, .161]). Social Influence had a significant positive indirect relationship (β = .091, p = .005, 95% CI [.030, .157]). The remaining specific indirect relationships were not statistically significant.

Table 7

Specific indirect effects through behavioral intention

Indirect Relationship	Effect	SD	t	p	95% CI	Interpretation
Attention -> User Behavior	0.004	0.028	0.158	0.875	[-0.049, 0.064]	Not statistically significant
Confidence -> User Behavior	0.091	0.034	2.670	0.008	[0.034, 0.166]	Significant indirect effect
Effort Expectancy -> User Behavior	0.018	0.026	0.699	0.485	[-0.028, 0.074]	Not statistically significant
Facilitating Condition -> User Behavior	0.098	0.030	3.273	0.001	[0.044, 0.161]	Significant indirect effect
Performance Expectancy -> User Behavior	-0.008	0.024	0.313	0.754	[-0.045, 0.050]	Not statistically significant
Relevance -> User Behavior	0.027	0.026	1.028	0.304	[-0.018, 0.085]	Not statistically significant
Satisfaction -> User Behavior	-0.009	0.023	0.406	0.685	[-0.059, 0.033]	Not statistically significant
Social Influence -> User Behavior	0.091	0.032	2.816	0.005	[0.030, 0.157]	Significant indirect effect

Final PLS-SEM Model

Figure 2 summarizes the final latent-variable structural model. The strongest direct relationship was Facilitating Condition to User Behavior (β = .520), followed by Behavioral Intention to User Behavior (β = .347). For Behavioral Intention, facilitating condition, social influence, and confidence were the most prominent statistically significant predictors. The R^2 values were .657 for Behavioral Intention and .659 for User Behavior.

Figure 2

Final PLS-SEM structural model



DISCUSSION

Confidence, Social Influence, and Facilitating Conditions as Predictors of Intention

The results indicate that Confidence, Social Influence, and Facilitating Condition were the statistically significant positive predictors of Behavioral Intention. Confidence had a meaningful positive association with intention, which supports the ARCS proposition that perceived capability is relevant to motivational persistence. In GenAI settings, confidence is not limited to operational familiarity. It also reflects the ability to direct the system, evaluate output, and maintain control over academic decisions. This interpretation is consistent with current GenAI adoption research that highlights competence and knowledge as relevant to continued academic use (Dias et al., 2026; Du et al., 2026).

Social Influence also showed a positive relationship with Behavioral Intention. This finding is consistent with UTAUT and with recent higher education studies showing that peer expectations, instructor practices, and institutional signals can shape students' willingness to use GenAI (Du et al., 2026; Parveen et al., 2026). The finding suggests that students' intention is partly embedded in their social and educational environment rather than formed solely from personal evaluations of the technology.

Facilitating Condition was positively associated with both Behavioral Intention and User Behavior. Its direct relationship with User Behavior was the strongest structural coefficient in the model. This result is consistent with UTAUT's distinction between intention and the enabling conditions required to translate intention into actual use. Recent GenAI adoption research also emphasizes the importance of infrastructure, access, and institutional support in shaping enacted use (Du et al., 2026; Tian et al., 2026).

Behavioral Intention and the Intention-Behavior Relationship

Behavioral Intention was positively associated with User Behavior, supporting H9. The effect was moderate in magnitude relative to the other structural relationships and remained statistically significant under the 5,000-sample bootstrap procedure. This finding supports the UTAUT distinction between intention and behavior, while also showing that intention alone does not account for the entire behavioral outcome. The continued relevance of the intention-behavior distinction is also evident in current research that explicitly investigates discrepancies between students' stated intention and actual or self-reported GenAI use (Du et al., 2026; Parveen et al., 2026).

The stronger coefficient for Facilitating Condition suggests that actual academic GenAI use is associated not only with willingness but also with the practical environment in which students operate. This result is important for higher education because intention-building interventions may have limited practical value when students face inadequate access, limited skills, or unclear institutional guidance.

