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Factors Affecting the Adoption of Artificial Intelligence in Engineering Education: Evidence from Students and Teachers

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ABSTRACT

Artificial intelligence (AI) is increasingly embedded in higher education, yet its adoption in engineering education remains uneven and shaped by technical, psychological, and institutional factors. This study examined the factors associated with AI adoption among engineering students and teachers. Drawing on the Technology Acceptance Model and the Theory of Planned Behaviour, the study measured perceived usefulness, perceived ease of use, perceived trust in AI, attitudes toward AI adoption, perceived barriers, and AI adoption. A quantitative cross-sectional survey was administered to 203 respondents, including 124 students and 79 teachers. Data were analyzed using SPSS through descriptive statistics, reliability analysis, Pearson correlations, multiple regression, and independent samples t-tests. The results showed high mean scores for all constructs, indicating generally positive perceptions and active engagement with AI tools. Perceived usefulness ($r = .459$, $p < .001$), perceived ease of use ($r = .478$, $p < .001$), and perceived barriers ($r = .825$, $p < .001$) were significantly related to AI adoption. Multiple regression showed that attitudes toward AI adoption (beta = .537, $p < .001$) and perceived trust in AI (beta = .405, $p < .001$) significantly predicted AI adoption, explaining 80.1% of the variance. No significant differences were found between students and teachers in attitudes toward AI adoption or actual AI adoption. The findings suggest that AI adoption in engineering education is driven less by role differences and more by users' attitudes, trust, perceived value, usability, and awareness of barriers. The study offers practical implications for universities seeking to design coherent, evidence-based AI integration strategies.

Keywords - Artificial intelligence; engineering education; technology acceptance; trust in AI; AI adoption; teachers; students

I. INTRODUCTION

Artificial intelligence (AI) has become one of the most influential technologies affecting contemporary higher education. Its uses now extend beyond administrative automation to include learning support, intelligent tutoring, feedback generation, problem-solving assistance, assessment support, and personalized learning [1]-[4]. Engineering education is a particularly important context for studying AI adoption because engineering programs depend on analytical reasoning, simulation, design thinking, technical calculation, and applied problem solving. These activities create opportunities for AI tools to support both students and teachers, while also creating concerns about reliability, trust, data privacy, institutional readiness, and responsible use.

Although AI tools are increasingly available, their educational value depends on whether users accept and integrate them into academic practice. The Technology Acceptance Model (TAM) suggests that perceived usefulness and perceived ease of use are central to technology adoption [5]. The Theory of Planned Behaviour (TPB) further emphasizes that attitudes toward a behavior shape intention and action [6]. In the context of AI in education, however, these traditional models require expansion because users also evaluate AI systems through trust, ethical acceptability, privacy risk, technical support, and institutional guidance. For this reason, the present study integrates TAM-related constructs with attitudes, trust, and perceived barriers to explain AI adoption in engineering education.

The study addresses a practical and empirical problem. Students may use AI tools informally for learning and academic tasks, while teachers may recognize the pedagogical value of AI but lack training, institutional support, or clear ethical guidance. Earlier studies have discussed teachers and students separately, but fewer studies have examined both groups within the same

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analytical framework. This limits understanding of whether adoption is mainly shaped by stakeholder role or by broader psychological and technological factors. Therefore, this study asks: what factors are associated with AI adoption in engineering education, and do students and teachers differ significantly in their attitudes and adoption levels?

The paper makes three contributions. First, it provides empirical evidence on AI adoption in engineering education using a sample that includes both students and teachers. Second, it compares the relative importance of usefulness, ease of use, trust, attitudes, and perceived barriers. Third, it shows that students and teachers in this sample do not significantly differ in attitudes or adoption, suggesting that institutional AI strategies may need to target both groups through shared frameworks rather than entirely separate interventions.

I.

