Cogent Education

ISSN: 2331-186X (Online) Journal homepage: www.tandfonline.com/journals/oaed20

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To cite this article: Chika Judith Abolle-Okoyeagu, Chinedu Pascal Ezenkwu, Ebuka Ibeke, Ojotule Paul Onoja & Victor Ugochukwu Ezeonwumelu (2026) Engineering students and AI in education: a TAM-based study of perceptions, acceptance, and barriers to adoption, Cogent Education, 13:1, 2614148, DOI: 10.1080/2331186X.2026.2614148

To link to this article: https://doi.org/10.1080/2331186X.2026.2614148

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COGENT EDUCATION
2026, VOL. 13, NO. 1, 2614148
https://doi.org/10.1080/2331186X.2026.2614148

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Engineering students and AI in education: a TAM-based study of perceptions, acceptance, and barriers to adoption

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ABSTRACT

Artificial intelligence (AI) is gradually being accepted into education and has the potential of transforming learning and teaching. It is therefore important to understand the perceptions of various stakeholders on the impact of AI in engineering education. This study is framed with the Technology Acceptance Model (TAM) and employs a mixed-method approach to assess the perception of engineering students on the adoption of AI. The quantitative analysis of the survey findings using partial least square structural equation modelling (PLS-SEM), reveals that perceived usefulness and the ease of use has a statistically significant relationship with AI adoption amongst engineering students. Moreover, their attitude towards AI did not influence their intention to use AI in their education. Through the qualitative analysis, the perceived usefulness of AI in personalized learning, solving complex problems, increasing efficiency and solving global problems were highlighted. However, it was noted that wider adoption of AI would be achieved when there are strategies to address the institutional barriers, ethical issues and funding. Another interesting finding is that students raised concern about the potential impairment in their cognitive abilities if they over-rely on AI.

ARTICLE HISTORY
Received 20 March 2025
Revised 22 August 2025
Accepted 5 January 2026

KEYWORDS
Adoption; Artificial Intelligence; education; engineering; perception; technology

SUBJECTS
Biomedical Engineering; Engineering & Technology; Technology, Chemical Engineering; Engineering & Technology; Technology, Structural Engineering; Civil, Environmental and Geotechnical Engineering; Engineering & Technology; Technology, Design; Art & Visual Culture; Arts; Arts & Humanities, Mechanical Engineering Design; Mechanical Engineering; Engineering & Technology; Technology

1. Introduction

Engineering education, just like several other sectors of human endeavor has seen a rapid transformation as a result of the emergence of Artificial Intelligence (AI). Recent research has highlighted the significant potential of AI in engineering education (David, 2023; Dignum, 2021). As an important component of the fourth industrial revolution, AI-driven technologies are increasingly being amalgamated into teaching and learning processes, with the potential to considerably impact the way engineering students are educated (Broo et al., 2022). To fully realise these potential benefits in engineering education, engineering students perceived usefulness, perceived ease of use and their attitude towards the use of AI technology adoption has to be understood. This is because their views on its usefulness and effectiveness could influence institutions and stakeholders to invest in AI integration, while potential

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/2331186X.2026.2614148.

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concerns may provide opportunity for innovative outcomes, as regards tailoring AI technologies for enhanced learning and outcomes (Bravo & Cruz-Bohorquez, 2024).

The societal and economic landscape significantly influences the incorporation of AI into engineering education. AI skills are among the top five skills that companies are likely to look for in the next 5 years. As industries increasingly implement AI technologies, the need for a skilled workforce in these areas has grown. This shift highlights the importance of training future engineers in AI applications relevant to fields like machine learning, natural language processing, robotics, manufacturing, healthcare, and transportation (Bongomin et al., 2020). As a result, engineering education programs are focusing on incorporating AI technologies into their curricula to equip graduates for the changing job market. With the rapid evolution of AI technologies and their increasing capabilities, especially in reducing the cost of computing power in complex task, the need for adoption of AI in engineering education continues to soar (Van der Vlies & Vincent-Lancrin, 2020).

The incorporation of AI in engineering education takes many forms, from intelligent tutoring systems that have the capability of providing personalized feedback and adaptive learning experiences to virtual simulations and augmented reality applications that allow students to experiment with complex engineering concepts in immersive environments (AlGeraf et al., 2023; Kaur et al., 2020; Ojha et al., 2023).

While there are various studies addressing the role of AI in education (Adiguze et al., 2023; Michel-Villarreal et al., 2023; Nikolic et al., 2023; Prahani et al., 2023; Qadir, 2023; Sánchez-Ruiz et al., n.d.; Tossell et al., 2024; Zou & Huang, 2023), only very few studies have been dedicated to understanding the perception of engineering students. Studies focusing on engineering students often examine their perceptions of specific tools, such as ChatGPT. Other studies are directed to understanding the perception of engineering students in the general application of AI. It is thus important to understand the general perception of engineering students on the use of AI in learning.

