



Unpacking the negative effects of generative AI on student motivation and procrastination

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ABSTRACT

Background: The rapid integration of Generative Artificial Intelligence (GenAI) in higher education has reshaped how students engage with academic work. While GenAI improves efficiency and accessibility, concerns arise regarding its effects on cognitive engagement and self-regulation.

Purpose: This study examined how Ease of Internet Access (EIA) and Frequency of GenAI Use (FGAI) influence Learning Motivation (LM), with Academic Procrastination (AP) as a mediating variable.

Method: A total of 205 undergraduate students from Politeknik AKA Bogor completed standardized questionnaires adapted to GenAI-related learning. Data were analyzed using multiple regression, mediation analysis based on Baron and Kenny's framework, and multi-group confirmatory factor analysis (MGCFA).

Findings: The results showed EIA and FGA did not significantly predict LM ($R^2 = .006$; $p > .05$). EIA significantly predicted AP ($\beta = .146$, $p = .039$), and AP negatively predicted LM ($\beta = -.603$, $p < .001$). Mediation analysis confirmed a significant indirect effect of EIA on LM through AP (Sobel = -2.075 , $p = .038$). MGCFA supported configural and metric invariance across GenAI-use groups ($\Delta CFI = .003$), with partial scalar invariance achieved.

Implication: These findings indicate that digital accessibility may indirectly reduce motivation by increasing procrastination, emphasizing the importance of self-regulation and guided AI integration in higher education.

KEYWORDS

Generative AI; academic procrastination; learning motivation; self-regulated learning; higher education

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Introduction

The digital transformation in higher education has fundamentally reshaped how students access, process, and complete academic tasks (Duhaylungsod & Chavez, 2023). One significant aspect of this shift is the emergence of Generative Artificial Intelligence (GenAI), which facilitates instant responses, structured arguments, and even complete academic essays (Duhaylungsod & Chavez, 2023; Pokkakillath & Suleri, 2023). While GenAI offers quick access to knowledge and information, its excessive use can negatively impact students' learning behaviors (Pokkakillath & Suleri, 2023). Farrelly & Baker (2023) highlighted that relying on GenAI without active learning strategies tends to reduce cognitive engagement. Supporting this, a survey by Akinwalere & Ivanov (2022) revealed that while 61% of students used GenAI to complete assignments, only 23% employed it as a tool for long-term learning.

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Learning motivation is a critical factor in academic success and can be influenced by both internal and external elements. In the digital era, students' motivation is shaped not only by individual intentions but also by the availability and ease of access to information and technology, including GenAI (Abd-alrazaq et al., 2023). The instant nature of GenAI may diminish intrinsic motivation, especially when students rely on it to complete tasks without understanding the underlying material (Cui & Alias, 2024). Lai et al. (2025) emphasized that the illusion of efficiency afforded by technology can hinder self-reflection and the development of learning regulation strategies. Furthermore, study by Zapata et al. (2024) confirmed that AI-generated feedback often creates a false sense of satisfaction, which undermines students' drive for critical evaluation.

In addition to learning motivation, academic procrastination emerges as a relevant behavioral consequence of GenAI usage. Procrastination refers to the conscious delay in completing academic tasks, which is exacerbated by digital convenience and the perception that tasks can be done at the last minute. Adiyono et al. (2025) found that students who frequently rely on GenAI are more prone to academic procrastination. This tendency reflects not merely poor time management, but also weakened self-control in navigating technology-driven learning environments. Over time, such patterns may disrupt learning rhythms, reduce academic achievement, and compromise students' academic resilience (Rahman et al., 2023). Xu et al. (2024) further supported this view, identifying procrastination and critical reflection as mediating mechanisms explaining how teacher autonomy support affects students' assessment literacy.

To date, few studies have integrated the relationship between digital accessibility, GenAI use, academic procrastination, and learning motivation within a unified model. Mediation analysis is essential to uncover indirect pathways from contextual variables to learning outcomes, particularly in higher education. The seminal work of Baron and Kenny (1986) provides a widely adopted framework for establishing mediation through three-step regression analysis in educational psychology. Xu et al. (2024) validated a chain mediation model where self-efficacy and critical reflection jointly mediated the relationship between teacher autonomy support and assessment literacy, reinforcing its relevance in the digital learning context.

