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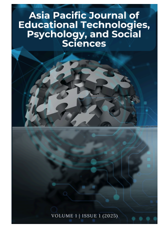

Research Article

Attitude of Engineering Students on AI System

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Abstract

This study explores the attitudes of engineering students toward artificial intelligence (AI) systems, addressing a critical gap in understanding how this demographic engages with and adapts to emerging technologies. Employing a descriptive quantitative research design, data were collected from 254 engineering students using a stratified random sampling technique. A validated self-reported questionnaire on a five-point Likert scale was administered online and analyzed using statistical methods, including reliability tests and structural equation modelling. The findings reveal generally positive attitudes toward AI, with cognitive engagement and self-efficacy improving as students progress academically. These findings provide actionable insights for improving AI education in engineering contexts. However, gender-based disparities in AI literacy and self-efficacy suggest the need for tailored educational interventions. Despite moderate levels of behavioral engagement, students demonstrated significant readiness to adopt AI systems, with AI literacy being the most influential factor shaping attitudes. The study concludes that integrating AI into engineering curricula can enhance student preparedness for technology-driven professions while addressing disparities to promote equitable learning experiences.

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Introduction

Artificial Intelligence (AI) is prevalent nowadays, simulating the attitude of the students, especially engineering students. As it continues to arise over the years, it presents challenges and opportunities for engineering students. However, regardless of its growing role in engineering education, there is still a limited understanding of how these students engage with and adapt the technology. As AI has been prominent in various sectors (Berdiyorova et al., 2021; Hall & Pesenti, 2017; Jindal et al., 2021; Paul et al., 2021), this technology has also been integrated into the field of higher education (Crompton & Burke, 2023; Pedro et al., 2019; Zawacki-Richter et al., 2019; Zhang & Aslan, 2021).

Students are adapting AI rapidly in terms of academics, which has become a key focus for engineering students. Engineering students are known as the future professionals who innovate designs, invent new technologies, improve AI-driven systems, and drive technological advancement. The importance of AI in higher education is widely discussed, with studies highlighting potential benefits such as improved critical thinking and automation of tasks (Luckin et al., 2016). In addition, prior studies explored people's attitudes toward and behavioral intention to use artificial intelligence (Obenza et al., 2024).

The positive relationship between AI awareness and students' attitudes and behavioral intentions to use AI underscores the critical role of knowledge and exposure in shaping perceptions of technology (Huang et al., 2023). Despite these advancements, challenges such as ethical concerns, potential over-reliance, and disparities in AI literacy persist. The adoption of AI in higher education, while promising, is met with apprehensions about its implications on traditional learning environments, as some students express fears of an "unnatural" learning space or misuse in assessments.

However, few studies have explicitly examined engineering students' views and readiness for AI systems despite AI's distinct significance in engineering. Current research often focuses on general student populations or industry professionals, overlooking the unique learning environments, educational opportunities, and expectations that engineering students bring to their studies (Dwivedi et al., 2021). They also have a positive attitude toward using AI because it engages students and accommodates their varying cognitive levels (Obenza et al., 2023; Pande et al., 2020). Engineering students play a vital role in all aspects of development and innovation.

This gap in research is significant. According to a study by Luckin et al. (2016), investigating the particular attitudes of engineering students can reveal opportunities for curriculum development, identify potential educational needs, and suggest ways to better prepare this group for entering increasingly AI-driven professional fields. Moreover, existing studies often lack a nuanced exploration of how demographic factors such as gender, academic exposure, and prior technology influence these attitudes (Alsaiari et al., 2024). This study aims to address this critical gap in the literature.

The main objective of this study is to address the gap in the attitude of engineering students toward artificial intelligence systems. The findings of this study aim to strengthen the teaching and methodologies. Furthermore, AI can support education and aid the technology sector. This study provides valuable insights for future researchers which provides insights in using AI.

Theoretical Framework

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According to the theory of planned behavior, the categories of reasons include people's attitudes toward the behavior, subjective norms, and perceived behavioral control (Ajzen, 1991). The general findings reported in numerous studies employing the theory of planned behavior indicate that when an action is perceived to produce positive results, be socially well accepted (i.e., conforming to subjective norms), and be perceived as within one's locus of control, strong behavioral intention is likely to be formed, and this is predictive of actual behavior (Liao et al., 2007).

As an organismic theory, self-determination theory assumes people are inherently prone to psychological growth and integration, thus toward learning, mastery, and connection with others. However, these proactive human tendencies are not seen as automatic—they require supportive conditions to be robust. SDT specifically argues that for healthy development to unfold, individuals require support for basic psychological needs (Ryan, Ryan, Di Domenico, & Deci, 2019).

