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AI IN LEARNING: EFFECTS ON UNDERGRADUATE CRITICAL THINKING SKILLS

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Abstract:

The growing presence of Artificial Intelligence (AI) tools in university learning has changed how students search for information, organise ideas, and approach academic tasks. However, the relationship between AI engagement and students' critical thinking skills remains an important issue for investigation. This study examines the relationships between AI Usage, Learning Attitude toward AI, academic performance (CGPA), and Critical Thinking Skill among engineering undergraduates. A quantitative survey was conducted involving 160 students, and the collected data were analysed using descriptive statistics, Pearson correlation analysis, and multiple linear regression. The findings indicate significant positive relationships between AI Usage, Learning Attitude toward AI, CGPA, and Critical Thinking Skill. The regression model was statistically significant and explained 82.6% of the variance in Critical Thinking Skill. Among the predictors, CGPA

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recorded the largest standardized regression coefficient, followed by AI Usage and Learning Attitude toward AI. However, the regression coefficients should be interpreted cautiously due to the strong association between AI Usage and Learning Attitude. The findings suggest that critical thinking in AI-assisted learning environments is related to multiple factors, including students' academic background, engagement with AI tools, and attitudes toward technology. This study provides insights for educators and higher education institutions in developing responsible AI integration approaches that encourage students to evaluate and engage critically with AI-generated information.

Keyword:

Artificial Intelligence (AI), AI-Assisted Learning, Critical Thinking Skills, Higher Education, Undergraduate Students.

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Introduction

AI tools are becoming part of everyday academic activities in higher education. Students now use generative AI platforms, research assistants, and writing support tools to search for information, organise ideas, and assist with coursework. Generative AI platforms, research assistants, and writing support tools are now commonly used in learning environments rather than being considered emerging technologies only (Bozkurt et al., 2023; Chai et al., 2021; Hassen, 2025; Binjwair, 2025). In engineering education, where students are expected to analyse problems, evaluate possible solutions, and apply systematic reasoning, the growing presence of AI introduces both opportunities and questions regarding its role in learning processes (Baidoo-Anu & Ansah, 2023; Faisal, 2024). Although AI can support information retrieval and idea development, concerns remain regarding how frequent engagement with these tools relates to students' independent thinking and analytical abilities (Dwivedi et al., 2023; Selwyn, 2019).

Existing literature presents different perspectives on the relationship between AI usage and critical thinking. Some researchers have highlighted the possibility of cognitive offloading when students rely excessively on automated systems and accept generated responses without sufficient evaluation (Sweller, 1988). In contrast, other studies suggest that AI tools may support reflective learning when students actively question, evaluate, and refine AI-generated information during academic tasks (Hassen, 2025; Binjwair, 2025). However, the relationship between AI usage and critical thinking may not depend on technology use alone. Students' attitudes toward AI and their existing academic background may also influence how they interact with these tools. In particular, the combined role of AI Usage, Learning Attitude toward AI, and academic performance (CGPA) remains less explored among engineering undergraduates. To address this gap, the present study examines the relationships between AI

International Journal of Modern Education
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Volume: 8 Issue: 31 (September 2026) PP. 765-779

Usage, Learning Attitude toward AI, CGPA, and Critical Thinking Skill among engineering undergraduates. Specifically, this study investigates whether these variables are significantly associated with critical thinking and examines the extent to which AI Usage, Learning Attitude toward AI, and CGPA contribute to the prediction of Critical Thinking Skill.

Based on these research questions, two main objectives guide the study. The first objective is to examine the relationships between AI Usage, Learning Attitude toward AI, CGPA, and Critical Thinking Skill among engineering undergraduates. The second objective is to determine the contribution of AI Usage, Learning Attitude toward AI, and CGPA within a multiple regression model predicting Critical Thinking Skill.

This study contributes to the literature on AI-assisted learning by examining technological, affective, and academic factors together rather than focusing on AI usage alone. From a practical perspective, the findings may provide useful considerations for higher education institutions and educators when developing approaches for responsible AI integration and supporting students' critical engagement with AI-generated information.