This study aims to examine the influence of Ease of Internet Access (EIA) and Frequency of Generative AI Use (FGAI) on Learning Motivation (LM), with Academic Procrastination (AP) serving as a mediating variable. A total of 205 students from Politeknik AKA Bogor participated in this study using standardized instruments. A quantitative approach was applied through linear regression and mediation analysis to assess the structural pathways among variables. The findings are expected to contribute empirically to self-regulated learning theory and offer practical recommendations for higher education institutions in designing adaptive and ethical AI literacy policies. By adopting a systematic scientific approach, this research seeks to build new insights into AI-based digital learning and its implications for students' academic well-being.

The use of generative AI in student learning: Generative AI (GenAI) has become a critical component in academic practices among students in the post-pandemic era. A study by Akinwalere and Ivanov (2022) found that 61% of students reported using GenAI to complete academic tasks, yet only 23% used it as a tool for deep learning. This indicates a shift in learning orientation from process-based learning to outcome-oriented approaches facilitated by technology. Rather than enhancing understanding, GenAI is often used as a shortcut to meet deadlines, posing potential risks when not accompanied by strong self-regulation. Farrelly and Baker (2023) observed that while GenAI increases access to information, it simultaneously decreases students' cognitive engagement. When students use technology as a substitute for thinking rather than as a supportive tool, learning quality tends to decline. In this context, the

instructor's role as a critical facilitator becomes increasingly important to guide the strategic and pedagogical use of GenAI. Without pedagogical integration, GenAI use may lead students to lose conceptual grounding in the material. Therefore, technology literacy strategies based on ethical learning practices are essential.

Zapata et al. (2024) support these findings by showing that students often feel satisfied with AI-generated feedback without engaging in deeper reflection. This superficial satisfaction reduces students' motivation to revise and improve their academic work. Such disengagement must be addressed within active learning environments. In education, AI should serve not only as a mechanical aid but also as a reflective tool that stimulates cognitive development.

Academic procrastination is one manifestation of self-regulation failure that is increasingly relevant in digital learning environments. Students who habitually delay assignments often perceive that technologies like GenAI enable last-minute task completion. Mohammed and Khalid (2025) confirmed that excessive use of GenAI strengthens this procrastinatory tendency as a form of pseudo-adaptive strategy. This behavior is reinforced when students perceive minimal consequences for their actions, making procrastination a persistent habit that negatively impacts academic performance over time. Non-reflective use of technology further diminishes the urgency to start or complete assignments independently. Students using GenAI tend to delay cognitive engagement, believing that final outputs can be generated instantly (Mohammed & Khalid, 2025). Dependence on AI thus evolves from being an academic aid into a tool for task avoidance. This indicates that unregulated technology use may reinforce dysfunctional learning behaviors. Within the self-regulated learning framework, academic procrastination serves as an internal barrier to achieving learning goals. If left unchecked, it may erode learning motivation and lead to recurring academic failure. Therefore, technology should be viewed critically—not as the sole cause, but as a trigger embedded in a broader behavioral system.

Mediation framework in digital learning contexts: Baron and Kenny (1986) introduced an analytical model to help researchers understand the mediating role of variables in explaining the relationship between predictors and outcomes. This model requires three conditions: (1) The predictor must influence the mediator, (2) the mediator must influence the outcome, and (3) the direct effect of the predictor on the outcome must weaken when the mediator is controlled. Applications of this mediation model in digital learning have been explored in contemporary studies, particularly those examining how AI affects students' self-efficacy and critical reflection. Xu et al. (2024) demonstrated that both constructs acted as mediators in the relationship between teacher autonomy support and students' assessment literacy. Their findings highlight that psychological factors serve as transitional mechanisms linking external influences to learning outcomes. In the context of GenAI, academic procrastination is considered a comparable mediating variable. Taken together, previous studies indicate the potential mediating role of academic procrastination in the relationship between digital technology exposure and learning motivation, particularly in the context of GenAI adoption. This study aims to test the hypothesis that ease of internet access and the frequency of Generative AI use influence learning motivation indirectly through academic procrastination among undergraduate students.

Method

This study employed a quantitative approach using an explanatory correlational design to explore the relationships (Creswell & Creswell, 2018) among Ease of Internet Access (EIA), Frequency of Generative AI Use (FGAI), Academic Procrastination (AP), and Learning Motivation (LM). The primary objective was to examine whether AP mediates the relationship between EIA

and FGAI on LM. This single mediation model was constructed based on the framework by Baron and Kenny (1986) and analyzed using stepwise linear regression and the Sobel test. Data collection was conducted over a two-week period during the odd semester of the 2024/2025 academic year, with a total of 205 undergraduate students from Politeknik AKA Bogor. This study received institutional ethical approval from Politeknik AKA Bogor under official letter number B/19/BPSDM/AKA/PL/III/2026 issued by the Director of Politeknik AKA Bogor, and all participants provided informed consent prior to data collection.