II. THEORITCAL BACKGROUND AND HYPOTHESIS

The conceptual model combines constructs from TAM and TPB with context-specific variables relevant to AI in education [5], [6]. Perceived usefulness refers to the degree to which students and teachers believe AI tools improve teaching, learning, academic performance, and understanding of engineering concepts. Perceived ease of use refers to the degree to which AI tools are perceived as easy to learn, clear, user-friendly, and usable without major technical difficulty. These two constructs are important because users are more likely to adopt a technology when they see both academic value and manageable effort. Related technology acceptance research also shows that adoption can be shaped by broader social and facilitating conditions [8].

Attitude toward AI adoption reflects users' positive or negative evaluation of using AI in education. TPB suggests that a favorable attitude increases the likelihood of behavioral intention and subsequent behavior [6]. In AI-supported engineering education, attitude may be shaped by perceived academic usefulness, comfort, willingness to use AI regularly, and support for integrating AI into teaching and learning. Trust in AI refers to confidence in AI systems' accuracy, reliability, fairness, and dependability [7]. Trust is especially important in academic settings because AI-generated outputs may influence learning, problem solving, and decision-making. Perceived barriers include lack of training, privacy concerns, technical difficulty, lack of institutional support, and limited trust in AI-based systems. These barriers do not necessarily prevent use; they may also become more visible as users gain more experience with AI tools.

Based on this framework, the following five merged hypotheses were tested: H1: Perceived usefulness and perceived ease of use are statistically significantly related to AI adoption in engineering education. H2: Perceived trust in AI and attitudes toward AI adoption have statistically significant positive effects on AI adoption in engineering education. H3: Perceived barriers are statistically significantly related to AI adoption in engineering education. H4: There are statistically significant differences between students and teachers in their attitudes toward AI adoption in engineering education. H5: There are statistically significant differences between students and teachers in their level of AI adoption in engineering education.

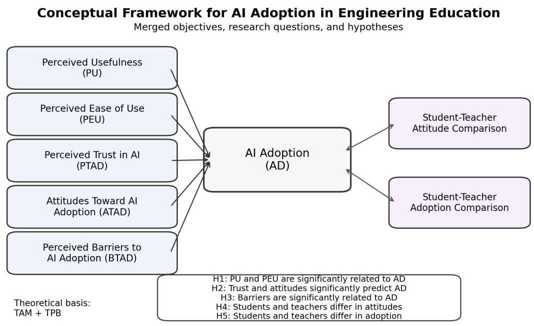

Fig. 1. Conceptual framework of the study.

III. METHODOLOGY

A. Research Design and Sample

A quantitative cross-sectional survey design was used. This design was appropriate because the study measured perceptions and adoption behavior at one point in time and tested relationships between variables statistically. The target population consisted of engineering students and teachers in higher education. Purposive sampling was used because respondents needed to be directly involved in engineering education and able to evaluate AI tools in academic contexts.

The final sample included 203 valid responses. Students represented 61.1% of the sample (n = 124), while teachers represented 38.9% (n = 79). Male respondents represented 67.0% of the sample and female respondents represented 33.0%. Most respondents were aged 31 or older, and most held postgraduate qualifications, with 49.8% reporting a master's degree and 42.4% reporting a PhD. This profile suggests that the sample was academically experienced and relevant to the study context.

Variable	Category	n	%

Gender	Male	136	67.0
Gender	Female	67	33.0
Age	18-22	2	1.0
Age	23-30	63	31.0
Age	31-40	66	32.5
Age	40+	72	35.5
Role	Professor/Teacher	79	38.9
Role	Student	124	61.1
Education	Bachelor	16	7.9
Education	Master	101	49.8
Education	PhD	86	42.4

Table 1: Demographic profile of respondents
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B. **Instrument and Measurement**

Data were collected using a structured questionnaire. The instrument included four demographic items and 30 Likert-scale items measured on a five-point scale from 1 = strongly disagree to 5 = strongly agree. Six constructs were measured: perceived usefulness, perceived ease of use, perceived trust in AI, attitudes toward AI adoption, perceived barriers to AI adoption, and AI adoption. Each construct was measured using five items. Construct scores were calculated by averaging the items within each scale.