The Multicomponent model of attitude, as proposed by Eagly and Chaiken (1993) and expanded by Zanna and Rempel (1998), attitudes are complex evaluations that encompass cognitive, affective, and behavioral dimensions (Fishbein & Ajzen, 1975; Kiesler et al., 1969; Mantle-Bromley, 1995). An individual's attitude is characterized as the expression of their preferences or aversions toward entities, involving judgment characterized by differing degrees of favor or dislike (Eagly & Chaiken, 1998). Attitudes are multidimensional, comprising cognitive, behavioral, and affective components, and individual differences can result in evaluations ranging from extremely favorable to negative (Wood, 2000).

Materials and Methods

A descriptive quantitative research design was employed to explore the attitude toward AI systems among university engineering students; as quantitative research involves generating numerical data to quantify attitudes, opinions, and behaviors, often generalizing results from larger sample populations (Creswell & Creswell, 2023). Aiming for at least two hundred respondents for the surveys ensured a sufficiently large sample size to allow for meaningful statistical analysis and generalization of findings to the broader population of university engineering students.

Researchers gathered two hundred fifty-four (254) students from the College of Engineering Education at the University of Mindanao who have been using or have experience using AI system/s were included as respondents for the study. Moreover, a stratified random sampling technique was used to select the respondents. This technique involved random selection and categorization to choose groups from a single population, stratifying the target population, and employing simple random sampling from each stratum (Soriano & Sumayo, 2024). Then, the selected samples from many strata are combined to generate a single sample (Iliyasu & Etikan, 2021).

The research questionnaires used were adapted from the survey of Suh and Ahn (2022), wherein they developed and validated a scale measuring student attitudes toward artificial intelligence to gather data. In addition, the questionnaires are close-ended questions and use a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), to collect data. Furthermore, the self-reported questionnaires are collected through an online survey, specifically by sending a Google Form questionnaire.

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Descriptive statistics were used to determine the overall patterns and score distributions within the dataset. The accepted questionnaires were tested for validity and reliability using Jamovi Software version 2.3.28. Cronbach's Alpha Test, Bartlett's Test, and Kaiser Meyer-Olkin statistics were used in the Jamovi Software. First, Cronbach's Alpha test was used to determine the reliability and internal consistency of the surveys and adhere to Cronbach's Alpha level of reliability (Hair et al., 2010, as mentioned in Ahdika, 2017). Second, Bartlett's evaluation of Sphericity was used to determine the suitability of data for factor analysis (Bartlett, 1937), and Bartlett's proposed testing procedure was used to evaluate the hypothesis of equal variances in k-normal populations (Witkovsky, 2019). Lastly, the Kaiser-Meyer-Olkin (KMO) statistics were used to establish whether the sample size is adequate for factor analysis while adhering to the KMO's level of approval (Field, 2013, referenced in Naseer et al., 2019).

The study strictly adhered to the provisions of the Data Privacy Act of 2012 throughout the processes of data collection, storage, and analysis. Personal information was safeguarded, and all data were handled responsibly to ensure privacy breaches were avoided (Dugho & Sumayo, 2025; Redocto & Sumayo, 2024). Participation in the study was entirely voluntary, with no coercion or undue pressure placed on respondents. Additionally, participants were assured of their right to withdraw from the study at any time without fear of any adverse consequences (Esto, 2024; Tanoja & Sumayo, 2024).

Results and Discussions

Evaluation of Measurement Model

Table 1 displays the validity and reliability of the instruments employed in the study utilizing Cronbach's alpha and McDonald's omega. It demonstrates the reliability of a scale designed to measure attitudes toward artificial intelligence (AI) systems, with high internal consistency across the overall scale and subcomponents, as reflected by Cronbach's α and McDonald's ω values exceeding the standard threshold of 0.7; both McDonald's ω and Cronbach's α, a value of ≥ 0.70 is the minimum acceptance level in most research contexts, while ≥ 0.80 is preferred for greater reliability (Taber, 2018; Hayes & Coutts, 2020). This aligns with studies on student attitudes toward technology, where similar measures have been used effectively to ensure scale reliability and validity.

The uniform reliability across dimensions like self-efficacy, literacy, and behavioral components mirrors findings in education and technology acceptance studies. For instance, the development of scales measuring attitudes toward computers and computing also reported high internal consistency reliability (Cronbach's $\alpha > 0.87$), demonstrating their reliability for capturing student attitudes toward technical constructs (Wanzer et al., 2019).

