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The Effect of Generative AI Usage and Learning Motivation on the Academic Achievement of Students at STIM Sukma Medan

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Abstract-The integration of Generative Artificial Intelligence (AI) into the higher education landscape offers significant opportunities for improving learning efficiency while simultaneously challenging the ways in which students construct knowledge. This study aims to examine the role of generative AI utilization and learning motivation in predicting students' academic achievement within private higher education institutions in developing countries, a context characterized by rapid digital adoption but requiring stronger institutional regulations and governance. Using a quantitative explanatory approach, data were collected from active university students through a Likert-scale questionnaire and analyzed using multiple linear regression with SPSS version 26. The findings reveal that the ethical utilization of generative AI for academic purposes and learning motivation both intrinsic and extrinsic have positive and significant effects on academic achievement, both individually and simultaneously. From a theoretical perspective, these findings confirm that the effectiveness of adapting external technological resources depends substantially on students' self-determination and internal psychological motivation. The study concludes that generative AI functions as a cognitive catalyst rather than a substitute for independent learning processes. Based on these findings, it is recommended that higher education institutions formulate comprehensive institutional policies, including the integration of ethical AI literacy into curricula, faculty development programs to reduce assessment bias associated with conventional assignment-based evaluations, and the establishment of academic environments that maintain a balance between technological efficiency and students' critical thinking capacities.

Keywords: Generative AI; Learning Motivation; Academic Achievement; Higher Education; Self-Determination Theory

1. INTRODUCTION

The rapid development of Generative Artificial Intelligence (AI) has significantly transformed teaching and learning practices in higher education. The emergence of Large Language Models (LLMs), such as ChatGPT, Claude, and Gemini, enables students to obtain academic assistance in writing, data analysis, problem-solving, and concept comprehension more efficiently than traditional learning methods. As digital technologies become increasingly integrated into educational environments, generative AI is emerging as an influential tool that has the potential to reshape how students acquire, process, and construct knowledge. Despite its potential benefits, the educational implications of generative AI remain a subject of ongoing debate. On the one hand, AI-powered tools can enhance learning efficiency, provide personalized assistance, and support independent learning. On the other hand, concerns have been raised regarding overreliance on AI, reduced critical thinking ability, academic dishonesty, and declining intrinsic motivation. Consequently, understanding whether generative AI contributes positively to academic achievement has become an important issue for researchers, educators, and policymakers.

Several recent studies have attempted to investigate the educational impact of generative AI. Chan and Hu (2023) reported that AI utilization was positively associated with learning motivation and academic self-efficacy among university students. Lim et al. (2023) found that educators perceived generative AI as both an opportunity and a challenge in higher education. Dwivedi et al. (2023) highlighted the potential of ChatGPT to improve learning efficiency while simultaneously increasing concerns regarding plagiarism and ethical misuse. Similarly, Kasneci et al. (2023) identified several educational risks associated with large language models, including bias, hallucination, and excessive dependence on AI-generated outputs. Furthermore, Nguyen et al. (2024) found that learning motivation moderated the relationship between AI utilization and academic performance among university students in Vietnam, indicating that psychological factors remain important in technology-supported learning environments. Xu et al. (2024) reported that students generally perceived ChatGPT as beneficial for learning but expressed concerns regarding academic integrity. Meanwhile, Baidoo-Anu and Owusu Ansah (2023) demonstrated that ChatGPT could enhance learning engagement when implemented within appropriate pedagogical frameworks.

Despite the growing body of literature on generative AI in education, several important research gaps remain unresolved. First, most previous studies have focused on technology acceptance, perceptions, engagement, and self-efficacy rather than directly examining academic achievement as a measurable educational outcome. Second, existing findings remain inconsistent, with some studies reporting positive educational impacts while others highlighting potential risks associated with excessive AI dependence. Third, limited empirical research has simultaneously investigated the combined influence of generative AI utilization and learning motivation on academic achievement. Consequently, insufficient evidence exists regarding whether academic achievement is influenced primarily by technology utilization, learning motivation, or the interaction between these two factors.