Ethical Considerations

The research protocol was reviewed and approved by the Senate of Politeknik AKA Bogor. Participation was voluntary, and all participants provided informed consent prior to completing the questionnaire. The study involved no experimental manipulation and posed minimal risk to participants; responses were recorded anonymously and used solely for research purposes.

Sample

The sample comprised 205 undergraduate students from Politeknik AKA Bogor who had prior experience using Generative Artificial Intelligence (GenAI) in academic activities. Participants were selected using a non-probability convenience sampling approach with clearly defined inclusion criteria: (1) Active enrollment in at least the third semester, (2) prior experience using GenAI tools (e.g., ChatGPT, Bard, or equivalent platforms) for academic purposes, and (3) voluntary participation. Participants were drawn from several study programs, including Analytical Chemistry, Food Quality Control, Industrial Waste Management, and Food Nanotechnology, with ages ranging from 19 to 23 years. Although the questionnaire was administered using an online platform (Google Forms), data collection was conducted during scheduled class sessions. Participants were instructed to complete the questionnaire in class under direct guidance from the researcher, using their own devices. This procedure was adopted to ensure participant eligibility, maintain a consistent data collection context, and minimize self-selection bias commonly associated with unsupervised online surveys.

Instrument

Learning motivation was measured using a 20-item questionnaire adapted from the Academic Motivation Scale developed by Akram and Li (2024) and contextualized for Generative AI-supported learning. The instrument assessed students' interest, enthusiasm, persistence, autonomy, and sense of responsibility in academic activities when using Generative AI tools. All items were unfavorable statements designed to capture potential motivational decline associated with GenAI reliance, with sample items including "I feel less motivated to complete assignments independently because Generative AI provides answers easily" and "Dependence on Generative AI reduces my curiosity about the learning material." Responses were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), where higher scores indicated lower levels of learning motivation. Content validity was confirmed by three experts in educational psychology and learning technologies, and the instrument demonstrated high internal consistency (Cronbach's $\alpha = .89$). Academic procrastination was measured using a 20-item questionnaire adapted from the Academic Procrastination Scale developed by Yockey (2016) and contextualized for Generative AI-assisted learning. The instrument assessed students' tendencies to delay academic tasks due to perceived efficiency, reduced urgency, and reliance on GenAI support. Sample items included statements such as "I tend to delay starting assignments because I believe Generative AI can help me complete them quickly" and "Using

Generative AI makes me more relaxed about completing tasks near the deadline.” All items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating greater levels of academic procrastination. The instrument demonstrated satisfactory content validity and high internal consistency (Cronbach’s $\alpha = .87$).

Frequency of Generative AI Use (FGAI)

The frequency of Generative AI use was measured using a single self-report item assessing how often students utilized GenAI tools (e.g., ChatGPT, Bard, or similar platforms) for academic purposes. Responses were rated on a three-point ordinal scale: 1 = Occasionally, 2 = Frequently, and 3 = Very Frequently. Higher scores indicate more frequent use of GenAI in academic activities.

Ease of Internet Access (EIA)

Ease of Internet Access (EIA) was measured using a single self-assessment item asking participants to rate their perceived ease of accessing the internet for academic purposes. Responses were categorized as Difficult, Easy, or Very Easy, reflecting increasing levels of perceived accessibility. The Difficult category referred to limited or unstable access that frequently interfered with academic activities, whereas Easy indicated adequate access with occasional constraints during learning tasks. The Very Easy category represented stable and unrestricted access that allowed continuous use of online academic resources without noticeable barriers. This perception-based measure was employed to capture students’ experiential access rather than objective technical indicators such as bandwidth capacity or infrastructure.

Learning Motivation (LM)

Learning motivation was measured using a 20-item questionnaire adapted from the Academic Motivation Scale (Akram & Li, 2024) and contextualized for GenAI-supported learning. The instrument assessed students’ interest, persistence, autonomy, and responsibility when using GenAI tools. All items were phrased as unfavorable statements to capture potential motivational decline associated with reliance on GenAI (e.g., “I feel less motivated to complete assignments independently because Generative AI provides answers easily”). Responses were rated on a 5-point Likert scale (1=strongly disagree to 5=strongly agree). Higher scores indicated lower learning motivation. Content validity was evaluated by three experts in educational psychology and learning technologies, and internal consistency was high (Cronbach’s $\alpha = .89$).