Literature Review

Theoretical Grounding

This study is guided by two complementary theoretical perspectives: Metacognitive Theory (Flavell, 1979) and the Technology Acceptance Model (TAM) (Davis, 1989). Metacognitive Theory emphasises the role of learners' ability to monitor, regulate, and reflect on their own thinking processes. These abilities are important when students evaluate information, make judgements, and develop higher-order thinking skills. In educational contexts, academic performance has been linked with self-regulatory learning processes that support students' ability to assess and process complex information (Phan, 2010).

The Technology Acceptance Model (TAM) provides another perspective by explaining how individuals' perceptions of usefulness and ease of use shape their acceptance of technology (Davis, 1989). In the context of AI-assisted learning, students' attitudes toward AI may influence how they engage with these tools during academic activities. By combining these two perspectives, this study considers both the behavioural aspect of AI usage and the affective aspect of learning attitude, while also recognising the role of academic performance in understanding differences in critical thinking skills.

Determinants of Critical Thinking Skills

The selection of AI Usage, Learning Attitude toward AI, and academic performance (CGPA) as predictors of Critical Thinking Skill is based on previous research in digital learning environments and self-regulated learning frameworks (Hassen, 2025; Faisal, 2024; Binjwair, 2025; Phan, 2010; Zimmerman, 2002). In engineering education, critical thinking involves the ability to analyse problems, evaluate evidence, identify weaknesses in reasoning, and develop appropriate solutions (Sosu, 2013). These skills are particularly relevant in technical disciplines where students are required to work through complex problems and justify their decisions.

The increasing use of generative AI tools, including ChatGPT, Claude, Perplexity, and Grammarly, has raised questions about how these technologies relate to students' thinking processes. Previous studies present different perspectives on AI engagement. When used purposefully, AI tools may provide support for activities such as brainstorming, receiving feedback, and organising information. Such interactions may encourage students to review and refine their ideas rather than relying solely on the generated responses (Hassen, 2025; Binjwair, 2025).

However, concerns have also been raised regarding passive dependence on AI-generated information. Excessive reliance on automated responses may reduce students' involvement in analysing information independently and may contribute to cognitive offloading (Faisal, 2024). Therefore, the relationship between AI usage and critical thinking may depend not only on how often students use AI tools, but also on how they approach and evaluate the information provided.

Learning attitude toward AI represents another important factor in understanding students' engagement with these technologies. Students who perceive AI as a learning support tool may be more likely to question, evaluate, and refine AI-generated outputs instead of accepting them without further consideration (Chai et al., 2021). In this sense, attitude toward AI may shape the way students interact with technology during learning activities.

Academic performance, represented by CGPA in this study, is also considered an important factor related to critical thinking. Previous research suggests that stronger academic performance is associated with self-regulation, prior knowledge, and learning strategies that support analytical thinking (Phan, 2010). Students with stronger academic foundations may be better positioned to evaluate the accuracy and relevance of AI-generated information within their disciplinary context (Faisal, 2024).

Taken together, previous studies indicate that critical thinking in AI-supported learning is unlikely to be explained by technology use alone. Students' engagement with AI, their attitudes toward the technology, and their existing academic background may all contribute to differences in critical thinking outcomes. AI Usage, Learning Attitude, and CGPA may represent different aspects of students' engagement with technology and learning processes. Examining these factors together provides a more comprehensive understanding of how AI-related behaviours and learner characteristics are associated with critical thinking among engineering undergraduates.

Conceptual Framework and Hypotheses Development

Based on the reviewed literature, the conceptual framework was developed to examine the relationships between AI Usage, Learning Attitude toward AI, CGPA, and Critical Thinking Skill. In this framework, AI Usage, Learning Attitude toward AI, and CGPA are considered independent variables, while Critical Thinking Skill is treated as the dependent variable (Figure 1).