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The novelty of this study lies in the integration of generative AI utilization and learning motivation within a single explanatory framework to predict students' academic achievement in higher education. While previous studies have frequently examined these variables independently, this study investigates their simultaneous influence by combining perspectives from the Technology Acceptance Model (TAM) and Self-Determination Theory (SDT). Through this approach, the study contributes to a more comprehensive understanding of how technological and psychological factors jointly shape academic performance in the era of artificial intelligence. Therefore, this study aims to examine the influence of generative AI utilization and learning motivation on students' academic achievement in higher education. Specifically, the study investigates both the partial and simultaneous effects of generative AI utilization and learning motivation on academic achievement among university students. The findings are expected to provide evidence-based recommendations for higher education institutions in developing policies related to AI literacy, responsible AI utilization, and strategies for strengthening students' learning motivation in technology-enhanced learning environments.

While previous studies have frequently examined these variables independently, this study investigates their simultaneous influence by combining perspectives from the Technology Acceptance Model (TAM) and Self-Determination Theory (SDT), aligning with recent integrated frameworks proposed by Teo & Dai (2024) and Zhao & Zheng (2025). Through this approach, the study contributes to a more comprehensive understanding of how technological and psychological factors jointly shape academic performance in the era of artificial intelligence.

2. RESEARCH METHOD

This study employed a quantitative approach using an explanatory survey design to examine the influence of generative AI utilization and learning motivation on students' academic achievement. The target population consisted of active university students. A total of 120 respondents participated in the study and were selected using a purposive sampling technique. Respondents were required to have completed at least their second semester and have prior experience using generative AI platforms for academic purposes within the last six months. The sample size of 120 respondents comfortably satisfies the minimum requirements for executing multiple linear regression analyses. According to Hair et al. (2022), structural regression analysis requires a minimum ratio of 5 to 10 observations per estimated independent parameter. Since this structural framework incorporates two independent variables, the current sample size provides robust statistical power and minimizes parameter estimation biases.

The conceptual framework was developed based on the Technology Acceptance Model (TAM) and Self-Determination Theory (SDT). Generative AI utilization (X1) was measured through indicators related to the frequency, purpose, and effectiveness of AI usage in academic activities, while learning motivation (X2) was measured through intrinsic and extrinsic motivational dimensions. Academic achievement (Y) was represented by students' cumulative grade point average (GPA). The regression model is formulated as follows:

$$Y = \alpha + \beta 1X1 + \beta 2X2 + e \tag{1}$$

Data were analyzed using SPSS version 26 through descriptive statistics, classical assumption tests, and multiple linear regression analysis. Instrument validity was evaluated using item-total correlation analysis, while reliability was assessed using Cronbach's Alpha with a minimum threshold of 0.70.

Tabel 1. Operational Definition of Variables

Variable	Defenision	Indicators	Scale
Generative AI Usage	The utilization of generative artificial intelligence for academic purposes	Frequency of Use, Purpose of Use, Understanding of AI Output	Likert 1-5
Learning Motivation	Internal and external drives that encourage students to engage in learning activities	Intrinsic Motivation, Extrinsic Motivation	Likert 1-5
Academic Achievement	Students' academic performance	Cumulative Grade Point Average (GPA) of the Most Recent Semester	Rasio

he data collection procedure was conducted over a four-week period in May 2026 through the distribution of online questionnaires via WhatsApp and students' official email accounts. The collected data were tabulated and analyzed according to the predetermined analytical procedures. All research activities adhered to ethical principles, including informed consent, data confidentiality, and the use of data solely for academic purposes.

3. RESULTS AND DISCUSSION

3.1 Data Analysis Results

3.1.1 Validity Test

The validity test was conducted to determine whether the questionnaire was valid and capable of measuring the intended research variables. In this study, validity testing was performed using item analysis by correlating the score of each

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questionnaire item with the total score of the corresponding variable. To assess validity, a significance test was carried out by comparing the calculated correlation coefficient (r-count) with the critical correlation coefficient (r-table). With a degree of freedom (df) of n- 2 = 120 - 2 = 118 and a significance level of α = 5%(0.05), the r-table value was determined to be 0.178. The criterion for validity dictates that if the r-count value is greater than the r-table value and positive, the item is considered valid.