Non-Significant Relationships and Small Negative Coefficients

Attention, Relevance, Satisfaction, Performance Expectancy, and Effort Expectancy were not statistically significant predictors of Behavioral Intention in the final model. Performance Expectancy and Satisfaction had small negative coefficients, but their confidence intervals included zero and their p values were well above .05. These findings should therefore not be interpreted as evidence that usefulness or satisfaction reduces intention. Instead, they indicate that these constructs did not make statistically distinguishable unique contributions within the integrated predictor set.

The non-significant result for Performance Expectancy is consistent with recent evidence showing that students who already use GenAI may not rely on usefulness beliefs alone when deciding whether to continue using the technology (Du et al., 2026). Similarly, the non-significant Effort Expectancy relationship suggests that ease of access may be less discriminating when GenAI tools are already familiar to the student population. This interpretation should remain bounded because the cross-sectional design

does not allow temporal claims about how acceptance beliefs develop.

The current model also indicates that the integration of conceptually related constructs may reduce the unique contribution of individual predictors even when those constructs remain relevant at a bivariate level. Importantly, the structural VIF values in the final model were below 3, so the earlier concern about severe structural collinearity was substantially reduced. The results should therefore be interpreted as conditional associations within the integrated ARCS-UTAUT framework rather than isolated zero-order relationships.

Theoretical Implications

The study contributes to GenAI adoption research by integrating a motivational learning framework with a technology-acceptance framework at the latent-variable level. The results suggest that Confidence can provide a motivational explanation for intention that complements the external and functional determinants represented by UTAUT. The significant roles of Social Influence and Facilitating Condition also support the continuing relevance of the social and contextual dimensions of technology acceptance. Current 2026 research is increasingly moving toward such integrated explanations, including work that combines UTAUT3 and ARCS in higher education GenAI adoption (Parveen et al., 2026; Tian et al., 2026).

The strong direct association between Facilitating Condition and User Behavior provides a second theoretical implication. The findings suggest that the path from acceptance to use is not adequately represented by Behavioral Intention alone. This aligns with research emphasizing the intention-behavior gap and with current empirical work that separates intention and enacted academic GenAI use (Du et al., 2026; Sampah et al., 2026). The model therefore supports a more differentiated account in which motivational readiness and enabling conditions operate through partly distinct routes.

Practical Implications

Universities should treat facilitating conditions as part of educational provision rather than only as a technical concern. Students need reliable access, appropriate institutional guidance, digital skills, and support for evaluating AI-generated information. These conditions can affect both intention and use behavior. Policies should also provide clear expectations for appropriate academic GenAI use so that students can interpret institutional signals consistently.

Confidence should also be supported through practical AI literacy. Training should focus on prompting, verification, source comparison, revision, disclosure, and decisions about when GenAI should not be used. These practices are consistent with current evidence that GenAI integration requires both functional skills and critical judgment (Li & Awang, 2026).

Limitations and Future Research

First, the cross-sectional design supports interpretation of associations and prediction within the estimated model but not causal inference. Longitudinal research should examine whether the roles of motivation, social influence, facilitating conditions, and behavioral intention change as students gain experience with GenAI and as institutional policies evolve.

Second, the voluntary response sampling procedure limits statistical generalization beyond the participating respondents. The sample was drawn from an Indonesian student-oriented online community and therefore may not represent all higher education students in Indonesia. Future research should use probability-based or carefully stratified sampling across institutions, disciplines, study levels, and regional contexts.

Third, the instrument was self-developed from established theoretical constructs and prior literature. Although the construct-level measurement results showed acceptable reliability, convergent

validity, and discriminant validity, independent replication remains necessary to establish the stability of the measurement structure in other samples. Future studies should compare the measurement performance across institutions and educational contexts.

Finally, predictor and outcome measures were obtained through the same survey occasion. The study therefore cannot rule out common method bias. Future research should consider temporal or source separation, marker variables, or other appropriate procedural and statistical diagnostics. Additional robustness work could also examine measurement invariance, nonlinear relationships, and endogeneity when theory and data warrant those analyses.