Academic Procrastination (AP)

Academic procrastination was measured using a 20-item questionnaire adapted from the Academic Procrastination Scale (Yockey, 2016) and contextualized for GenAI-assisted learning. The instrument assessed delays in academic tasks related to perceived efficiency, reduced urgency, and reliance on GenAI support (e.g., “I tend to delay starting assignments because I believe Generative AI can help me complete them quickly”). Items were rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree), with higher scores indicating greater academic procrastination. The scale demonstrated satisfactory content validity and high internal consistency (Cronbach’s $\alpha = .87$).

Data Analysis

We utilize multiple linear regression tests to examine how internet accessibility and AI usage frequency together influence Learning Motivation and Academic Procrastination. For studying mediation effects, we applied Baron and Kenny's (1986) approach alongside Sobel tests.

We looked at two main pathways: How Learning Motivation mediates between technology use and Procrastination, and how Procrastination mediates between technology use and Learning Motivation. Our initial analysis showed that the data met key assumptions for parametric testing, including normal distribution, linearity, and homoscedasticity. The Kolmogorov-Smirnov test gave significance values above the .05 threshold ($p = .20$), which confirms we could appropriately use parametric statistical tests. All analyses were performed using IBM SPSS Statistics version 25.

Measurement invariance across GenAI-use frequency groups (Occasionally, Frequently, and Very Frequently) was examined using multi-group confirmatory factor analysis (MGCFA) with maximum likelihood estimation in IBM SPSS AMOS 23. A two-factor measurement model (Learning Motivation and Academic Procrastination), each represented by four item parcels, was evaluated following a hierarchical sequence of configural, metric, and scalar invariance. Item parcels were created by aggregating scale items using a balanced parceling approach to ensure comparable factor loadings across indicators. Metric invariance was assessed by constraining factor loadings to equality across groups, while scalar invariance additionally constrained item intercepts. Model comparisons were based on changes in the comparative fit index ($\Delta CFI \leq .010$) and the root mean square error of approximation ($\Delta RMSEA \leq .015$). When full scalar invariance was not supported, partial scalar invariance was established by freeing non-invariant intercepts based on modification indices.

Result

Participant Demographics

The study comprised 205 participants with most being 20 years old (51.22%), followed by 21-year-olds (27.32%). The vast majority resided in West Java (89.27%) with small representations from DKI Jakarta (4.88%) and Banten (4.39%). Regarding academic majors, Analytical Chemistry students constituted the largest group (68.78%), followed by Industrial Waste Management (23.90%). Most participants were in their fifth semester (121 students). For internet connectivity, participants were almost evenly split between mobile data (49.27%) and WiFi (45.85%) users. Most respondents reported having "very easy" internet access (50.73%) or "easy" access (47.80%). In terms of Generative AI usage for academic learning, most students used it "frequently" (63.90%) while 14.63% used it "very frequently" and 21.46% used it "occasionally." Empirical evidence from recent large-scale studies indicates that between approximately 60% and 80% of higher education students globally have reported using ChatGPT or similar generative AI tools for academic purposes, with a substantial proportion engaging in frequent or routine use for tasks such as summarizing and drafting written assignments (Morell-Mengual et al., 2025; Ravšelj et al., 2025; Zhang et al., 2025).

Table 1

Sample Demographics

Category	Frequency	%
Age	18	5.37
	19	12.20
	20	51.22
	21	27.32
	22	2.93
	23	.49
	24	.49
Total	205	100.00

Table 1
Sample Demographics

Category		Frequency	%
Major	Analytical Chemistry	141	68.78
	Food Nanotechnology	2	.98
	Industrial Waste Management	49	23.90
	Food Quality Control	13	6.34
	Total	205	100.00
Semester	1	14	1
	3	67	3
	5	121	5
	6	2	6
	7	1	7
	Total	205	100.00
Internet Network Usage	Mobile Data	101	49.27
	Wifi	94	45.85
	Others	10	4.88
	Total	205	100.00
Ease of Internet Access	Difficult	3	1.46
	Easy	98	47.80
	Very Easy	104	50.73
	Total	205	100.00
Frequency of Generative AI Use in Academic Learning (FGAI)	Occasionally	44	21.46
	Frequently	131	63.90
	Very Frequently	30	14.63
	Total	205	100.00
Learning Motivaton (LM)	Low	30	14.63
	Moderate	146	71.22
	High	29	14.15
	Total	205	100.00
Academic Procrastination (AP)	Low	30	14.63
	Moderate	148	72.20
	High	27	13.17
	Total	205	100.00

Note. N = 205. Percentages may not sum exactly to 100% due to rounding.