International Journal of Modern Education
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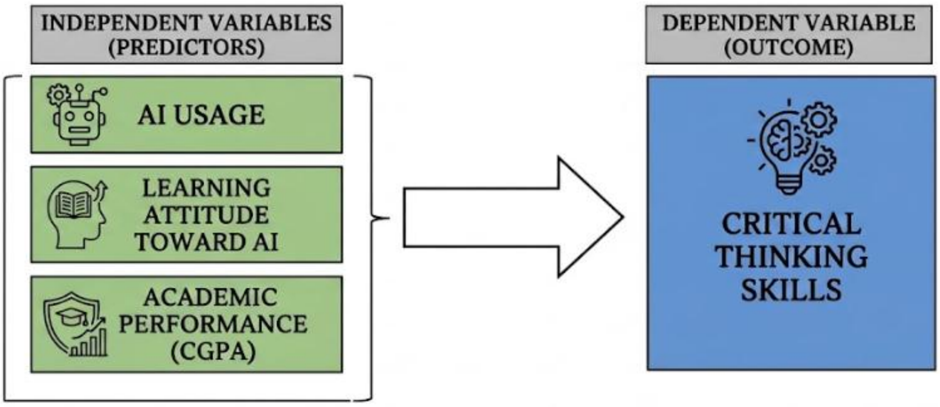

Figure 1: Conceptual Framework

Based on the proposed framework, four hypotheses were developed to examine the relationships among the study variables:

H_1: There is a significant positive relationship between AI Usage and Critical Thinking Skill among engineering undergraduates.
H_2: There is a significant positive relationship between Learning Attitude toward AI and Critical Thinking Skill among engineering undergraduates.
H_3: There is a significant positive relationship between CGPA and Critical Thinking Skill among engineering undergraduates.
H_4: AI Usage, Learning Attitude toward AI, and CGPA significantly contribute to the prediction of Critical Thinking Skill among engineering undergraduates.

Methodology

Research Design

This study employed a quantitative cross-sectional survey design to examine the relationships between AI Usage, Learning Attitude toward AI, CGPA, and Critical Thinking Skill among engineering undergraduates. The target population consisted of Diploma and Bachelor's Degree students enrolled in engineering programmes at Universiti Teknologi MARA (UiTM) Pulau Pinang Branch. A cluster sampling approach was applied by grouping students according to their engineering programmes and year of study to obtain representation from different academic levels. At the beginning of the questionnaire, a screening question was included to identify students who had previous experience using AI tools for academic purposes. Only respondents who indicated that they had used AI tools for learning-related activities proceeded to complete the full questionnaire. A total of 160 valid responses were obtained from undergraduate students who reported prior academic use of AI tools.

Research Instrument

Data were collected using a structured self-administered questionnaire consisting of four sections. The first section gathered demographic information, including gender, year of study, CGPA, the type of AI tools most frequently used, participation in AI-related workshops, and subscription status for premium AI services. The second section measured students' AI Usage based on six items adapted from the Scale for Individual Use of AI Tools (SIUAIT; Chai et al.,

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
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2021) and the Perception and Engagement with Higher Education AI Tools Scale (PEHIATA; Hassen, 2025). The items assessed the frequency and extent of AI application in academic activities using a five-point Likert scale ranging from 1 (Never) to 5 (Always).

The third section assessed Critical Thinking Skill using five items adapted from the Critical Thinking Questionnaire (CThQ; Sosu, 2013). The items covered aspects related to analysis, evaluation, interpretation, and reflective judgement. Responses were measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The final section measured students' Learning Attitude toward AI through four items related to confidence, perceived learning support, and the integration of AI into academic activities. These items were also rated using a five-point Likert scale. The questionnaire was distributed electronically to engineering undergraduate students. Before completing the survey, participants were informed about the purpose of the study, the voluntary nature of participation, and the confidentiality and anonymity of their responses.