Recent research underscores various factors influencing student perceptions, including trust in AI systems, worries about cognitive overload, and the potential impacts on academic integrity and fairness in automated assessments. For example, Leinonen et al. examined students' views on the effectiveness and credibility of AI-generated code explanations, finding that students generally find these explanations helpful but perceive them as less reliable than those provided by humans, raising concerns about their depth and thoroughness (Leinonen et al., 2023). Additionally, Barretto et al explored reasons why underrepresented students are less inclined to pursue studies in AI and machine learning, identifying barriers such as the belief that AI requires innate brilliance and ethical concerns related to AI technologies. These findings highlight the need to address biases and misconceptions early in education to foster more inclusive and diverse participation in AI fields (Barretto et al., 2021).

Furthermore, this study will help understand the challenges of adopting AI in engineering education, which could lead to the development of more robust mitigating strategies that accommodate the interests of various stakeholders. In addition, most studies that try to understand the perceived usefulness and effectiveness of individual stakeholders have used the quantitative approach (Zou & Huang, 2023). In this study, a mixed approach is used to get a holistic understanding of the stakeholders' perception. We measure the perceived usefulness and perceived effectiveness with the quantitative approach and explore the underlying reasons with the qualitative approach.

In summary, this paper seeks to respond to the following key research questions:

RQ1: How does the attitude of engineering students toward AI influence their intention to use technology?

RQ2: In what way does the perceived ease of use of AI tools shape engineering students' attitudes toward AI technology?

RQ3: How does the perceived ease of use of AI tools affect engineering students' perception of their usefulness?

RQ4: To what extent does the perceived usefulness of AI tools shape engineering students' attitudes toward the technology?

RQ5: How does the perceived usefulness of AI tools influence engineering students' intention to use the technology?

2. Role of AI in engineering education

Global shift toward digitalization and the rise of Industry 4.0 also plays a role in the adoption of AI in engineering education. As engineering industries become more data-driven and reliant on AI technologies, educational institutions are recognizing the need to integrate AI into curricula to prepare students for the workforce (Baker et al., 2020).

The use of AI in engineering education covers a broad range of stakeholders, each utilizing technology for various applications. The primary beneficiaries are students as they interact directly with AI-powered tools to improve their learning experiences. They engage with intelligent tutoring systems, adaptive learning platforms, and virtual laboratories designed to address their specific learning requirements (Gligorea et al., 2023) and (Pratama et al., 2023).

Educators represent another important group using AI in engineering education, academics use AI tools for a variety of tasks such as: (1) generating insights into student performance and engagement, allowing them to detect at-risk students early on leading to timely intervention if required (Tan, 2023) and (Holmes & Porayska-Pomsta, 2023), (2) creating customized learning pathways by tailoring course materials and activities to accommodate the diverse needs of students (Bittencourt et al., 2020), (3) assessing students' knowledge and development more precisely and targeted to meet the learning needs of the students, creating a more productive and interesting learning environment (González-Calatayud et al., 2021)and (4) using AI-driven data analytics provide educators with valuable insights into student performance, facilitating the implementation of more targeted and effective teaching strategies (Mercier et al., 2023).

AI technologies can enable universities to enhance their institutional performance by utilizing data-driven decision-making processes, evaluating the effectiveness of teaching and the level of student satisfaction (Ahmad et al., 2024). With AI technologies, institutions become more attuned to student needs and improve the use of resources, guaranteeing that students receive the highest quality learning environment possible. However, extremely restrictive policies may hinder innovation and limit students' ability to explore and learn from AI technologies, while overly lenient policies may result in problems with academic integrity, such as plagiarism and misuse of AI-generated content (Johnson & Smith, 2014).

A key factor driving AI adoption is the growing demand for personalized learning, conventional uniform strategies in education frequently do not address the varied needs of different student groups. AI technologies allow for adaptive learning experiences that can adjust content based on the student's progress, learning style, and areas of difficulty, offering more effective and engaging educational experiences (Rane et al., 2024). This customization caters to the different learning speeds of students, making sure that every learner, regardless of their background knowledge or skill level, can still achieve success.

However, despite the optimism, factors such as data privacy, academic impropriety, lack of institutional support, reduced human-human interactions have a significant role in shaping the attitude towards AI use among engineering students (Obenza et al., 2024). Also, some students are concerned about their long-term work prospects because they believe that the development of AI may result in job displacement in their future jobs (Hala et al., 2023). While others have raised concern on the impact of AI on their cognitive ability (Marrone et al., 2022).