The results from Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (MSA) provide critical insights about the dataset's suitability for factor analysis. Bartlett's test, yielding a chi-square value of 11,477 with 1,176 degrees of freedom and a p-value less than 0.001, suggests that the correlation matrix is not an identity matrix. Suggests that for a sample size of $254 < 300$, the average communality of the retained items has to be tested (Tabachnick & Fidell, 2013, p. 200). The KMO value of 0.958, which falls in the "marvellous" range, verifies the sample's adequacy by suggesting that the variables share common factors and support robust factor extraction. These statistical measures show that the dataset was suitable for multivariate techniques such as exploratory factor analysis. Strong sampling adequacy and significant

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correlations provide a solid foundation for uncovering latent structures in the data (Zakariya, 2017).

Table 1: Reliability Analysis and Assumption Checks

Scale Reliability Statistics		
	Cronbach's α	**McDonald's ω**
scale	0.916	0.919
Item Reliability Statistics		
	Cronbach's α	**McDonald's ω**
AI SELF EFFICACY	0.899	0.902
AI LITERACY	0.882	0.885
BEHAVIORAL COMPONENT	0.888	0.892
AFFECTIVE COMPONENT	0.893	0.9
Cognitive Component	0.922	0.924
Bartlett's Test of Sphericity		
χ^2	**df**	**p-value**
11477	1176	<.001
KMO Measure of Sampling Adequacy (MSA)		0.958

The statistical analysis of engineering students' attitudes toward artificial intelligence (AI) systems reveals significant insights across cognitive, affective, and behavioral components, as well as AI literacy and self-efficacy. All components demonstrated high and statistically significant factor loadings ($p < .001$), reflecting positive and meaningful relationships. For instance, the Cognitive Component showed loadings between 0.657 and 0.891, indicators CC1 (0.714), CC3 (0.891), and CC4 (0.870) exceed a threshold of 0.7 highlighting a strong influence of knowledge and beliefs on students' perceptions of AI. The indicator CC2 (0.657) exhibits a slightly weaker relationship, suggesting it might require refinement (Black & Babin, 2019). The Affective Component, which assesses emotional responses, presented overall robust factor loading (0.564–0.872), indicating consistent emotional alignment with AI; lower loadings such as AC2 (0.564<0.7) and AC8 (0.58<0.7) may indicate potential issues of reliability and require refinement (Schumacker & Lomax, 2016). The Behavioral Component, which emphasizes students' strong intentions to engage with AI systems, exhibits robust factor loadings with most exceeding 0.80 that ranges from 0.819-0.902; exceptions of indicators BC11 (0.677) and BC12 (0.642) may need re-evaluation or refinement (Byrne, 2013). AI Literacy construct also exhibited strong scores, with most indicators ≥0.7 (0.7-0.904) and some lower but still significant estimates (0.576-0.626) that may need refinement, further suggesting students' readiness to engage with AI applications (Ng et al., 2021). Finally, the AI Self-Efficacy component demonstrated high loadings ranging from 0.708-0.876, reflecting students' confidence in utilizing AI effectively (Tabachnick & Fidell, 2013).

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Table 2: Factor Loadings

Factor	Indicator	Estimate	SE	Z	p
COGNITIVE COMPONENT	CC1	0.714	0.0465	15.36	<.001
	CC2	0.657	0.0465	14.12	<.001
	CC3	0.891	0.0551	16.17	<.001
	CC4	0.87	0.0473	18.41	<.001
AFFECTIVE COMPONENT	AC1	0.675	0.0547	12.34	<.001
	AC2	0.564	0.0546	10.33	<.001
	AC3	0.779	0.0617	12.63	<.001
	AC4	0.808	0.0666	12.12	<.001
	AC5	0.819	0.0574	14.26	<.001
	AC6	0.872	0.0654	13.33	<.001
	AC7	0.68	0.0588	11.57	<.001
	AC8	0.58	0.052	11.15	<.001
	AC9	0.735	0.0556	13.23	<.001
	AC10	0.731	0.0638	11.45	<.001
BEHAVIORAL COMPONENT	BC1	0.851	0.0599	14.21	<.001
	BC2	0.83	0.0593	14	<.001
	BC3	0.889	0.0577	15.41	<.001
	BC4	0.899	0.0557	16.14	<.001
	BC5	0.889	0.0543	16.38	<.001
	BC6	0.902	0.0539	16.72	<.001
	BC7	0.849	0.0609	13.94	<.001
	BC8	0.889	0.0567	15.69	<.001
	BC9	0.896	0.0588	15.25	<.001
	BC10	0.819	0.054	15.17	<.001
	BC11	0.667	0.0607	10.98	<.001
	BC12	0.642	0.0592	10.84	<.001
AI LITERACY	AIL1	0.804	0.0524	15.32	<.001
	AIL2	0.811	0.0529	15.33	<.001
	AIL3	0.904	0.0571	15.85	<.001
	AIL4	0.838	0.0537	15.59	<.001
	AIL5	0.844	0.0522	16.17	<.001