Instrument Reliability and Validity

The internal consistency of the research instrument was assessed using Cronbach's Alpha. As shown in Table 1, all constructs recorded alpha values above the recommended threshold of 0.70 (Hair et al., 2019), indicating acceptable to high internal consistency among the measurement items. The Critical Thinking Skill scale, consisting of five items, produced a Cronbach's Alpha value of 0.918. The AI Usage scale with six items recorded an alpha value of 0.809, while the Learning Attitude scale comprising four items achieved a value of 0.847. These results suggest that the items within each construct were sufficiently consistent for measuring the respective variables in this study. Based on these reliability results, all three constructs were retained for subsequent statistical analyses, including correlation and regression analysis.

Table 1: Cronbach's Alpha Value

Variable	Cronbach's Alpha	No of Items	Result
Critical Thinking Skill	0.918	5	high reliability
AI Usage	0.809	6	high reliability
Learning Attitude	0.847	4	high reliability

Data Analysis

The collected survey data were analysed using IBM SPSS Statistics. Descriptive analyses were first conducted to summarise the characteristics of the respondents and the main study variables. Frequencies, percentages, means, standard deviations, and skewness values were examined to describe the demographic profile, assess the distribution of CGPA scores, and identify general patterns of AI usage and exposure among the respondents. Following the preliminary analysis, inferential statistical tests were performed to address the research objectives. Pearson correlation analysis was used to examine the direction and strength of the relationships between the independent variables (AI Usage, Learning Attitude, and CGPA) and the dependent variable (Critical Thinking Skill).

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 765-779

Multiple linear regression analysis was subsequently conducted to examine the extent to which AI Usage, Learning Attitude, and CGPA were associated with variations in Critical Thinking Skill. The analysis examined the overall model fit, the proportion of variance explained (R^2), and the individual contribution of each predictor based on standardized regression coefficients (β).

Results and Discussion

The demographic profile of the respondents is presented in Table 2 and Figure 2. A total of 160 engineering undergraduates participated in this study. In terms of gender distribution, female respondents represented a slightly larger proportion of the sample, with 94 students (58.8%), while male respondents accounted for 66 students (41.2%). The respondents represented all four years of undergraduate study. Second-year students formed the largest group, comprising 62 respondents (38.8%), followed by third-year students with 44 respondents (27.5%). First-year students accounted for 36 respondents (22.5%), while fourth-year students represented the smallest group with 18 respondents (11.2%).

The higher proportion of second- and third-year students indicates that the sample included a greater number of respondents who had progressed beyond the initial stage of their engineering programme. This distribution provides representation from students across different levels of academic experience, allowing the study to examine variations in AI usage, learning attitudes, and critical thinking skills among undergraduate learners.

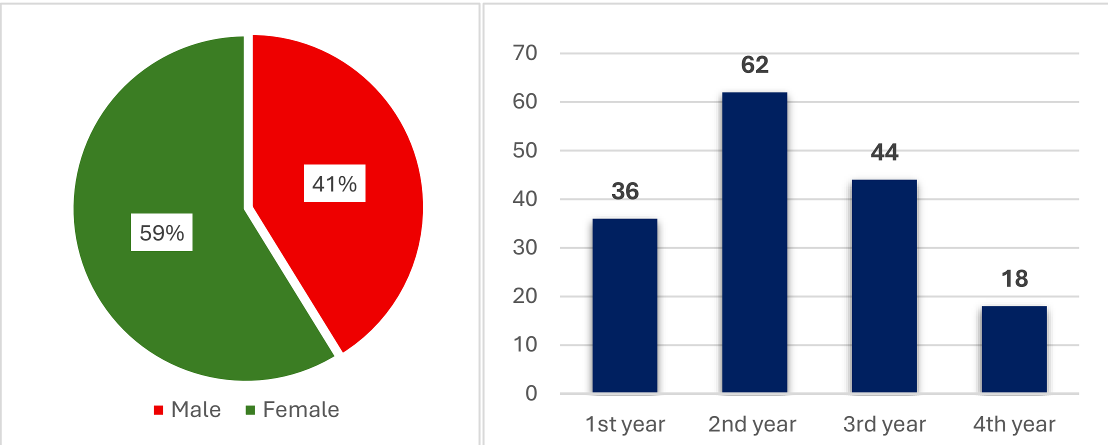

Figure 2: Distribution of Engineering Undergraduates by Year of Study (Bar Chart) and Gender (Pie Chart)