2.1. Theoretical framework—technology acceptance model (TAM)

TAM is widely used to explore the perception of users on their willingness to accept and use a technology (Davis, 1989). TAM states that users are likely to use a technology if they perceive its usefulness and ease of use.

Perceived usefulness (PU) of a technology is how users perceive it useful to complete a task or solve a problem. While the perceived ease of use (PEU) is how easy users can use a technology to complete a

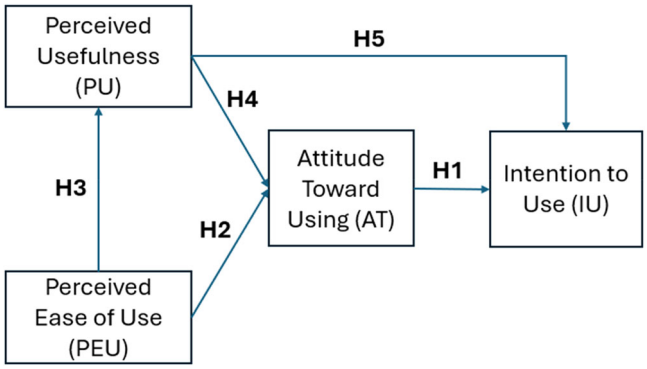

Figure 1. TAM framework used in the study.

task (Davis, 1989). Attitude towards (AT) using AI is the perception by an individual of the positive or negative consequences related to adopting the technology (Zou & Huang, 2023).

Other variables like perceived effectiveness have also been used in TAM. It is defined as the potential positive impacts or benefits of using AI in engineering education (Sharma et al., 2024). Other extended TAM models allow the integration of external variables, such as social influences (Venkatesh & Davis, 2000), institutional interventions (Venkatesh & Bala, 2008) to understand the user's willingness to accept a technology.

TAM has been proven to be effective for exploring user perception of AI in education because the relationship between all the constructs of TAM is significant (Ali et al., 2025). In addition, it has been proven to give the best fit in comparison with Unified Theory of Acceptance and Use of Technology (UTAUT) for measuring the acceptance and use of AI applications in the education sector (Ali et al., 2025).

By using TAM, this study will explore the role of PU, PEU, and AT of engineering students on their intention to use (IU) AI in engineering education (Figure 1). However, the original scale by Davis (1989) supports more general workplace IT context, which may not be suitable for an emerging, specialised technology such as AI education. TAM has always been applied by adapting and validating scales that meet a given technological context, while still retaining the ideas behind the original TAM constructs (Davis & Venkatesh, 1996). This paper will follow this approach employing scales designed for the original TAM constructs by Gagnon et al. (2012).

Engineering students' opinions of the value of AI technologies may be influenced by how simple they are regarded. TAM states that perceived usefulness, which in turn affects technology uptake and acceptance, is directly impacted by ease of use (Davis, 1989). Engineering students are more likely to see AI tools as beneficial teaching tools when they are easy to use and intuitive (Dempere et al., 2023). Easy-to-use AI technologies reduce the cognitive load on students, freeing up more mental energy for studying and comprehending engineering concepts rather than figuring out how to use the tools (Humble & Mozelius, 2024).

According to the Technology Acceptance Model (TAM) (Davis, 1989), engineering students' intention to use AI tools may also be influenced by how useful they believe the technology to be. When they see how useful and relevant AI tools are to their academic and professional goals, they may be more willing to adopt and integrate them. One important factor in this relationship is how well those tools align with educational objectives. Engineering students are driven by concrete results and real-world applications (Santana & Lopes, 2024), and they are more likely to view AI tools as valuable resources when they improve their problem-solving skills, offer real-time feedback, and provide individualized learning experiences (Dempere et al., 2023).

Another important factor is positive reinforcement. Students are more inclined to stick with AI technologies if they succeed and do better as a result of utilizing them (Salman & Chaya, 2024).

Finally, the support of educational institutions and leaders is essential for the adoption of AI in engineering education. Institutions that embrace new teaching methods and recognize the benefits of AI tools play a crucial role in successfully incorporating these technologies. Their openness to experimenting with AI-enhanced curricula, collaborating with researchers, and partnering with industry helps integrate AI into engineering programs effectively (Luckin et al., 2022).

In addition, negative attitude towards AI may result from the frustration to interact with AI tools, which can impact the adoption (Bravo & Cruz-Bohorquez, 2024). For instance, when students come across AI technologies that are difficult to use, they could find it difficult to incorporate them into their learning procedures, which could result in a decline in interest and involvement. The significance of effort expectation, or perceived ease of usage, in shaping students' attitudes has been emphasized in research (Almassaad et al., 2024).

Strong intentions to embrace and regularly use AI technologies in academic contexts are fostered by a favorable user experience (Ali et al., 2025).