Reliability was assessed using Cronbach's alpha. Corrected item-total correlations were also examined to ensure that each item contributed adequately to its scale. All Cronbach's alpha values were above the commonly accepted threshold of .70, ranging from .794 to .945. All corrected item-total correlations exceeded .30, indicating that all items were retained for analysis.

Construct	Items	Valid n	Cronbach alpha	Corrected item-total range
Perceived usefulness	5	203	.944	.800-.909
Perceived ease of use	5	202	.945	.815-.911
Perceived trust in AI	5	203	.881	.646-.806
Attitudes toward AI adoption	5	203	.880	.650-.753
Perceived barriers	5	203	.794	.509-.664
AI adoption	5	203	.836	.529-.800

Table 2: Reliability and item-total correlation summary

C. **Data Analysis**

The data were analyzed using SPSS. Frequencies and percentages were used to describe demographic characteristics. Means and standard deviations were used to answer the descriptive research questions. Pearson correlation was used to test the relationships between perceived usefulness, perceived ease of use, perceived barriers, and AI adoption. Multiple regression was used to examine the effects of trust and attitudes on AI adoption. Independent samples t-tests were used to compare students and teachers in attitudes toward AI adoption and AI adoption. All hypotheses were tested at the .05 significance level.

IV. RESULTS

A. Descriptive Findings and Research Question Answers

The descriptive results show that all constructs recorded high mean scores. Attitudes toward AI adoption had the highest mean (M = 3.907, SD = .825), followed by perceived trust in AI (M = 3.869, SD = .886), perceived barriers (M = 3.853, SD = .778), perceived ease of use (M = 3.827, SD = .902), AI adoption (M = 3.819, SD = .792), and perceived usefulness (M = 3.818, SD = .902). These findings answer the first six research questions: respondents reported high perceived usefulness, high perceived ease of use, high trust in AI, positive attitudes, high awareness of barriers, and high AI adoption.
The high attitude score indicates that respondents were generally open to AI integration in engineering education. The high adoption mean suggests that AI tools were not merely viewed as future possibilities but were already being used for academic purposes. At the same time, the high perceived barriers mean demonstrates that adoption does not remove concern. Respondents may use AI while still recognizing privacy risks, training needs, technical challenges, and institutional gaps.

Construct	n	Mean	SD	Interpretation

Perceived usefulness	203	3.8177	.90175	High
Perceived ease of use	202	3.8267	.90233	High
Perceived trust in AI	203	3.8690	.88596	High
Attitudes toward AI adoption	203	3.9074	.82468	High
Perceived barriers	203	3.8532	.77761	High
AI adoption	203	3.8187	.79169	High

Table 3: Descriptive statistics of main constructs

B. *Hypothesis Testing*

The five merged hypotheses were tested using the same statistical structure reported in the final thesis. H1 was tested through Pearson correlations for perceived usefulness and perceived ease of use. H2 was tested through multiple regression for perceived trust in AI and attitudes toward AI adoption. H3 was tested through Pearson correlation for perceived barriers. H4 and H5 were tested through independent samples t-tests comparing students and teachers.

- **H1: Technology acceptance factors and AI adoption**

Statistic	Value
PU - AI adoption Pearson r	.459
PU significance	p < .001
PEU - AI adoption Pearson r	.478
PEU significance	p < .001
Sample size	n = 203
Decision	Supported

Table 4: Statistical result for H1

H1 proposed that perceived usefulness and perceived ease of use are statistically significantly related to AI adoption in engineering education. Pearson correlation showed significant positive relationships for perceived usefulness ($r = .459$, $p < .001$) and perceived ease of use ($r = .478$, $p < .001$). Therefore, H1 was supported. This means that respondents who viewed AI tools as useful and easy to use were more likely to adopt AI tools in engineering education.