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	AIL6	0.874	0.0543	16.1	<.001
	AIL7	0.702	0.0558	12.58	<.001
	AIL8	0.729	0.0555	13.14	<.001
	AIL9	0.765	0.0558	13.72	<.001
	AIL10	0.767	0.0612	12.53	<.001
	AIL11	0.727	0.0614	11.84	<.001
	AIL12	0.778	0.0542	14.34	<.001
	AIL13	0.79	0.0539	14.66	<.001
	AIL14	0.578	0.0673	8.58	<.001
	AIL15	0.626	0.0675	9.28	<.001
	AIL16	0.576	0.0699	8.24	<.001
	AIL17	0.7	0.069	10.15	<.001
AI SELF-EFFICACY	ASE1	0.708	0.0491	14.41	<.001
	ASE2	0.771	0.0516	14.94	<.001
	ASE3	0.784	0.0541	14.48	<.001
	ASE4	0.876	0.0513	17.06	<.001
	ASE5	0.839	0.0491	17.08	<.001
	ASE6	0.801	0.0541	14.8	<.001

Evaluation of Structural Model

The data below shows the mean scores for various inquiries ranging between 3.27 and 3.80, collected and analyzed from 254 completed responses. Participants exhibit a high understanding and positive perception of the potential of AI systems (Mean = 3.80, SD = 0.83). This data aligns with findings that positive emotions and digital efficacy significantly influence continued AI usage, emphasizing the role of emotional engagement in technology adoption (Wang & Li, 2024). Additionally, the affective component expressed a generally positive emotional response towards the AI system (Mean = 3.37, SD = 0.76), which resonates with research showing that emotionally enriched AI feedback can enhance emotional well-being and reduce negative feelings (Alsaiari et al., 2024). The behavioral component demonstrates moderately positive engagement with AI (Mean = 3.20, SD = 0.86), consistent with findings that self-efficacy strongly predicts engagement and confidence in interacting with AI tools (Chang et al., 2024).

Participants revealed a moderate level of AI literacy, including a decent understanding of AI concepts and moderate confidence in using AI tools (Mean = 3.17, SD = 0.7). This finding is supported by research indicating that emotional clarity and resilience correlate with perceived self-efficacy in technology use (Morales-Rodríguez & Pérez-Mármol, 2019). Participants also displayed moderate levels of AI self-efficacy (Mean = 3.22, SD = 0.83), paralleling evidence that self-efficacy enhances user engagement and facilitates the successful

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adoption of AI tools (Henkel et al., 2020). These findings collectively underline the importance of fostering emotional engagement and self-efficacy to maximize the benefits of AI integration.

Table 3: Descriptives

	N	Mean	SD	Description
Cognitive Component	254	3.80	0.83	Highly Positive
AFFECTIVE COMPONENT	254	3.37	0.76	Moderately Positive
BEHAVIORAL COMPONENT	254	3.20	0.86	Moderately Positive
AI LITERACY	254	3.17	0.79	Moderate Level
AI SELF EFFICACY	254	3.22	0.83	Moderate Level

The cognitive component demonstrates a clear upward trend, with the highest mean score (4.00) achieved in the fourth year and the lowest (3.65) in the first year. This suggests a positive correlation between academic progression and cognitive engagement, aligning with research indicating that cognitive engagement increases with prolonged academic exposure, critical thinking development, and skill enhancement (Reeve et al., 2020). The decrease in standard deviation from the second year (0.881) to the fourth year (0.715) suggests that senior students exhibit more consistent cognitive performance, potentially due to curriculum standardization or cumulative learning effects (Corno & Mandinach, 1983).

The affective component shows more stability across the years, with the highest mean score (3.56) in the fourth year and the lowest (3.25) in the third year. This relatively small range in means, along with the fluctuation observed, suggests that while affective engagement remains relatively consistent, there are notable variations across the academic years. The highest standard deviation (0.936) in the second year indicates greater emotional variability during this transitional period, which is consistent with research highlighting emotional engagement challenges in transitional years (Engels et al., 2019).