Therefore, the following hypothesis will be investigated in this research:

H1: Engineering students' attitude towards AI influences their intention to use the technology.

H2: Perceived ease of use of AI tools contributes to shaping their attitude of engineering students towards the technology.

H3: Perceived ease of use of AI tools influences its perceived usefulness among engineering students.

H4: Perceived usefulness of AI tools among engineering students contributes to shaping their attitude towards the technology.

H5: Perceived usefulness of AI tools among engineering students influences their intention to use the technology.

3. Methodology

3.1. Research design

The research design for this study employs a mixed method approach to assess the perception of engineering students on the adoption of AI. The study specifically conducted by a quantitative analysis of the survey findings using partial least square structural equation modelling (PLS-SEM) and qualitative thematic analysis of open-ended questions.

A modified TAM questionnaire was used to assess the perception of engineering students regarding the use of AI in engineering education (Gagnon et al., 2012). The questionnaire was designed to capture the perceived usefulness, perceived ease of use and attitude of engineering students toward the use of AI in their educational experience.

This data collection complies with the ethical principles set forth by Jisc online survey and Robert Gordon University's Data Management Plan ID 169353. It is conducted according to ethical standards aimed at safeguarding the rights, dignity, and confidentiality of participants throughout the study.

Prior to completing the questionnaire, informed consent was obtained from each participant, confirming their voluntary agreement to participate and their understanding of their right to withdraw at any time without any consequences. The questionnaire was structured to minimize risks, no personal identifiers were collected, guaranteeing the anonymity of all participants.

To protect confidentiality, all data collected was anonymized and stored securely in accordance with data protection regulations. Access to the data was restricted to the research team, and any findings presented in the paper have been aggregated to further ensure individual privacy.

3.2. Participants

The intended audience for this study is engineering students from a Federal University in Nigeria (Nnamdi Azikiwe University) with about 40,000 students. The selected participants are a sample size of 150 engineering students, which is large enough for worthwhile statistical evaluation and to collate varying experiences with AI in education was used.

The survey was conducted in January 2025, and the students were recruited from various departments in engineering. Jisc online surveys (a renowned secure platform that ensured compliance with data protection regulations and ethical standards) was employed in the electronic distribution of the

survey ensuring anonymity as well as seamless accessing for all respondents. It thus ensured all responses and personal details of the participants were held confidentially.

3.3. Questionnaire structure and measures

As can be seen in Appendix B, the questionnaire is grouped into various sections, each tackling separate aspects of the impact of AI on education. The first aspect is the demographic section which collected some information for each participant including their course of study, and previous experience with AI technologies in education.

The second section of the questionnaire tests the items on the 33 TAM questionnaire (Gagnon et al., 2012). While the TAM is most frequently employed using the original items developed by Davis (1989), this study chose adapted items by Gagnon et al. (2012) that are consistent with the original constructs, such as Perceived Usefulness, Perceived Ease of Use, and Behavioural Intention or Intention to Use (Park & Kim, 2014), proposed by Davis. Although developed in the context of healthcare, the Gagnon et al. scale is suitable for assessing the adoption of emerging, specialised technologies such as AI-based tools in higher education rather than the more general workplace IT context that the original scale by Davis (1989) targeted. The validity and reliability of the adapted scale for measuring AI adoption among engineering students have been tested to ensure internal consistency, satisfactory composite reliability, and construct validity via confirmatory factor analysis. This section examined the perceived usefulness and perceived ease of use students regarding the use of AI and their attitude toward the technology. Finally, an open-ended question was asked to understand the barriers and challenges of using AI in engineering education.

The demographic information was captured with items (Q1-Q9) on the questionnaire. The latent variables were measured using the 33 questions in the questions. Perceived usefulness was measured with items (Q23, Q18, Q27, Q31, Q37 and Q44) in the questionnaire. Perceived ease of use was measured using items (Q19, Q24, Q28, Q32, Q40 and Q47). Attitude towards AI was measured using (Q30, Q17, Q39, Q46) and the intention to use were measured with the items (Q21, Q34 and Q44). The final open question was captured in Q48.

3.4. Data analysis

3.4.1. Quantitative data analysis

The survey data was analyzed using SmartPLS version 4 after preparation using Python. The sample size is 150 which supersedes the minimum sample size required to use PLS-SEM in the context of this research, following the '10-times rule' (Kock & Hadaya, 2018). The preparation process involves the replacement of missing values with the median. Moreover, a range of metrics were used to test the reliability and validity of the latent variables. Specifically, these include Cronbach's alpha, composite reliabilities (rho_a and rho_c) and average variance extracted (AVE) (Table 2). Then, the hypotheses were assessed using PLS-SEM.