As presented in Table 1, 71.22% of students reported moderate motivation, while 72.20% demonstrated moderate levels of procrastination. This aligns with the study by (Mohammed & Khalid, 2025), which indicates that AI-generated feedback may foster a false sense of competence and reduce students' self-reflective engagement in learning (Li et al., 2025). In terms of human resource psychology, this reflects a form of pseudo-engagement, in which access to technology does not automatically translate into cognitive productivity (Kohnke & Moorhouse, 2025). Consequently, the availability of AI, without structured reflective learning strategies, may amplify passive learning behaviors that undermine long-term academic performance.

Regression Analysis

The multiple regression analysis examined the relationship between ease of internet access and the frequency of Generative AI use with learning motivation and academic procrastination using AI-contextualized measures as outcomes. Results indicated that neither ease of internet access nor the frequency of Generative AI use significantly predicted students' learning

motivation ($R^2 = .006, p > .05$). Individually ease of access ($\beta = -.066, t = -.93, p = .355$) and GenAI use ($\beta = .057, t = .81, p = .420$) did not show meaningful associations. This suggests minimal influence of these factors on motivation as measured within the AI context.

For academic procrastination, the model explained 2.1% of the variance ($R^2 = .021, p > .05$). While the frequency of Generative AI use was not a significant predictor ($\beta = -.004, t = -.06, p = .953$), ease of internet access showed a small but statistically significant positive relationship ($\beta = .146, t = 2.08, p = .039$). This may imply that a more accessible internet could slightly increase procrastination tendencies, although further investigation using non-contextualized measures would be required to clarify these patterns.

Regression analysis (Table 2) further supports this observation. Neither ease of internet access (EIA) nor the frequency of Generative AI use (FGAI) significantly predicted learning motivation ($R^2 = .006, p > .05$). Specifically, EIA ($p = .355$) and FGAI ($p = .420$) showed no meaningful association with motivation. Prior studies have reported that internet connectivity quality and access conditions are often associated with academic motivation and learning effectiveness in higher education settings, particularly when digital learning depends on stable online participation (Amin et al., 2025; Enciso-Huamani et al., 2025; Lopez, 2025). However, EIA significantly predicted increased academic procrastination ($\beta = .146, p = .039$). This resonates with (Acosta-Enriquez et al., 2025), that while digital accessibility may increase usage intent, it does not necessarily foster effective learning behaviors (Barra et al., 2024). Jafarian & Kramer (2025) similarly noted that flexible AI tools, such as audio learning, may decrease deep cognitive engagement when used without disciplined learning habits. This pattern parallels the concept of technostress and cognitive overload in digital workplaces, where abundant resources paradoxically impair task alignment and focus (Strielkowski et al., 2024).

Table 2

Regression Analysis Results

Independent Variable	Dependent Variable	R^2	β (Beta)	t	Sig.
EIA, FGAI	LM	.006	-.066, .057	-.93, .81	.355, .420
EIA, FGAI	AP	.021	.146, -.004	2.08, -.06	.039, .953

Note. EIA = Ease of Internet Access; FGAI = Frequency of Generative AI Use in Academic Learning; LM = Learning Motivation; AP = Academic Procrastination. β represents standardized regression coefficients.

Mediation Analysis

The mediation analysis identified four potential pathways, with only one demonstrating significant effects (Table 3). Academic procrastination mediated the relationship between ease of internet access and learning motivation (Sobel test = $-2.075, p = .038$). Regression path analysis confirmed that ease of internet access positively predicted procrastination ($\beta = 3.309, p = .037$), while procrastination negatively influenced learning motivation ($\beta = -.603, p < .001$). This indirect pathway suggests that greater internet accessibility may foster procrastination tendencies, ultimately diminishing students' motivation in AI-assisted learning contexts (Amarnath et al., 2023; Lai et al., 2025).