The behavioral component displays considerable variability, with the lowest mean score (2.97) in the third year and the highest (3.28) in the fourth year. The highest standard deviation (0.981) is observed in the second year, suggesting diverse behavioral engagement among students at this stage. In contrast, the third year shows the lowest standard deviation (0.7), indicating more uniform behavioral engagement. This pattern aligns with observations of a "junior year slump," a phenomenon where behavioral and emotional engagement may decline due to academic burnout (Schnitzler et al., 2020). Targeted interventions could potentially improve engagement consistency (Pohl, 2020).

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Table 4: Group Descriptives by Year Level

	Year Level	N	Mean	SD	SE
Cognitive Component	1st Year	117	3.65	0.837	0.0774
	2nd Year	43	3.96	0.881	0.1344
	3rd Year	37	3.78	0.816	0.1342
	4th Year	57	4	0.715	0.0947
AFFECTIVE COMPONENT	1st Year	117	3.26	0.705	0.0652
	2nd Year	43	3.5	0.936	0.1427
	3rd Year	37	3.25	0.707	0.1162
	4th Year	57	3.56	0.739	0.0979
BEHAVIORAL COMPONENT	1st Year	117	3.22	0.857	0.0792
	2nd Year	43	3.25	0.981	0.1495
	3rd Year	37	2.97	0.7	0.115
	4th Year	57	3.28	0.859	0.1138
AI LITERACY	1st Year	117	3.13	0.797	0.0737
	2nd Year	43	3.33	0.899	0.1371
	3rd Year	37	3.08	0.632	0.1039
	4th Year	57	3.18	0.766	0.1014
AI SELF EFFICACY	1st Year	117	3.21	0.775	0.0716
	2nd Year	43	3.34	1.034	0.1577
	3rd Year	37	3.11	0.659	0.1083
	4th Year	57	3.21	0.878	0.1163

Table 5 shows descriptive statistics in every category, men reported mean scores that were consistently higher. Although their median scores were similar (3.75), men scored higher (Mean = 3.87) than women (Mean = 3.67) on the cognitive component. Males also had higher means (3.44 and 3.25, respectively) than females (3.22 and 3.11) in the affective and behavioral components. In a similar vein, men reported higher levels of self-efficacy (Mean = 3.33) and AI literacy (Mean = 3.24) than women (3.03 and 3.00, respectively). However, a significant gender gap exists in how ease of use impacts perceived usefulness, with men finding AI more useful when it is easier to use (Al-Ayed & Al-Tit, 2024).

Males generally report greater interest in AI compared to females, although both genders show similar levels of knowledge and general attitudes towards AI (Kovačević & Demic, 2024). Men tend to view AI applications more positively, rate their own AI competencies higher, and have more trust in the technology compared to women (Armutat et al., 2024).

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Table 5: Group Descriptives by Gender

	Group	N	Mean	Median	SD	SE
Cognitive Component	Female	87	3.67	3.75	0.837	0.0897
	Male	167	3.87	3.75	0.814	0.063
AFFECTIVE COMPONENT	Female	87	3.22	3.3	0.754	0.0809
	Male	167	3.44	3.4	0.76	0.0588
BEHAVIORAL COMPONENT	Female	87	3.11	3.17	0.874	0.0937
	Male	167	3.25	3.25	0.851	0.0658
AI LITERACY	Female	87	3.03	3	0.75	0.0804
	Male	167	3.24	3.18	0.798	0.0617
AI SELF EFFICACY	Female	87	3	3	0.828	0.0888
	Male	167	3.33	3.17	0.811	0.0627

Table 6 illustrates the result of the One-Way ANOVA (Welch's) test, which evaluates the differences in various components related to attitudes and competencies in AI among all engineering students. It revealed a significant difference in the cognitive component across the groups. Moreover, in the affective component, there is a significance indicating that emotional responses toward an AI may vary slightly but do not meet the standard threshold for significance. However, the behavioral component, AI Self-Efficacy, and AI Literacy indicate that there is no significant difference observed, implying that actions or behaviors related to AI are consistent across groups.

Analysis of Variance (ANOVA) is a statistical method used to compare group means and assess whether observed differences are statistically significant. It partitions data variability into components attributed to different factors, relying on the F-test for hypothesis testing (Nowakowski, 2019). ANOVA adaptations, like latent variable approaches, allow for the analysis of interindividual differences in repeated measures (Langenberg et al., 2020). Despite these innovations, its core assumptions, such as normality and homoscedasticity, remain critical to its validity (Blanca et al., 2023).