Table 2: Demographic Characteristics of Respondents

	Sample	Frequency	Percentage (%)
Gender	Male	66	41.2
	Female	94	58.8
Year of Study	1st year	36	22.5
	2nd year	62	38.8
	3rd year	44	27.5
	4th year	18	11.2

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 765-779

Descriptive analysis was conducted to examine the academic profile of the respondents. As presented in Table 3 and illustrated in Figure 3, the respondents recorded a mean CGPA of 3.3658 (SD = 0.4376), with scores ranging from 2.40 to 3.95. The median value of 3.4650 indicates that half of the respondents achieved a CGPA above this level. The distribution of CGPA scores showed a negative skewness value of -0.621, suggesting that more respondents were clustered towards the higher end of the academic performance range. The skewness value remained within the commonly accepted range of -1 to +1, indicating that the distribution did not show substantial deviation from normality and was considered suitable for subsequent parametric analyses, including Pearson correlation and multiple linear regression.

The relatively high academic performance observed among the respondents provides useful context for interpreting the subsequent findings. As the sample consisted of undergraduate engineering students, the concentration of higher CGPA scores may reflect the academic demands and selection characteristics of the study population. However, CGPA was analysed together with AI Usage and Learning Attitude rather than being interpreted as an independent indicator of critical thinking ability.

Table 3: Descriptive Statistics for Respondents' CGPA

CGPA	Statistic	Std. Error
Mean	3.3658	0.03192
Median	3.4650	
Std. Deviation	0.4376	
Minimum	2.40	
Maximum	3.95	
Skewness	-0.621	0.192

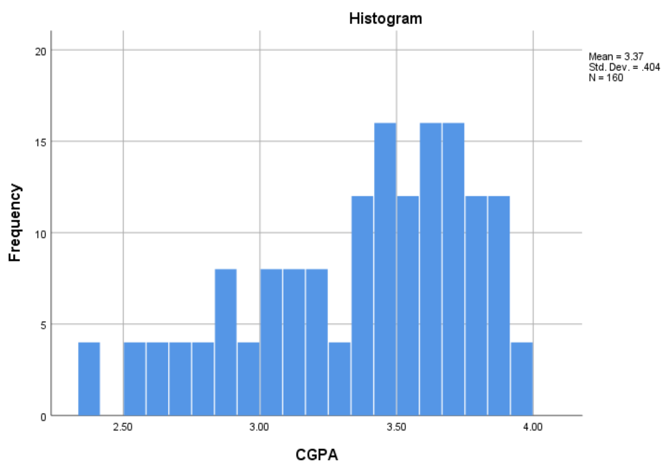

Figure 3: Distribution of CGPA Scores among Undergraduate Respondents

Patterns of AI Adoption and Exposure

Beyond demographic characteristics, this study examined students' patterns of AI adoption, exposure to institutional AI-related activities, and access to premium AI services. As presented in Table 4, text-based generative AI tools were the most frequently used category, with 47.5%

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 765-779
(n=76) of respondents reporting them as their primary AI tool. Research and search-based AI platforms accounted for 27.5% (n=44), while grammar and writing assistants represented 25.0% (n=40) of reported usage.

The findings also indicate that formal exposure to AI-related training remains limited among the respondents. More than half of the students (57.5%, n=92) reported that they had not attended any AI workshops or seminars, while 42.5% (n=68) had received some form of institutional exposure. In terms of access to AI services, most respondents relied on free-tier platforms (80.0%, n=128), whereas only 20.0% (n=32) reported using premium AI subscriptions.

The preference for text-based generative AI tools may reflect the convenience of conversational platforms in supporting common academic activities, such as organising ideas, seeking explanations, and assisting with writing-related tasks. This pattern is consistent with previous discussions on the role of generative AI as an interactive learning support tool in higher education (Kohnke et al., 2023; Hassen, 2025). However, the widespread use of AI tools alongside limited formal training highlights the need for greater attention to AI literacy among university students. Access to AI technology alone does not necessarily ensure effective academic use, as students still require the ability to evaluate information quality, recognise limitations of AI-generated outputs, and apply appropriate judgement during learning activities (Faisal, 2024; Binjwair, 2025).