Table 3
Mediation Analysis Results

Mediation Path	Regression Path	β (Beta)	<i>t</i>	<i>Sig.</i>	Sobel Test	<i>Sig. Sobel</i>
EIA → AP → LM	EIA → AP	3.309	1.578	.037	-2.075	.038
	AP → LM	-.603	.042	.000		
FGAI → LM → AP	FGAI → LM	1.026	1.522	.501	-.67	.501
	LM → AP	-.839	.059	.000		
EIA → LM → AP	EIA → LM	-1.095	1.347	.417	.811	.427
	LM → AP	-.829	.058	.000		
FGAI → AP → LM	FGAI → AP	.467	1.802	.796	-.26	.558
	AP → LM	-.599	.042	.000		

Note. EIA: Ease of Internet Access; FGAI: Frequency of Generative AI Use in Academic Learning; LM: Learning Motivation; AP: Academic Procrastination. Sobel test was used to evaluate the significance of mediation effects. β represents standardized regression coefficients.

The remaining models failed to establish significant mediation effects. For instance, learning motivation did not mediate the relationship between frequency of Generative AI use and procrastination (Sobel test = -0.670 , $p = .501$), as AI use did not significantly influence motivation ($\beta = 1.026$, $p = .501$). Similarly, when learning motivation was tested as a mediator between internet access and procrastination, the pathway was incomplete since ease of access did not significantly predict motivation ($\beta = -1.095$, $p = .417$). Academic procrastination also failed to mediate between AI use and motivation (Sobel test = -0.260 , $p = .558$), given the nonsignificant direct effect of AI use on procrastination ($\beta = .467$, $p = .796$). The final mediation model EIA, FGAI, AP, and LM were illustrated in Figure 1. This model indicates that only the indirect pathway through AP was statistically supported, while other structural relationships did not reach significance.

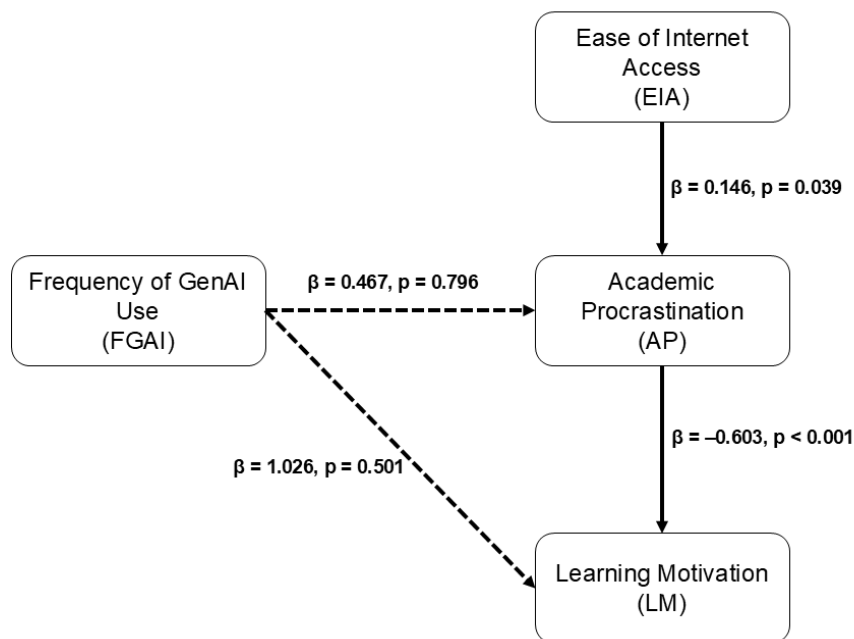


Figure 1. Final mediation model illustrating the effect of EIA and FGAI on LM, mediated by AP. Solid arrows (—) indicate significant regression paths ($p < .05$), whereas dashed arrows (---) represent hypothesized but statistically non-significant relationships.

Table 4 presents the results of MGCFA conducted across three GenAI-use frequency groups. The model demonstrated acceptable fit and supported measurement invariance at the configural and metric levels. However, full scalar invariance was not achieved, indicating partial invariance across groups. These results confirm that the measurement model is sufficiently stable for comparing structural relationships.

Table 4

Measurement invariance results across GenAI-use frequency groups (MGCFA)

Invariance Steps	Model	χ^2	df	CFI	RMSEA	ΔCFI	$\Delta RMSEA$
Configural	Unconstrained	122.821	57	.951	.076	-	-
Metric	Model 2 (equal loadings)	131.782	69	.954	.067	.003	-.009
Scalar	Model 3 (equal loadings + intercepts)	161.853	85	.943	.067	-.011	0

Note. χ^2 = Chi-square statistic; df = degrees of freedom; CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation.