Table 6: One-Way ANOVA (Welch's)

	F	df1	df2	p
Cognitive Component	3.086	3	100.3	0.031
AFFECTIVE COMPONENT	2.652	3	97.2	0.053
BEHAVIORAL COMPONENT	1.477	3	101.9	0.225
AI LITERACY	0.77	3	102.6	0.514
AI SELF EFFICACY	0.488	3	99.5	0.691

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Table 7 shows the independent samples t-test that compares the means of two groups (Ross & Willson, 2017). The component of cognitive with (t-statistic= -1.88 and p-value=0.061) since the p-value is close to the significance level of 0.05, so the result should be interpreted with caution. The P value is the probability of rejecting or failing to reject the null hypothesis H0 (Thiese et al., 2016), affective components show (t-statistic= -2.19 nad p-value= 0.029) along the ai literacy (t-statistic= -2.04 and p-value= 0.042) and AI self-efficacy (t-statistic= -3.06 and p-value= 0.002) the data suggest that there is a statistically significant difference between the means of the two groups for this variable. self-efficacy exerts an influence on attitude, signifying that higher levels of technology self-efficacy correspond to a perception of enhanced capabilities in making effective decisions related to automated technology, facilitating ease of interaction, and control over its impacts (Montag et al., 2023).

However, the behavioral component suggests that there is no statistically significant difference between the two groups since the p-value of 0.21 is greater than the common significance level of 0.05. This means that there is a 21% chance of observing a t-statistic as extreme as -1.26 if there were truly no difference between the means of the two groups.

Table 7: Independent Samples T-Test

		Statistic	df	p
Cognitive Component	Student's t	-1.88	252	0.061
AFFECTIVE COMPONENT	Student's t	-2.19	252	0.029
BEHAVIORAL COMPONENT	Student's t	-1.26	252	0.21
AI LITERACY	Student's t	-2.04	252	0.042
AI SELF EFFICACY	Student's t	-3.06	252	0.002

Table 8 presents the Tukey Post-Hoc Test Cognitive Component that provides details of the mean differences and corresponding p-values. The P value is the probability of rejecting or failing to reject the null hypothesis H0 (Thiese et al., 2016).

The comparison between 1st-year and 4th-year students reveals a statistically significant difference, with a mean difference of -0.3462 and a p-value of 0.045. This indicates a meaningful change over time. However, the comparison between 1st year and 2nd year or 2nd year and 3rd year does not show significant differences, as their p-values exceed the common significant level of 0.05. This means that the cognitive components may evolve significantly between the 1st year and 4th year, but they remain stable during intermediate academic years.

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Table 8: Tukey Post-Hoc Test – Cognitive Component

		1st Year	2nd year	3rd year	4th year
1st Year	Mean difference	—	-0.305	-0.123	-0.3462
	p-value	—	0.156	0.854	0.045
2nd year	Mean difference		—	0.182	-0.0407
	p-value		—	0.752	0.995
3rd year	Mean difference			—	-0.223
	p-value			—	0.568
4th year	Mean difference				—
	p-value				—

Using structural equation modelling (SEM), the relationships between AI literacy, AI self-efficacy, attitudes toward AI systems, and their subsequent affective, cognitive, and behavioral components are analyzed. From the figure below, the path coefficients highlight strong relationships across variables. For instance, "AI Literacy" exerts a substantial positive effect on "Attitude on AI System" (O = 0.774, $p < 0.001$), while "AI Self-Efficacy" has a weaker yet statistically significant impact (O = 0.209, $p < 0.001$). This suggests that engineering students' understanding of AI concepts plays a dominant role in shaping their attitudes compared to their confidence in AI-related skills. Furthermore, "Attitude on AI System" strongly influences all three outcome components, with the highest effect observed on the "Behavioral Component" (O = 0.919, $p < 0.001$), followed by the "Affective Component" (O = 0.868, $p < 0.001$) and "Cognitive Component" (O = 0.727, $p < 0.001$). These findings align with previous research emphasizing the pivotal role of attitudes in shaping behavioral intentions and emotional connections toward technology (Hwang & Kang, 2022).

The f-square values reveal the relative impact of predictors on outcomes. "AI Literacy" has a large effect size on "Attitude on AI System" (f-square = 2.057), while "AI Self-Efficacy" shows a smaller effect (f-square = 0.15). Additionally, "Attitude on AI System" demonstrates significant effects on all three outcome components, with the "Behavioral Component" showing the largest effect size (f-square = 5.463). These data underline that students' attitudes toward AI systems substantially drive their behavioral responses, echoing findings in educational psychology research (Huang et al., 2023). Metrics of T-statistics and p-values further validate the strength of these relationships, with all T-values exceeding thresholds for statistical significance (e.g., $T > 1.96$ for 95% confidence) and p-values consistently at 0. This statistical robustness underscores the reliability of the findings, as seen in other SEM-based studies (Woo & Kang, 2023).