- **H2: Perceived trust, attitudes, and AI adoption**

Statistic	Value
R	.895
R square	.801
Adjusted R square	.799
F(2, 200)	403.344
Model significance	p < .001

Table 5: Regression model summary for H2

Predictor	Result
Perceived trust in AI	B = .362; beta = .405; t = 7.705; p < .001
Attitudes toward AI adoption	B = .516; beta = .537; t = 10.219; p < .001

Table 6: Regression coefficients for H2

H2 proposed that perceived trust in AI and attitudes toward AI adoption have statistically significant positive effects on AI adoption in engineering education. The regression model was significant and explained 80.1% of the variance in AI adoption ($R2 = .801$, $p < .001$). Both perceived trust in AI ($beta = .405$, $B = .362$, $t = 7.705$, $p < .001$) and attitudes toward AI adoption ($beta = .537$, $B = .516$, $t = 10.219$, $p < .001$) significantly predicted AI adoption. Therefore, H2 was supported.

- **H3: Perceived barriers and AI adoption**

Statistic	Value
Perceived barriers - AI adoption Pearson r	.825
Significance	p < .001
Sample size	n = 203
Decision	Supported

Table 7: Statistical result for H3

H3 proposed that perceived barriers are statistically significantly related to AI adoption. Pearson correlation showed a strong positive relationship, $r = .825$, $p < .001$. Therefore, H3 was supported. The positive direction should be interpreted as awareness rather than proof that barriers cause adoption; respondents who use AI more may also be more aware of privacy concerns, training needs, technical difficulty, institutional support, and limited trust.

- **H4: Student-teacher differences in attitudes toward AI adoption**

Statistic	Value
Teacher mean	M = 3.8911
Student mean	M = 3.9177
Mean difference	-.02660
t	-.231
Significance	p = .818
Decision	Not supported

Table 8: Statistical result for H4

H4 proposed statistically significant differences between students and teachers in attitudes toward AI adoption in engineering education. The independent samples t-test showed no statistically significant difference, $p = .818$. Students had a slightly higher mean score ($M = 3.9177$) than teachers ($M = 3.8911$), but the difference was not statistically meaningful. Therefore, H4 was not supported.

- **H5: Student-teacher differences in AI adoption**

Statistic	Value
Teacher mean	M = 3.7747
Student mean	M = 3.8468
Mean difference	-.07209
t	-.637
Significance	p = .525
Decision	Not supported

Table 9: Statistical result for H5

H5 proposed statistically significant differences between students and teachers in their level of AI adoption. The independent samples t-test showed no statistically significant difference, $p = .525$. Students again reported a slightly higher mean score ($M = 3.8468$) than teachers ($M = 3.7747$), but the difference was not statistically significant. Therefore, H5 was not supported.

H	Result	Decision
H1	PU: r = .459; PEU: r = .478; p < .001	Supported
H2	Trust: beta = .405; Attitudes: beta = .537; p < .001	Supported
H3	r = .825; p < .001	Supported
H4	p = .818	Not supported
H5	p = .525	Not supported

Table 10: Summary of hypothesis testing.

V. IMPLICATIONS

A. Theoretical and Practical Implications

The findings have theoretical and practical implications. Theoretically, the study supports TAM by confirming the relationships of perceived usefulness and perceived ease of use with AI adoption [5]. It also supports TPB by showing that attitudes are a strong predictor of adoption [6]. At the same time, the study extends these models by showing the importance of trust and perceived barriers in AI-supported engineering education. AI adoption cannot be understood only as a usability issue; it also involves ethical, institutional, and psychological dimensions.

Practically, universities should prioritize attitude-building initiatives such as AI awareness sessions, demonstrations, and guided hands-on practice. Since attitudes were the strongest predictor of adoption, these activities may help users move from passive awareness to confident and responsible use. Institutions should also strengthen trust by developing clear AI policies, transparent evaluation standards, and guidance on how to verify AI-generated content. Finally, perceived barriers should be addressed through training, privacy safeguards, technical support, and infrastructure investment.