Discussion

These findings highlight that digital accessibility, without structured behavioral regulation, may undermine academic performance. The significant EIA → AP → LM pathway underscores how abundant internet access can catalyze procrastination, lowering motivation (Gui et al., 2025; Manninen et al., 2022). This aligns with evidence that AI-enabled feedback may foster pseudo-engagement rather than deep learning (Mohammed & Khalid, 2025; Li et al., 2025). Without reflective learning strategies, students risk passive interaction with AI, reinforcing dependency and cognitive disengagement (Adiyono et al., 2025).

As illustrated in Figure 1, only the pathway from Ease of Internet Access (EIA) to Learning Motivation (LM) through Academic Procrastination (AP) was statistically significant, while all links involving Frequency of GenAI Use (FGAI) remained nonsignificant. Theoretically, these results challenge traditional models of technology adoption, such as TAM and UTAUT2, which emphasize perceived usefulness and ease of use. Our findings indicate that these constructs alone cannot explain motivation outcomes without incorporating behavioral regulation. Psychological empowerment and self-regulation are essential for meaningful AI-assisted learning, as highlighted by Kong et al. (2025) and Acosta-Enriquez et al. (2025). This implies that digital integration strategies must move beyond infrastructure provision to fostering ecosystems that strengthen self-discipline, resilience, and collaborative values in academic contexts (Jiang et al., 2024).

Although technology adoption models such as TAM and UTAUT emphasize access and perceived usefulness as drivers of technology-related outcomes, the present findings indicate that motivational consequences in AI-supported learning contexts are better explained through behavioral regulation mechanisms. The significant EIA → AP → LM pathway suggests that higher perceived digital accessibility may reduce task-initiation urgency and increase procrastination, consistent with evidence that flexible online learning environments amplify self-regulatory demands, particularly for time management and task initiation (Reinhold et al., 2021; Xu, 2025; Huang & Lee-Post, 2025). This aligns with the research showing that procrastination in online learning is closely related to self-regulated learning processes and students' task management in digitally flexible environments (Cheng & Xie, 2021; Pogorskiy & Beckmann, 2022; Cheng et al., 2023). Importantly, increased digital availability does not automatically translate into improved

self-regulation, as digital-only interventions may have limited impact on procrastination without sustained guidance and structured support (Åsberg et al., 2024). This interpretation also aligns with experimental evidence showing that the benefits of LLMs depend on pedagogically guided integration, whereas unguided use may not reliably enhance engagement or learning quality (Zhang, 2025). Moreover, pre-post evidence from AI-enhanced classrooms suggests that engagement-related perceptions may shift across a semester, implying that cross-sectional designs may not fully capture temporal changes in motivational and regulatory dynamics (Bognár & Khine, 2025). These studies strengthen the argument that institutional strategies should move beyond infrastructure provision to include AI literacy and self-regulation scaffolding to mitigate procrastination risks in GenAI-supported learning.

The study's cross-sectional design limits the ability to capture the temporal dynamics of AI usage and motivational changes. Potential moderators such as gender, academic major, or learning styles were not controlled, which may have influenced the observed effects. Future research should adopt longitudinal or mixed-method designs, incorporating self-regulation interventions to mitigate procrastination risks (Tsai et al., 2025). Differentiated approaches, tailored to students' profiles, are needed to design more adaptive, human-centered technology management frameworks in higher education (Lai et al., 2025).

Multi-group CFA (ML estimation) was conducted to test measurement invariance of the two-factor model (Learning Motivation and Academic Procrastination; four item parcels per construct) across three GenAI-use frequency groups. The configural model demonstrated adequate fit ($\chi^2 = 122.821$, $df = 57$, $CFI = .951$, $RMSEA = .076$). Imposing equality constraints on factor loadings (metric invariance) did not substantially degrade model fit ($\chi^2 = 131.782$, $df = 69$, $CFI = .954$, $RMSEA = .067$; $\Delta CFI = .003$; $\Delta RMSEA = .009$), consistent with prior MGCFA studies showing that metric invariance is typically achievable across educational subgroups (Martinez-Gomez et al., 2016; Natoli et al., 2022; Sudarshan et al., 2016). However, further constraining item intercepts (scalar invariance) produced a marginal decline in CFI beyond the recommended threshold ($\chi^2 = 161.853$, $df = 85$, $CFI = .943$; $\Delta CFI = -.011$), a pattern commonly reported in applied psychology where baseline response tendencies differ across groups (Bertola et al., 2020; Chan et al., 2020). Accordingly, partial scalar invariance was deemed necessary prior to latent mean comparisons, aligning with established practice in large-scale educational and psychological measurement (Immekus, 2021; Wurster, 2022).