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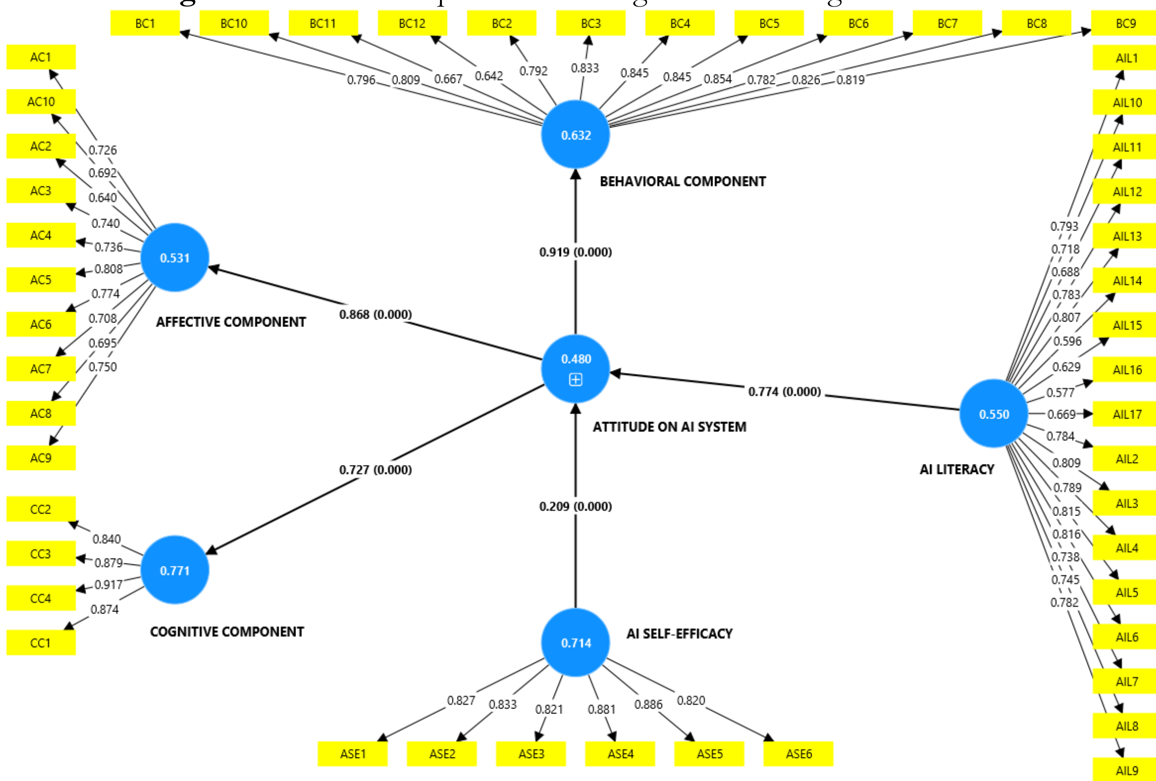
Figure 1: Structural Equation Modeling - Results Using SmartPLS4.0



The R-squared and adjusted R-squared values for attitude on AI systems exhibit high explanatory power with 91.3% of the variance explained ($R^2 = 0.913$) and an adjusted R^2 of 0.912, reflecting an excellent fit. In general, R-squared and Adjusted R-squared thresholds suggest that values above 0.7 indicate a strong fit, values between 0.4 and 0.7 reflect a moderate fit, and values below 0.4 indicate a weak fit (Hair et al., 2010). Adjusted R^2 accounts for the number of predictors, and a smaller difference between R^2 and adjusted R^2 reflects a more efficient model with minimal overfitting (Tabachnick & Fidell, 2013).