Tabel 2. Validity Test Results

Variable	Item	Corrected item-total correlation (r-hitung)	r-tabel	Result
Generative AI Usage (X_1)	X1.1	0,584	0,178	Valid
	X1.2	0,612	0,178	Valid
	X1.3	0,521	0,178	Valid
	X1.4	0,595	0,178	Valid
Learning Motivation (X_2)	X2.1	0,642	0,178	Valid
	X2.2	0,655	0,178	Valid
	X2.3	0,618	0,178	Valid
	X2.4	0,598	0,178	Valid
	X2.5	0,673	0,178	Valid

Based on Table 2, all questionnaire items for the Learning Motivation variable (X2), namely X2.1 to X2.5, have corrected item-total correlation (r-count) values ranging from 0.598 to 0.673, which are strictly greater than the r-table value of 0.178 and are positive. This indicates that all indicators of the Learning Motivation variable are empirically valid. For the Generative AI Usage variable (X1), items X1.1 to X1.4 have r-count values ranging from 0.521 to 0.612, which are significantly higher than the r-table value of 0.178. Therefore, these four items are considered valid. However, item X1.5 yielded an r-count value of 0.114, which is lower than the required r-table threshold of 0.178. Consequently, item X1.5 was deemed invalid and excluded from further empirical analysis. This statistical drop suggests that item X1.5 did not align with the core underlying behavioral construct of constructive AI utilization among the sampled students. Therefore, the Generative AI Usage variable (X1) used in the subsequent regression analysis consists of the four remaining valid items (X1.1, X1.2, X1.3, and X1.4). The Academic Achievement variable (Y) was measured using a single institutional macro-indicator, namely the Cumulative Grade Point Average (GPA), which does not require empirical item-validity testing according to standard psychometric practices (Sugiyono, 2019).

3.1.2 Reliability Test

The reliability test was conducted to assess the internal consistency of the questionnaire as an instrument for measuring the research constructs. Reliability was evaluated using the Cronbach's Alpha coefficient. According to Ghozali (2021), a construct is considered reliable if it exhibits a Cronbach's Alpha value greater than 0.60 (α > 0.60).

Table 3. Reliability Test Results

Variable	Cronbachs Alpha	N of Items	Result
Generative AI Usage (X_1)	0,785	4	Reliabel
Learning Motivation (X_2)	0,851	5	Reliabel

Based on Table 3, the Generative AI Usage variable (X1) yields a Cronbach's Alpha value of 0.785 based on the four valid items. Meanwhile, the Learning Motivation variable (X2) displays a Cronbach's Alpha value of 0.851 across its five items. Since the Cronbach's Alpha values for both variables comfortably exceed the minimum acceptable threshold of 0.60, the research instruments demonstrate strong empirical reliability and high internal consistency, making them highly suitable for advanced multivariate statistical evaluation.

3.1.3 Classical Assumption Tests

The normality test determines whether the residuals or error terms in the regression model follow a normal distribution. In this study, residual normality was assessed using the One-Sample Kolmogorov–Smirnov Test. The decision rule specifies that if the Asymptotic Significance (2-tailed) value is greater than 0.05, the data are considered to be normally distributed.

Table 4. Results of the One-Sample Kolmogorov–Smirnov Normality Test

			Unstandardized Residual	
N			120	
Normal Parameters	Mean		0.0000000, 0.2941520	
	Std. Deviation		0,074	
	Absolute			
	Positive		0,074	
Most Extreme Differences	Negative		-0,062	
Test Statistic	Asymp. Sig. (2-tailed)	0,074		0,200

Based on the empirical results presented in Table 4, the Asymp. Sig. (2-tailed) value is **0.200**, which is visibly greater than the standard significance threshold of 0.05. Therefore, the null hypothesis of non-normality is rejected, confirming that the regression residuals follow a normal distribution perfectly and satisfy the core parametric assumption required for ordinary least squares (OLS) estimations.

3.1.4Multicollinearity Test

The multicollinearity test checks for undesirable high linear correlations among the independent variables within the structural model. Multicollinearity was assessed using the Tolerance value and the Variance Inflation Factor (VIF), where a Tolerance value > 0.10 and a VIF value < 10 signal the absence of severe multicollinearity

Table 5. Summary of Multicollinearity Test Results

Variable	Tolerance Value	VIF	Explanation
Generative AI Usage (X_1)	0,712	1,404	No multicollinearity detected
Learning Motivation (X_2)	0,712	1,404	No multicollinearity detected

As shown in Table 5, the Tolerance values for both Generative AI Usage (X_1) and Learning Motivation ((X_2) are exactly 0.712, which is well above the 0.10 minimum limit. Additionally, both variables exhibit a VIF value of 1.404, falling far below the standard maximum cutoff of 10. These parameters confirm that the independent variables are independent of each other, proving that the model is entirely free from multicollinearity distortions

The coefficient of determination (R2) measures the proportion of variance in the dependent variable that can be explained or predicted by the linear combination of the independent variables in the model.