Although AI Usage was positively associated with Critical Thinking Skill in this study, the relationship should be interpreted carefully. The current findings do not directly measure how students verify AI responses or how they interact with AI-generated information during actual academic tasks. Future studies could examine these behaviours more closely through qualitative approaches or task-based observations to better understand how AI usage contributes to students' learning processes.

Table 4: Frequency and Percentage Distribution of AI Tool Preferences, Workshop Attendance, and Premium Subscriptions

Variable	Category	Frequency	Percentage (%)
Most Frequently Used AI Tool	Text-based AI	76	47.5
	Research/Search-based AI	44	27.5
	Grammar/Writing Assistant	40	25
Attendance in AI Workshops/Seminars	YES	68	42.5
	NO	92	57.5
Subscription to Premium AI Tools	YES	32	20.0
	NO	128	80.0

Figure 4 provides an initial view of the relationships among CGPA, AI usage, learning attitude, and critical thinking skills. Across the scatterplots, the observations generally follow an upward and approximately linear pattern. There is no clear indication of a curvilinear relationship, and the plots therefore provide reasonable support for the linearity assumption required for Pearson

International Journal of Modern Education
EISSN: 2637-0905
Volume: 8 Issue: 31 (September 2026) PP. 765-779

correlation. Pearson's correlation analysis was then used to quantify the direction and strength of these associations, with the results reported in Table 5.

Pearson correlation analysis was used to examine the associations between AI Usage, Learning Attitude, CGPA, and Critical Thinking Skill. As shown in Table 5, all three variables were positively and significantly associated with critical thinking. AI Usage showed the highest correlation with Critical Thinking Skill ($r=0.859$, $p<0.001$), followed closely by Learning Attitude ($r=0.849$, $p<0.001$) and CGPA ($r=0.838$, $p<0.001$). These coefficients indicate strong positive relationships, suggesting that students who reported higher AI usage, more positive learning attitudes, and stronger academic performance also tended to report higher levels of critical thinking. Accordingly, H1, H2, and H3 were supported.

The pattern is broadly consistent with previous work suggesting that active engagement with AI can be associated with reflective learning practices when students use the technology to question, compare, and evaluate information rather than simply accept generated responses (Hassen, 2025; Binjwair, 2025). The strong association between Learning Attitude and Critical Thinking Skill also supports the view that students' orientation toward technology may shape how actively they engage with information during learning (Chai et al., 2021). Similarly, the positive relationship between CGPA and Critical Thinking Skill is consistent with research linking academic performance with self-regulation and established reasoning practices (Phan, 2010). These findings should nevertheless be interpreted as associations rather than evidence that AI use, learning attitude, or CGPA causes improvements in critical thinking.

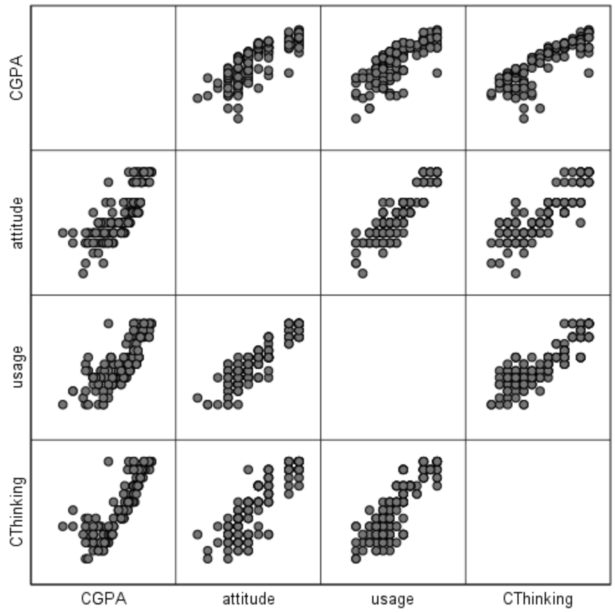

Figure 4: Scatterplot Matrix Illustrating Linear Relationships Among CGPA, AI Usage, Critical Thinking Skills, and Learning Attitude