3.4.2. Qualitative data analysis

The open question asked in the survey on the 'What do you think are the broader benefits, challenges, or concerns associated with the use of AI in engineering education?' will be analysed using thematic analysis. Thematic analysis is a method of identifying, analysing and explaining patterns from themes (Braun & Clarke, 2006). This approach allows the generation of insights from the open question in a systematic way. The thematic analysis followed the six steps highlighted by Braun and Clarke (2006). (1) familiarisation with the data (2) generating initial codes (3) Searching for themes (4) reviewing themes (5) defining and naming themes and (6) writing the findings.

All the responses were read several times to get and in-depth understanding of the perception of engineering students on the benefits and challenges of using AI in their education. The reoccurring ideas and concepts were noted, the data was checked for duplicates and incomplete responses were marked and not selected for the final analysis.

Data was systematically coded by looking for popular themes that emerged from the data. Two researchers conducted the thematic analysis independently. Each researcher coded the data manually in Microsoft Excel for proper organisation of the dataset and identifying themes directly from the data. Similar themes were then grouped into broader themes by the identification of relationship between themes. The coding results were recorded in a shared Microsoft Word document. An open review process followed, where both the themes were read and comments added by the researchers suggesting which themes to keep, refine, or remove. Themes were reviewed by checking their frequency and alignment with the benefits and challenges of AI in engineering education. Each theme was then supported with quotes from the participants to add context. Findings were then interpreted with respect to the research question. This qualitative analysis was used to further support the insights from the qualitative analysis.

4. Results

4.1. Descriptive statistics

4.1.1. Age

There are 150 participants spread across various age groups. The 18–24 age group has the highest count (90), followed by 25–34 (57), then 35–44 (2), and finally the Under 18 group with the lowest count (1).

4.1.2. Gender

There are 76 males and 74 females, indicating a relatively balanced representation of both genders among the participants.

4.1.3. Academic level

We examined the academic level of participants, and this indicates that the Undergraduate level has the highest count with 128 participants, while the other levels - Postgraduate (Taught) - 20, Postgraduate (Research) - 1, and Other - 1, have significantly lower counts.

4.1.4. Field of engineering

There are a wide range of engineering disciplines studied by the participants. The data revealed that Electrical Engineering has the highest count with 27 individuals, followed by Petroleum Engineering (22), Chemical Engineering (17), Computer Engineering (15), Civil Engineering (15), Materials Engineering (15), and Mechanical Engineering (15). The count gradually decreases for other fields, with Biomedical Engineering (13), Industrial Engineering (12), Software Engineering (8), Robotics Engineering (3), Nuclear Engineering (1), and Others (1) having the lowest counts.

4.1.5. Experience with AI tools

We explored the distribution of participants based on their prior experience with AI tools. A significant majority (86) reported extensive use of AI tools regularly, while the number of participants decreases as the level of experience and usage decreases, with only 4 reporting no prior experience.

4.1.6. Access to computer and stable internet

All participants reported access to computers or similar devices. A large majority of respondents (145) have access to a stable internet connection, while only 5 respondents indicated they do not have access to a stable internet connection.

4.1.7. Learning style

On the distribution of participants based on their preferred learning style, reading/writing is the most common preference (50 participants), followed by auditory (39), visual (35), kinesthetic (15), and mixed/other (11).

4.1.8. Comfortability with ICT

The majority of respondents (74) 'Totally agree' that they feel comfortable using information and communication technologies in their studies. A smaller number 'Agree' (50), 'Slightly agree' (25), or 'Neither agree nor disagree' (10). Only a few respondents 'Slightly disagree' (10) or 'Totally disagree' (1) with the statement.

4.1.9. Efficiency of AI tools in completing assignments

A significant majority of respondents agree to the efficiency of AI Tools in completing assignments (49.3% 'Totally agree', 33.3% 'Agree', 16.7% 'Slightly Agree'), while 0.7% 'Neither agrees nor disagrees'.

4.1.10. AI tools could help me complete assignments and projects more efficiently

A strong majority of respondents agree with this statement. 44% 'Totally agree', 42% 'Agree' and 11.3% 'Slightly agree' with the statement. 1.3% 'Neither agrees nor disagrees', and 1.3% 'Slightly disagrees'.

4.1.11. AI tools could improve academic work and performance

Considering whether AI tools could improve academic work and performance, a strong majority of respondents agree with this statement, with 42.7% 'Totally agreeing', 42.7% 'Agreeing', and 12% 'Slightly agreeing'. 1.3% 'Neither agrees nor disagrees', and 0.7% 'Slightly disagrees'.

4.1.12. Broader benefits, challenges, or concerns associated with the use of AI in engineering education

A thematic analysis reveals a complex and multifaceted perception of AI usage in engineering education, particularly among students. The findings, grouped into four major categories—academic benefits, challenges, concerns, and recommendations—highlight both the transformative potential and the practical limitations of AI integration.