These indicate that Learning Motivation and Academic Procrastination retain equivalent construct meaning across GenAI-use levels, supporting valid comparisons of structural relations between groups. The absence of full scalar invariance suggests subtle differences in baseline response calibration, which mirrors prior evidence that demographic and experiential factors frequently induce intercept noninvariance in educational assessments (Chan et al., 2020; Natoli et al., 2022). This pattern converges with emerging GenAI literature showing that intensive AI engagement reshapes students' internal standards of effort and self-evaluation, sometimes enhancing performance while simultaneously fostering metacognitive overreliance or motivational recalibration (Fan et al., 2025; Yang et al., 2025). Importantly, the establishment of metric invariance confirms that observed mediation effects are not artifacts of measurement bias but reflect genuine behavioral dynamics, consistent with studies demonstrating that procrastination and self-regulated learning critically shape how learners benefit from AI tools (Ng et al., 2024; Shahat et al., 2025). Collectively, these results reinforce academic procrastination as a key regulatory mechanism linking digital accessibility to motivation, underscoring the necessity of pedagogically guided GenAI integration that strengthens self-regulation rather than amplifying passive learning habits (Ng et al., 2024; Shahat et al., 2025).

Implication

The findings indicate that neither ease of internet access (EIA) nor the frequency of Generative AI use (FGAI) are significantly associated with learning motivation ($R^2 = .006, p > .05$), suggesting that increased access and usage intensity alone cannot be assumed to enhance motivational outcomes. However, EIA showed a small but significant positive relationship with academic procrastination ($\beta = .146, p = .039$), and procrastination exerted a strong negative effect on learning motivation ($\beta = -.603, p < .001$), with mediation analysis confirming procrastination as a significant pathway linking EIA to reduced motivation (Sobel $p = .038$). These findings suggest that digital and AI integration in higher education should prioritize behavioral regulation, particularly task initiation and time management. This is supported by the observation that most participants reported easy or very easy internet access (98.53%), frequent GenAI use (63.90%), and moderate levels of both motivation (71.22%) and procrastination (72.20%). These results imply that digital and AI integration strategies in higher education should prioritize behavioral regulation-particularly task initiation and time management-to mitigate procrastination risks that may arise in highly accessible digital learning environments, rather than focusing solely on infrastructure provision or increased technology use.

Limitation

This study is subject to several limitations. First, its cross-sectional nature precludes causal interpretation and does not reflect longitudinal dynamics in GenAI engagement, academic procrastination, or learning motivation. Second, both EIA and FGAI were operationalized using single-item, perception-based ordinal measures, which limit measurement granularity and fail to capture differences in access quality, duration of use, or specific GenAI-supported learning activities. Third, although multi-group CFA enhanced cross-group comparability, reliance on item parcels and partial scalar invariance may have attenuated sensitivity to item-level heterogeneity, indicating the need for future validation using full-item models and longitudinal invariance frameworks. In addition, participants were recruited from a single institution, with a predominance of Analytical Chemistry students from West Java, thereby restricting the broader applicability of the findings across disciplinary and regional contexts. Finally, potentially influential moderators such as AI literacy, learning strategies, academic workload, and individual differences were not modeled, which may partially account for the nonsignificant effects of FGAI and should be addressed in subsequent research.

Conclusion

This study shows that ease of internet access and the frequency of Generative AI use do not directly increase students' learning motivation. Instead, greater access to digital resources tends to elevate academic procrastination, which in turn reduces motivation. This indicates that behavioral regulation plays a central role in shaping how students engage with AI-supported learning. These results suggest that commonly used technology adoption constructs, such as perceived usefulness and ease of use, are not sufficient to explain motivation without considering self-regulation. Students' ability to manage attention, effort, and learning strategies becomes a determining factor in whether AI supports or disrupts academic engagement.

From a human resource management perspective, students can be viewed as developing human capital whose performance is influenced by early patterns of self-regulation. Educational systems therefore need to move beyond access and focus on cultivating disciplined learning

behavior and responsible AI use. Future research should examine intervention-based approaches that strengthen self-regulation within AI-supported learning environments.

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