International Journal of Modern Education
EISSN: 2637-0905
IJMOE
Volume: 8 Issue: 31 (September 2026) PP. 765-779

Table 5: Summary of Pearson Correlation Analysis Between Predictors And Critical Thinking Skill

Variable	Critical Thinking Skill, r	p-value
AI Usage	0.859	0.000
Learning Attitude	0.849	0.000
CGPA	0.838	0.000

Table 6: Model summary of Multiple Linear Regression

Model	R	R Square	Adjusted R Square	Std. Error of the estimates	Durbin-Watson
1	0.909	0.826	0.822	0.28521	2.050

Table 7: ANOVA Test Results for Regression Model

	Sum of Squares	degree of freedom	Mean Square	F	p-value
Regression	60.109	3	20.036	246.312	0.000<0.001
Residual	12.690	156	0.081		
Total	72.799	159			

Table 8: Multiple Linear Regression Coefficients and Collinearity Diagnostics for Predicting Critical Thinking Skill

Predictor	B	β	p-value	Tolerance	VIF
AI Usage	0.448	0.348	<0.001	0.171	5.841
Learning Attitude	0.273	0.232	0.005	0.168	5.935
CGPA	0.724	0.394	<0.001	0.382	2.616

Multiple linear regression was then conducted to examine the extent to which AI Usage, Learning Attitude, and CGPA were jointly associated with Critical Thinking Skill. The model was statistically significant, $F = 246.312$, $p<0.001$. As reported in Table 6, the model produced an R value of .909 and explained 82.6% of the variance in Critical Thinking Skill ($R^2 = 0.826$). The standard error of the estimate was 0.28521.

The Durbin-Watson statistic was 2.050, which is close to the expected value of 2 and provides no indication of substantial autocorrelation in the regression residuals. Taken together, these results indicate that AI Usage, Learning Attitude, and CGPA account for a substantial proportion of the observed variation in Critical Thinking Skill within the present sample. H4 was therefore supported at the model level. However, the high proportion of explained variance should be interpreted in conjunction with the relationships among the predictors and the collinearity diagnostics rather than as evidence of causal effects.

Examination of the individual regression coefficients showed that all three predictors remained statistically significant when entered simultaneously in the model. CGPA had an unstandardized coefficient of B = 0.724 and the largest standardized coefficient β=0.394. AI Usage was also positively associated with Critical Thinking Skill, while Learning Attitude showed a smaller but significant coefficient (p=0.005).

The standardized coefficients suggest that CGPA had the largest relative coefficient in the model, followed by AI Usage and Learning Attitude. This comparison is based on standardized beta values rather than the unstandardized B coefficients, because the predictors were measured on different scales.

The positive coefficient for CGPA is consistent with the view that students with stronger academic foundations may have greater subject knowledge and self-regulatory resources for evaluating information critically (Phan, 2010). AI Usage also retained a significant association with critical thinking after the other predictors were considered. This finding is compatible with previous studies suggesting that AI can support analytical activity when students actively evaluate, revise, and verify generated information (Faisal, 2024; Hassen, 2025; Binjwair, 2025). Learning Attitude remained significant as well, indicating that students' orientation toward AI is related to critical thinking even after differences in AI Usage and CGPA are considered.

The individual coefficients should, however, be interpreted cautiously because the collinearity diagnostics indicated considerable overlap between AI Usage and Learning Attitude. AI Usage recorded a VIF of 5.841 with a tolerance of 0.171, while Learning Attitude recorded a VIF of 5.935 with a tolerance of 0.168. CGPA showed a lower VIF of 2.616 and a tolerance of 0.382. This pattern is consistent with the strong correlation between AI Usage and Learning Attitude (r = 0.904). Thus, although all three predictors remained statistically significant, their unique contributions should not be interpreted as completely independent of one another.