Academic Benefits were the most frequently discussed, with students acknowledging that AI tools significantly ease academic workloads ($n = 47$), provide quick access to information ($n = 32$), and support research and project development ($n = 41$). This suggests a strong student endorsement of AI as a facilitator of efficiency and innovation in their learning experience. Other benefits as presented in Table 1 included adaptive learning support ($n = 14$), improved problem-solving ($n = 18$), and enhanced accuracy in academic tasks ($n = 11$), reflecting the versatility of AI in diverse academic applications.

However, significant challenges were also reported. The top among them as presented in Table 2 were high costs associated with AI tools ($n = 33$), limited infrastructure ($n = 29$), and insufficient access to the technology ($n = 25$). These challenges underscore the digital divide, particularly in under-

Table 1. Academic benefits of AI.

Theme	Frequency
Eases academic workload and task completion	47
Provides fast and easy access to information	32
Supports research and project work	41
Enhances personalized/adaptive learning	14
Improves problem-solving and engineering practice	18
Promotes innovation and real-time feedback	7
Aids in simulation and practical training	5
Enhances accuracy and efficiency	11

Table 2. Challenges in AI adoption.

Theme	Frequency
High cost/subscription issues	33
Lack of resources/infrastructure (power, internet, tools)	29
Lack of institutional/government support	18
Limited availability and access to AI tools	25
AI literacy/awareness gap among students and educators	9
Technical glitches or reliability issues	4
Curriculum and standard alignment issues	3

Table 3. Concerns about over-reliance and negative impact.

Theme	Frequency
Reduced research participation and intellectual rigor	30
Decline in creativity and critical thinking	28
Loss of originality in student work	11
Laziness and dependency among students	17
Reduced human interaction (teacher-student engagement)	7
Ethical concerns (data privacy, bias, plagiarism)	10
Fear of AI replacing teachers	3

Table 4. Recommendations.

Theme	Frequency
Need for awareness and training	10
Call for better support/infrastructure	21
Optimism about AI's future role	8

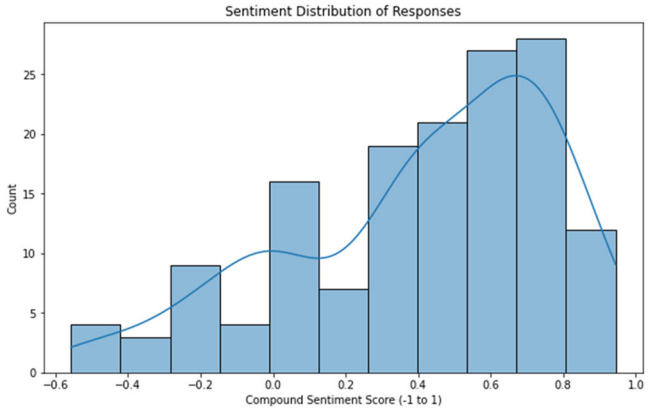

Figure 2. Sentiment distribution of responses from the survey.

resourced educational settings, and suggest that without institutional and governmental support, equitable AI adoption may remain elusive. Additionally, a lack of AI literacy among both students and educators ($n = 9$) points to the need for foundational training.

Concerns regarding over-reliance on AI emerged strongly, with students expressing worries about reduced engagement in research ($n = 30$), a decline in critical thinking ($n = 28$), and growing dependency on AI for basic tasks ($n = 17$). These sentiments reflect a broader tension between embracing AI and preserving academic integrity, creativity, and human interaction within the learning environment (Table 3).

However, students offered several recommendations, including calls for greater awareness and training ($n = 10$) and enhanced institutional support ($n = 21$). Table 4 shows that despite the concerns, there was a notable sense of optimism ($n = 8$) about AI's long-term contribution to education, provided it is implemented responsibly and inclusively.

The Sentiment distribution of responses from the survey is shown in Figure 2. The histogram displays the distribution of sentiment scores associated with a set of responses. The scores range from −1 (very negative) to 1 (very positive).

The distribution is roughly bell-shaped, suggesting a normal distribution, with a peak around 0.7, indicating a prevalence of positive sentiments which aligns with the frequent positive terms observed in the word cloud.

Summary of Descriptive Analysis

1. *Technology Access & Learning Preferences*: Most participants have strong technological access, with 98% having regular computer access and 95% stable internet connectivity. Reading/Writing learning styles are the most preferred (65%), followed by Auditory and Visual methods, reflecting diverse preferences for knowledge acquisition.