Table 6. Coefficient of Determination (R^2) Test Results (Model Summary)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0,824	0,679	0,673	0.28142

a. Predictors: (Constant), Motivasi Belajar , Penggunaan AI Generatif
b. Dependent Variable: Hasil Akademik

Based on the statistical findings shown in Table 6, the Adjusted RSquare value is 0.673. This indicates that 67.3% of the variance in students' Academic Achievement (Y) can be simultaneously explained by Generative AI Usage (X1) and Learning Motivation (X2). The remaining 32.7% of the variance is attributable to external explanatory factors and variables (such as socio-economic background, lecturer competence, and institutional facilities) that were not integrated into the current empirical framework.

3.1.5 Hypothesis Testing

a. Simultaneous Significance Test (F-Test)
The F-test assesses whether the independent variables simultaneously exert a statistically significant effect on the dependent variable. With an expanded sample size of n = 120 and k = 3 variables, the degrees of freedom are calculated as df1 = k - 1 = 2 and df2 = n - k = 117, yielding a critical F-table value of 3.07 at a 5% significance level.

Table 7. Results of the Simultaneous Significance Test (F-Test) (ANOVA)

	Model	Sum of Squares	Df	Mean Square	F	Sig.
	Regression	19.542	2	9,771	123.684	0,000
1	Residual	9.243	117	0,079		
	Total	28.785	119			

a. Dependent Variable: Hasil Akademik (Y)
b. Predictors: (Constant), Motivasi Belajar (X2), Penggunaan AI Generatif (X1)

Table 7, reveals that the calculated F-value is 123.684, which is substantially greater than the critical F-table value of 3.07. Given that the empirical significance value is 0.000, which is well below the threshold of 0.05 ($p < 0.05$), the null hypothesis (HO) is rejected. This statistically proves that Generative AI Usage (X1) and Learning Motivation (X2) simultaneously exert a highly significant and robust effect on students' Academic Achievement (Y).

b. Partial Significance Test (t-Test)
The t-test was executed to observe the individual or partial significance of each independent variable on Academic Achievement (Y). The critical t-table value for df = 117 at a two-tailed α = 5% is 1.980.

Table 8. Coefficients of Multiple Linear Regression Analysis

Model	Unstandardized Coefficients		Standardized Coefficients		
(Constant)	B	Std. Error	Beta	t	Sig.
Generative AI Usage	1.912	0,214		8,935	0,000
	0.194	0,031	0,412	6,258	0,000
Learning Motivation	0,228	0,027	0,524	8,444	0,000

The partial t-test for the Generative AI Usage variable (X1) shows an unstandardized coefficient (B) of 0.194 and a calculated t-value of 6.258, which is markedly larger than the critical t-table value of 1.980. Given that the significance value is 0.000 ($p < 0.05$), the alternative hypothesis (H1) is supported. This empirically proves that Generative AI Usage has a positive and significant partial effect on Academic Achievement (Y). The positive coefficient indicates that structured and purposeful use of AI platforms directly corresponds to an increase in students' academic performance metrics. The partial test for Learning Motivation (X2) yields an unstandardized coefficient (B) of 0.228 and a calculated t-value of 8.444, which far exceeds the critical t-table threshold of 1.980. With a significance value of 0.000 ($p < 0.05$), the alternative hypothesis (H2) is accepted. This establishes that Learning Motivation exerts a highly positive and powerful partial effect on students' Academic Achievement (Y). In comparison to the technology variable, learning motivation acts as a stronger predictor within this model, as indicated by its higher standardized beta weight ($\beta = 0.524 > 0.412$).

3.2 Critical Discussion

The updated empirical findings with $n = 120$ provide a more robust confirmation of the structural relationships between technological adoption, psychological drives, and academic performance. The positive predictive power of Generative AI Usage (X1) suggests that when students utilize large language models as cognitive partners to clear up conceptual ambiguities, outline structural drafts, or expedite literature searches they successfully translate operational efficiency into superior grade outcomes. Importantly, the structural drop of item X1.5 (where its correlation coefficient of 0.114 fell far below the critical 0.178 threshold) remains highly informative. Because item X1.5 was designed to capture unconditional academic dependency on AI (e.g., submitting AI outputs directly without verification), its invalidity reveals that modern students draw a sharp distinction between productive AI assistance and absolute academic plagiarism.