Critical Thinking Skill = -1.322 + 0.448 (AI Usage) + 0.273 (Learning Attitude) + 0.724 (CGPA)

The equation represents the predicted Critical Thinking Skill score based on the three predictors while holding the other variables constant. Because the coefficients are unstandardized, they are primarily useful for prediction in the original measurement units and should not be used to rank the relative importance of the predictors.

Conclusion

This study examined the relationships between AI Usage, Learning Attitude toward AI, academic performance (CGPA), and Critical Thinking Skill among engineering undergraduates at Universiti Teknologi MARA (UiTM) Pulau Pinang Branch. The findings indicate that all three factors were positively and significantly associated with students' critical thinking skills. AI Usage, Learning Attitude, and CGPA each contributed significantly to the regression model, suggesting that critical thinking in AI-assisted learning environments is related to both technological engagement and learner-related characteristics.

International Journal of Modern Education
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The multiple linear regression analysis showed that the combined model explained 82.6% of the variance in Critical Thinking Skill. Among the predictors, CGPA demonstrated the largest standardized regression coefficient, followed by AI Usage and Learning Attitude. However, the interpretation of individual predictors should be made cautiously due to the strong relationship between AI Usage and Learning Attitude. These findings suggest that AI engagement should not be considered independently from students' academic background and attitudes toward technology.

From a theoretical perspective, this study extends discussions on AI-assisted learning by highlighting the importance of considering behavioural, affective, and academic factors together when examining critical thinking outcomes. These findings suggest that the value of AI in learning may depend less on access to the technology itself and more on how students interact with and evaluate AI-generated information.

Practically, the results suggest that higher education institutions should focus on developing responsible AI learning practices rather than viewing AI adoption only from the perspective of frequency of use. Guidelines, digital literacy initiatives, and instructional approaches that encourage students to evaluate and reflect on AI-generated information may help maximise the educational value of these tools. Future studies using longitudinal or experimental designs are recommended to further examine how AI engagement may relate to changes in critical thinking development over time.

Limitations and Directions for Future Research

Several limitations should be considered when interpreting the findings of this study. First, the cross-sectional design captures students' responses at a single point in time. Therefore, the findings describe the relationships among AI Usage, Learning Attitude, CGPA, and Critical Thinking Skill within the sampled group, but they do not establish how these relationships may change over time. Future research could adopt longitudinal or experimental approaches to examine whether patterns of AI engagement are associated with changes in students' critical thinking development across different learning periods.

Second, the participants were limited to engineering undergraduates from a single UiTM branch. Although this context provides insights into AI-assisted learning among technical students, the findings may not represent students from other disciplines or institutions. Future studies could extend the investigation to students from different academic backgrounds, such as social sciences, medicine, and business, as well as multiple higher education institutions, to provide a broader understanding of AI-related learning behaviours.

Finally, this study relied on self-reported questionnaire responses, which may not fully capture how students interact with AI tools during actual learning activities. Future research could complement survey-based approaches with qualitative methods, such as interviews, learning diaries, or observation of AI-assisted tasks, to better understand how students formulate prompts, evaluate AI-generated responses, and apply AI tools during academic work.

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Ethics Statement:	This study was conducted in accordance with accepted academic and ethical research standards. Formal institutional ethics approval was exempted as the study involved a minimal-risk, anonymous survey. Participation was entirely voluntary, and informed consent was obtained from all participants prior to data collection. Strict confidentiality and anonymity were maintained, and all collected data were used solely for academic research purposes.
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Declaration on the Use of Artificial Intelligence (AI):	The authors declare that OpenAI ChatGPT was used during the preparation and revision of this manuscript for language editing, grammatical improvement, sentence restructuring, and improving the clarity of the writing. All AI-assisted content was carefully reviewed, edited, and verified by the authors, who take full responsibility for the accuracy, originality, integrity, and final content of the manuscript. Generative AI was not used to generate or alter the study data.

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