Table 9: Path Coefficients, f-square, R-squared, and Adjusted R-squared

	Original sample (O)	Sample mean (M)	f-square	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI LITERACY -> ATTITUDE ON AI SYSTEM	0.774	0.774	2.057	0.04	19.23	0.001
AI SELF-EFFICACY -> ATTITUDE ON AI SYSTEM	0.209	0.208	0.15	0.044	4.75	0.001
R-square	0.480					
R-square adjusted	0.481					

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Theoretical Implications

Interpreting the findings using the Theory of Planned Behavior (TPB) and Self-Determination Theory (SDT), attitudes, subjective norms, and perceived behavioral control are key determinants of behavioral intentions, which then predict actual behaviors. The strong cognitive engagement observed among engineering students, particularly in senior academic levels, shows a robust perceived behavioral control, as students' increased exposure to AI education boosts their confidence in navigating and using these systems. This is consistent with TPB's assertion that when individuals believe they can effectively perform a behavior, their intention to engage in it strengthens (Ajzen, 1991). Additionally, the affective and behavioral components, which showed moderate but positive correlations, suggest that students' emotional attitudes and societal norms within academic settings play a supportive role in developing their behavioral intentions toward AI.

SDT complements this interpretation by emphasizing the need for autonomy, competence, and relatedness in fostering intrinsic motivation and sustained engagement. The observed progression in cognitive and self-efficacy scores as students advance through academic levels highlights how structured AI education fulfills the need for competence, a core element of SDT (Ryan & Deci, 2019). Moreover, gender discrepancies in AI literacy and self-efficacy are consistent with SDT's focus on the influence of social contexts. Female students' lower self-efficacy may indicate unmet psychological needs or insufficient support systems compared to their male counterparts, underscoring the role of the environment in shaping educational outcomes. Together, TPB and SDT provide a comprehensive framework for understanding how individual beliefs, motivational states, and supportive academic contexts interact to influence attitudes and behaviors toward AI in engineering education.

The findings of the study align with the Multicomponent Model of Attitude by Eagly and Chaiken (1993), demonstrating the multidimensional nature of engineering students' attitudes toward AI systems. The cognitive component reveals a progressive improvement in engagement as students advance academically, with mean scores increasing from 3.65 in the first year to 4.00 in the fourth year. This pattern highlights the impact of academic exposure on knowledge and beliefs, consistent with the model's assertion that cognitive evaluations shape attitudes. The affective component, reflecting emotional responses, shows generally positive reactions with a mean of 3.37, though variability across year levels and gender groups indicates differences in emotional alignment influenced by external factors such as academic challenges or personal interests. The behavioral component, with moderate engagement indicated by a mean score of 3.20, suggests that the practical adoption of AI systems is directly linked to attitudes. Strong factor loadings, such as 0.902 for behavioral indicators, support the model's claim that attitudes significantly influence behavioral intentions.

Conclusion

This study provides significant insights into the attitudes of engineering students toward artificial intelligence (AI) systems, highlighting the interplay between cognitive, affective, and behavioral dimensions. The progressive rise in cognitive engagement as students grow academically reflects the impact of increased exposure and educational scaffolding. However, the study also uncovers significant gender discrepancies, particularly in AI literacy and self-efficacy, suggesting a need for targeted interventions to bridge these gaps. The findings

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are consistent with the Theory of Planned Behavior, which emphasizes the influence of attitudes, norms, and perceived control on behavioral intentions, and Self-Determination Theory, which underscores the importance of supportive environments for fostering engagement and growth, and the Multicomponent Model of Attitude that demonstrates the students' attitude toward AI systems. These results call for inclusive and adaptive curricula that not only enhance AI competencies but also address disparities to prepare a diverse and competent engineering workforce. Future research should investigate longitudinal effects and explore contextualized interventions to promote equitable and robust AI literacy across all demographic groups.

Limitations and Future Directions

While this study offers valuable insights into the attitudes of engineering students toward artificial intelligence (AI) systems, it is not without limitations. The research relied on self-reported data, which may be subject to social desirability bias, potentially influencing the accuracy of responses. Additionally, the study sample was limited to a single institution, which may restrict the generalizability of the findings to broader populations of engineering students. The cross-sectional design also prevents examination of changes in attitudes over time or the causal relationships between variables. Future research could address these limitations by adopting longitudinal designs to track attitudinal shifts over students' academic progression and incorporating more diverse samples from multiple institutions to enhance generalizability. Exploring qualitative methodologies, such as interviews or focus groups, could provide deeper insights into the underlying reasons behind observed gender disparities and other demographic trends. Furthermore, investigating the effects of targeted interventions, such as curriculum revisions or conducting AI literacy programs, could offer actionable strategies for fostering equitable and robust AI education.

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The author acknowledges the role of AI technologies during the preparation of this work. Employing the services of ChatGPT, Grammarly, and Quillbot to enhance the statistical interpretation, paraphrase citation, and proofreading of the study, the authors will review and edit the publication's content as needed and take full responsibility for the uses of the AI tools/service to follow the recommendations of Kaebnick et al. (2023) in the responsible use of AI technologies in scholarly journal publishing.

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