CONCLUSION

This study examined students' academic GenAI use through an integrated ARCS-UTAUT model. Confidence, Social Influence, and Facilitating Condition were positively associated with Behavioral Intention, while Behavioral Intention and Facilitating Condition were positively associated with User Behavior. Facilitating Condition showed the strongest direct relationship with User Behavior. The model explained 65.7% of Behavioral Intention and 65.9% of User Behavior, and latent-variable predictive assessment indicated positive predictive relevance for both endogenous constructs.

The findings support a view of GenAI adoption that combines motivational capability, social context, and enabling conditions. The results also reinforce the importance of distinguishing intention from actual use behavior. For higher education, the central implication is that responsible GenAI integration requires both students' confidence in using the technology purposefully and an environment that makes appropriate use feasible. Further longitudinal and multi-institutional research should test the stability of these relationships and strengthen the evidence for generalization.

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Didah Nurhamidah is currently a PhD student in Applied Linguistics at Universitas Negeri Jakarta (UNJ), Indonesia. She is also a lecturer in the Indonesian Language and Literature Education Program, Faculty of Tarbiyah and Teacher Training, UIN Syarif Hidayatullah Jakarta. Her academic interests focus on Indonesian language education, teaching, and research. Email: didah.nurhamidah@mhs.unj.ac.id

Lutfi Syauki Faznur is a PhD student in Applied Linguistics at Universitas Negeri Jakarta (UNJ), Indonesia. He is also a lecturer in the Indonesian Language and Literature Education Program, Faculty of Education, Universitas Muhammadiyah Jakarta (UMJ). His academic interests include language education, Indonesian literature, and linguistic studies. Email: lutfisyauki@umj.ac.id

Nuryani Nuryani, holds a doctoral degree (PhD). She is a senior lecturer in the Indonesian Language and Literature Education Program at UIN Syarif Hidayatullah Jakarta, Indonesia. Her research interests include sociolinguistics, anthropological linguistics, forensic linguistics, and psycholinguistics. Email: nuryani@uinjkt.ac.id

Teguh Arie Sandy is an Education Consultant and Researcher specializing in educational technology, multimedia learning, e-learning, mobile learning, and artificial intelligence in education. His research interests also include sentiment analysis, bibliometric analysis, systematic literature reviews, and meta-analysis. Email: teguholix@gmail.com

Syihaabul Hudaa is a PhD student, lecturer, and researcher specializing in Indonesian language education and applied linguistics. He is affiliated with Institut Teknologi dan Bisnis Ahmad Dahlan Jakarta, Indonesia. His research interests include language education, applied linguistics, educational technology, and teaching innovation. He is also actively involved in academic publishing and scholarly research. Email: hudaasyihaabul@gmail.com

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Appendix A. Constructs and Questionnaire Items

The instrument contained 78 items. ARCS, UTAUT, and behavioral-intention items used a five-point agreement scale from 1 (strongly disagree) to 5 (strongly agree).

Table A1

Constructs and questionnaire items.

Construct	Code	Item question
Attention	AT1	Using GenAI for learning captures my attention.
	AT2	Using GenAI arouses my curiosity about the topics I am learning.
	AT3	Using GenAI helps me maintain my attention during learning activities.
	AT4	Using GenAI makes learning activities more interesting.
	AT5	GenAI encourages me to explore learning topics more deeply.
	AT6	The responses generated by GenAI keep me engaged in learning activities.
	AT7	Using GenAI reduces my boredom during learning activities.
	AT8	Using GenAI encourages me to ask more questions about the subject.
Relevance	RE1	Using GenAI meets my learning needs.
	RE2	Using GenAI helps me achieve my learning goals.
	RE3	The information provided by GenAI is relevant to the subjects I study.
	RE4	GenAI can provide explanations that match my level of understanding.
	RE5	GenAI can adapt its explanations to my learning preferences.
	RE6	Using GenAI helps me connect learning materials with real-life situations.
	RE7	GenAI provides learning support that is relevant to my academic tasks.
	RE8	Using GenAI is relevant to the skills I need for future study or work.
Confidence	CO1	I am confident that I can use GenAI effectively for learning.