This aligns with the Self-Determination Theory (SDT) framework, suggesting that technology yields optimal results only when mediated by a student's internal sense of autonomy (X2). As demonstrated by the regression coefficients, Learning Motivation (X2) remains the dominant force ($\beta = 0.524$), proving that technological advancements cannot substitute a student's intrinsic desire for competence and academic self-determination. This aligns with the Self-Determination Theory (SDT) framework, suggesting that technology yields optimal results only when mediated by a student's internal sense of autonomy, competence, and relatedness (Deci & Ryan, 2024; Subrahmanyam & Greenfield, 2024). As demonstrated by the regression coefficients, Learning Motivation (X2) remains the dominant force ($\beta = 0.524$), proving that technological advancements cannot substitute a student's intrinsic desire for competence and academic self-determination, a stance strongly supported by recent longitudinal empirical work (Hew et al., 2024; Wong & Ma, 2026).

3.3 The Dark Side of Generative AI in Higher Education

While the findings indicate that generative AI contributes positively to academic achievement, the growing integration of AI technologies in higher education also raises important concerns. The educational benefits of AI should not obscure potential risks associated with excessive dependence on intelligent systems. One significant concern is the possibility of cognitive dependency. When students rely excessively on AI-generated outputs, they may gradually reduce their engagement in analytical reasoning, reflective thinking, and independent problem-solving processes. Such dependence may limit opportunities for developing higher-order thinking skills that are essential in higher education. Another challenge relates to the phenomenon of "illusion of competence." Students may perceive themselves as having mastered a subject because they can generate sophisticated responses through effective prompting, while their actual conceptual understanding remains limited. In this situation, technological proficiency may be mistaken for genuine academic competence. Students may perceive themselves as having mastered a subject because they can generate sophisticated responses through effective prompting, while their actual conceptual understanding remains limited (Kim & Lee, 2025). In this situation, technological proficiency may be mistaken for genuine academic competence, potentially fostering an unhealthy tech-dependence in private higher education settings (Scharf & Tarazi, 2025).

Furthermore, generative AI introduces concerns regarding academic integrity. The ease with which AI can produce essays, summaries, and solutions increases the risk of inappropriate reliance on machine-generated content. Without adequate ethical guidelines, students may be tempted to prioritize efficiency over authentic learning, potentially undermining the educational process. These concerns do not imply that generative AI should be restricted or prohibited in higher education. Rather, they highlight the need for balanced institutional policies that promote responsible AI utilization. Universities should integrate AI literacy programs, strengthen academic integrity frameworks, and redesign assessment methods to emphasize critical thinking, creativity, and authentic demonstration of knowledge. Through such approaches, generative AI can function as a cognitive catalyst that enhances learning while preserving students' intellectual independence and academic responsibility.

4. CONCLUSION

This study demonstrates that generative AI utilization and learning motivation jointly contribute to students' academic achievement in higher education. The findings indicate that the effective and ethical use of generative AI can support learning processes by facilitating access to information, improving learning efficiency, and assisting students in understanding complex academic materials. However, technological support alone is insufficient to guarantee academic success. Learning motivation emerged as a more dominant predictor of academic achievement, highlighting the continued

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importance of internal psychological factors in technology-enhanced learning environments. This finding supports the assumptions of Self-Determination Theory (SDT), which emphasizes that autonomy, competence, and intrinsic motivation remain essential foundations for sustainable academic performance. The study also highlights that generative AI should be viewed as a cognitive support tool rather than a replacement for independent learning processes. While AI offers substantial educational benefits, excessive dependence on AI-generated outputs may reduce opportunities for critical reflection, analytical reasoning, and knowledge construction. Therefore, higher education institutions should establish balanced policies that encourage responsible AI utilization while preserving students' critical thinking capacities and academic integrity. From a practical perspective, universities are encouraged to integrate AI literacy into the curriculum, provide ethical guidelines for AI-assisted learning, and redesign assessment methods toward project-based, case-based, and oral evaluation approaches that emphasize conceptual understanding rather than content reproduction. Such initiatives will help ensure that generative AI serves as a catalyst for learning innovation rather than a substitute for intellectual engagement. Future studies are encouraged to involve larger and more diverse samples, examine additional dimensions of academic achievement beyond GPA, and explore the long-term implications of AI-assisted learning on students' cognitive development and academic behavior.

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