2. *Perceived Usefulness of AI Tools*: A large majority (87%) believe AI enhances academic performance, with 82% agreeing that it improves time management. Postgraduate students rate AI's usefulness higher than undergraduates, with efficiency in completing assignments and projects identified as a key driver of this perception.
3. *Perceived Ease of Use*: While 75% feel confident about learning to use AI tools and 68% find them user-friendly, 22% express concerns about acquiring the necessary skills. Students in Computer Engineering report greater ease of use compared to those in Biomedical and Chemical Engineering, highlighting field-specific differences.
4. *Attitude Towards AI*: AI is viewed positively, with 89% finding it beneficial for academic growth and 78% intending to use it regularly. However, concerns persist, as 30% worry that AI use may reduce critical thinking and active participation in research and increase over-reliance on the technology.

4.2. Results of partial least squares structural equation modelling (PLS-SEM)

Through PLS-SEM, this section tests the following hypotheses:

H1: Engineering students' attitude towards AI influences their intention to use the technology.

H2: Perceived ease of use of AI tools contributes to shaping their attitude of engineering students towards the technology.

H3: Perceived ease of use of AI tools influences its perceived usefulness among engineering students.

H4: Perceived usefulness of AI tools among engineering students contributes to shaping their attitude towards the technology.

H5: Perceived usefulness of AI tools among engineering students influences their intention to use the technology.

4.2.1. Test of multicollinearity

Using collinearity statistics, we tested the multicollinearity among the different independent variables to identify any high correlations. Following (Hair et al., 2019) recommendations, the Variance Inflation Factor (VIF) of less than 5 for each indicator shows that there is no substantial multicollinearity among the indicators (Table 5).

4.2.2. Multivariate analysis

4.2.2.1. Measurement Model analysis. To analyse the relationships between observed and latent variables, we utilise a range of metrics in SmartPLS version 4.0 to evaluate the items' reliability and validity.

Table 5. Collinearity statistics (variance inflation factor).

	VIF
Q18	2.720
Q19	2.137
Q20	1.716
Q21	1.725
Q23	2.408
Q24	2.024
Q27	2.458
Q28	2.344
Q31	3.017
Q32	2.133
Q33	2.211
Q34	1.538
Q37	2.131
Q39	2.479
Q40	1.913
Q43	1.956
Q44	1.709
Q47	1.878
Q48	

Table 6. Measurement Model analysis.

Latent variables	Items	Factor loadings (*p*-values)	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Perceived Usefulness (PU)	Q23	0.832 (0.000)	0.91	0.911	0.93	0.691
	Q18	0.852 (0.000)				
	Q27	0.831 (0.000)				
	Q31	0.871 (0.000)				
	Q37	0.807 (0.000)				
	Q44	0.791 (0.000)				
Perceived Ease of Use (PEU)	Q19	0.800 (0.000)	0.884	0.886	0.912	0.634
	Q24	0.800 (0.000)				
	Q28	0.830 (0.000)				
	Q32	0.812 (0.000)				
	Q40	0.765 (0.000)				
	Q47	0.758 (0.000)				
Attitude Towards Using AI (AT)	Q30	0.798 (0.000)	0.851	0.853	0.9	0.692
	Q17	0.855 (0.000)				
	Q39	0.878 (0.000)				
	Q46	0.793 (0.000)				
Intention to Use (IU)	Q21	0.849 (0.000)	0.786	0.789	0.875	0.7
	Q34	0.807 (0.000)				
	Q44	0.854 (0.000)				