Empirical finding	Recommendation	Stakeholders
Attitudes were the strongest predictor of AI adoption (beta = .537, p < .001).	Integrate AI awareness sessions, demonstrations, and hands-on exposure into engineering teaching and learning.	University administration; curriculum developers; faculty

Trust positively affected AI adoption (beta = .405, p < .001).	Develop transparent AI-use policies, ethical guidelines, reliable platforms, and standards for checking AI outputs.	Universities; policymakers; AI system developers
Perceived barriers were significantly related to AI adoption (r = .825, p < .001).	Reduce barriers through training, privacy protection, institutional support, and continuous technical assistance.	Institutional leadership; IT departments; policymakers
No significant student-teacher differences were found.	Implement unified AI adoption strategies for both students and teachers, with role-specific examples where needed.	Educational institutions; academic departments

Table 11: Evidence-based recommendations

Practical Interpretation for Engineering Education

For curriculum design, the results suggest that AI should not be introduced as a separate technical novelty only. Instead, AI-related activities should be embedded into engineering tasks where students and teachers can see clear academic value. Examples include guided problem solving, simulation explanation, code review, design ideation, literature search support, and feedback generation. This approach may strengthen perceived usefulness because users can observe how AI supports the actual work of engineering education rather than hearing only general claims about AI.

For professional development, the findings suggest that training should address both competence and confidence. Since trust and attitudes significantly predicted adoption, training should not be limited to tool operation. It should include how to evaluate AI outputs, identify hallucinations or incorrect reasoning, protect data privacy, and maintain academic integrity. This type of training may reduce unrealistic expectations while also preventing unnecessary fear of AI tools.

For institutional policy, the lack of significant difference between students and teachers indicates that AI governance should be designed as a shared institutional framework. Separate instructions may still be needed for assessment, teaching preparation, and student learning tasks, but the overall principles should be consistent. A common institutional framework can clarify acceptable use, privacy rules, citation of AI assistance, verification responsibilities, and the limits of AI-generated content

VI. LIMITATIONS AND FUTURE RESEARCH

This study has several limitations. First, it used a cross-sectional survey design, which means that the results describe relationships at one point in time and cannot establish causality. Second, the study used purposive sampling, which limits generalizability. Third, the data were self-reported, so responses may reflect perceptions rather than observed behavior. Fourth, while the study included both students and teachers, it did not examine differences by engineering discipline, year of study, teaching experience, or type of AI tool used.

Future research should use longitudinal designs to examine how AI adoption changes over time. Qualitative interviews may also help explain why users trust or distrust AI and how they experience barriers in practice. Future studies may also compare different engineering disciplines or examine specific AI tools used for design, coding, simulation, assessment, and feedback. Finally, future research could test an expanded structural model including institutional support, ethical awareness, AI literacy, and behavioral intention.

VII. CONCLUSION

This study examined the factors affecting AI adoption in engineering education among students and teachers. The results showed high levels of perceived usefulness, perceived ease of use, trust in AI, positive attitudes, perceived barriers, and AI adoption. Five hypotheses were supported: perceived usefulness, perceived ease of use, perceived barriers, trust, and attitudes were significantly associated with AI adoption, with attitudes and trust serving as significant predictors. Two hypotheses were not supported: students and teachers did not significantly differ in attitudes toward AI adoption or actual AI adoption.

Overall, the study suggests that AI adoption in engineering education is driven primarily by users' attitudes, trust, perceived usefulness, ease of use, and awareness of barriers rather than by stakeholder role. For institutions, the main message is clear: effective AI adoption requires more than providing tools. It requires positive attitudes, trustworthy systems, training, ethical guidance, privacy protection, and institutional support. In this sense, AI adoption should be treated as an educational transformation process rather than only a technological implementation.

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