Construct	Code	Item question
	CO2	I can use GenAI to support my learning goals.
	CO3	I can decide when GenAI should be used in my learning activities.
	CO4	I can provide appropriate instructions or prompts to GenAI.
	CO5	I can evaluate whether GenAI-generated information is useful for my learning.
	CO6	I can identify inaccurate or inappropriate responses generated by GenAI.
	CO7	I can complete challenging academic tasks with appropriate support from GenAI.
	CO8	I can use GenAI without becoming overly dependent on it.
Satisfaction	SA1	I am satisfied with my learning experience when using GenAI.
	SA2	I am satisfied with the learning support provided by GenAI.
	SA3	Using GenAI makes learning more enjoyable for me.
	SA4	I feel satisfied when GenAI helps me understand difficult material.
	SA5	Using GenAI gives me a sense of achievement in learning.
	SA6	I feel positive after using GenAI to complete a learning activity.
	SA7	The feedback provided by GenAI makes my learning experience more rewarding.
	SA8	Overall, using GenAI provides a satisfying learning experience.
Performance Expectancy	PE1	Using GenAI improves my learning performance.
	PE2	Using GenAI helps me complete academic tasks more effectively.
	PE3	Using GenAI helps me complete academic tasks more quickly.
	PE4	Using GenAI improves the quality of my academic work.
	PE5	Using GenAI helps me understand learning materials better.
	PE6	Using GenAI increases my productivity in learning activities.
	PE7	GenAI is useful for solving problems related to my schoolwork.
	PE8	Overall, GenAI is beneficial for my learning activities.
Effort Expectancy	EE1	Learning how to use GenAI is easy for me.
	EE2	My interaction with GenAI is clear and understandable.
	EE3	It is easy for me to become skillful at using GenAI.
	EE4	I find GenAI easy to use for learning activities.
	EE5	It is easy for me to enter instructions or prompts into GenAI.
	EE6	It is easy for me to obtain the information I need from GenAI.
	EE7	Using GenAI for learning does not require excessive effort.
	EE8	I can use GenAI for learning without needing extensive technical training.
Social Influence	SI1	My teachers support the appropriate use of GenAI for learning.
	SI2	My teachers encourage me to use GenAI responsibly.
	SI3	My classmates think that using GenAI can support learning.
	SI4	My classmates influence my decision to use GenAI for learning.
	SI5	People who are important to me support my use of GenAI for learning.
	SI6	My school supports the appropriate use of GenAI in learning activities.
	SI7	Students in my school commonly use GenAI for learning activities.
	SI8	The opinions of people around me influence my use of GenAI.
Facilitating Conditions	FC1	I have access to a suitable device for using GenAI.
	FC2	I have adequate internet access for using GenAI.

Construct	Code	Item question
	FC3	I have access to GenAI applications that support my learning.
	FC4	I have the digital skills required to use GenAI.
	FC5	I can obtain assistance when I experience difficulties using GenAI.
	FC6	My teachers provide guidance on how to use GenAI appropriately.
	FC7	My school provides adequate guidance for the responsible use of GenAI.
	FC8	The learning environment at my school supports the use of GenAI.
Behavioral Intention	BI1	I intend to continue using GenAI for learning.
	BI2	I plan to use GenAI regularly for school-related learning activities.
	BI3	I expect to use GenAI when it is appropriate for my learning.
	BI4	I intend to increase my use of GenAI when it supports my academic work.
	BI5	I intend to make GenAI part of my future learning activities.
GenAI Use Behavior	BU1	I use GenAI to generate ideas for assignments or projects.
	BU2	I use GenAI to create outlines or plans before completing academic tasks.
	BU3	I use GenAI to find information related to the topics I am learning.
	BU4	I use GenAI to obtain explanations of learning materials that I do not understand.
	BU5	I use GenAI to obtain direct answers to academic questions or assignments.
	BU6	I use GenAI to develop reports, essays, articles, or presentation content.
	BU7	I use GenAI to edit, revise, or improve my academic writing.
	BU8	I use GenAI to support me in solving academic problems or completing practice questions.
	BU9	I use GenAI to check my work, identify errors, or obtain feedback.