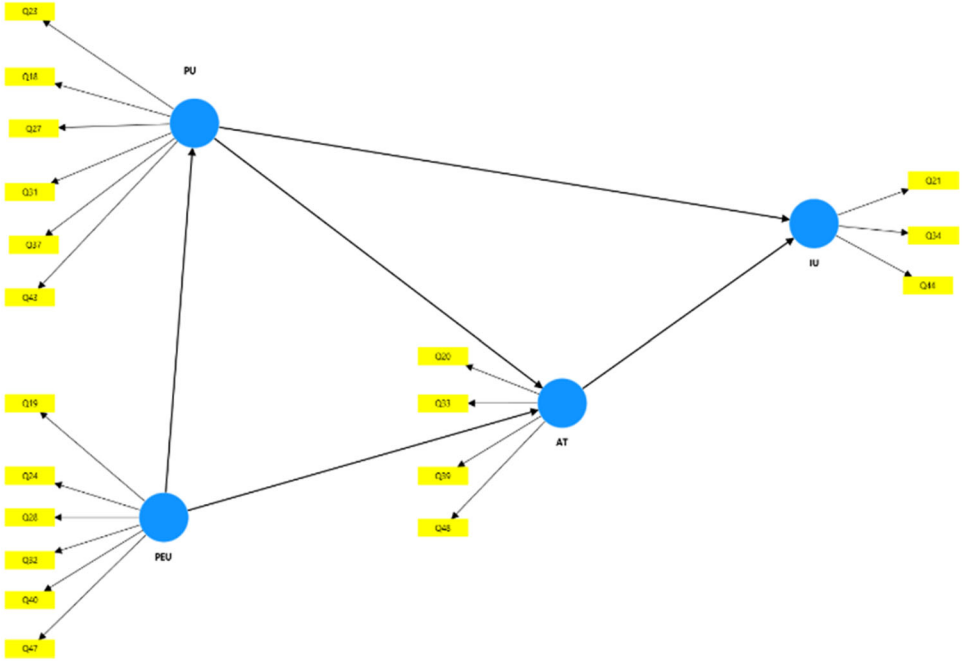

Figure 3. Structural model diagram.

Table 6 shows the reliability measures such as Cronbach's Alpha (CA) scores and composite reliability (CR) values. All alphas for each of the latent variables are above the required threshold of 0.7 (Taber, 2018). Moreover, the composite reliability and average variance extracted show sufficient internal consistency and convergent validity. The factor loadings are statistically significantly greater than 0.70, meaning they are acceptable and show good indicator reliability. Moreover, the AVE of 0.50 or higher demonstrates that the latent construct contributes to at least 50% of the variance in the measured variables.

4.2.2.2. Structural model analysis and hypothesis testing. The structural model shown in Figure 3 follows the validity check of the measurement model to verify the hypotheses (Hair et al., 2019). Based on the statistics and p-value, the hypotheses are either supported or not using structural model analysis

Table 7. Structural model analysis results.

Hypothesis	Path	Path coefficient (β)	*t*-Statistic	*p* Value	Result
H1	AT –> IU	0.158	1.258	0.208	Insignificant
H2	PEU –> AT	0.483	5.362	0.000**	Significant
H3	PEU –> PU	0.920	42.637	0.000**	Significant
H4	PU –>–> AT	0.469	5.381	0.000**	Significant
H5	PU –> IU	0.723	5.977	0.000**	Significant

Note. $^{**}p < 0.01$, $^{*}p < 0.05$, based on a two-tailed test; $t = 1.96$.

(Byrne, 2013; Lomax, 2004) .We have used a bootstrapping approach with a subsample of 5000 for the structural model analysis (Ringle et al., 2022). The model has been executed using bootstrapping to reduce the impact of uncounted potential parametric assumptions. The standardised Root Mean Square Residual (SRMR) values of 0.059 and 0.060 for the saturated and the estimated models demonstrate an acceptable model fit. Path coefficients (β), t statistics, and the associated p-values are presented in Table 5. The t-value is statistically significant in two-tailed testing when it is outside the range of −1.96 and +1.96, and the p-value is less than 0.05 (Byrne, 2013).

Among the five hypotheses tested, four (H2, H3, H4, and H5) have been supported by the analysis, while one (H1) has not been supported. The results demonstrate that participants attitude towards using AI (β= 0.158, $t = 1.258$) has a statistically insignificant relationship with the intention to use AI amongst engineering students. Perceived usefulness, on the contrary, has shown the strongest direct impact on the participants intention to use AI in their learning (β= 0.723, $t = 5.977$). The preceding results (Table 7) shows that engineering students are more likely to use AI as part of their learning toolbox if they believe it will be useful to them. Furthermore, perceived ease of use of an AI tool strongly influences its perceived usefulness among the participants ($\beta = 0.920$, $t = 42.637$). This preceding finding reveals the role of intuitive AI system designs in improving its usefulness and consequently its adoption or users' intention to use. Finally, perceived usefulness ($\beta = 0.469$, $t = 5.381$) and perceived ease of use ($\beta = 0.483$, $t = 5.362$) are key in shaping users' attitude towards AI technology.

4.3. Qualitative analysis

The qualitative analysis seeks to understand the benefits and challenges of using AI in engineering education. This will help to place the findings of the quantitative assessment in the proper context. We define the perceived usefulness of AI in engineering as how engineers perceive the usage of AI tools or technologies to complete a task or provide solution to engineering, administrative and complex problems (Davis, 1989). While we defined the perceived ease of use (PEU) according to (Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, 1989) as how easy users can use AI to perform a task. The attitude towards using AI is the perception by an individual of the positive or negative consequences related to adopting the technology (Zou & Huang, 2023).

The finding reveals interesting themes such as revolutionising learning and teaching; enhancing research and innovation; bridging theory and practice, efficiency, and accessibility; fostering creativity and collaboration; addressing global challenges, ethical, technical, and practical challenges; and preparing for an AI-drive future. The coding of the key themes is highlighted in the Appendix A (Table 1(A)). What constitutes each of these themes is shown in (Figure 4 and 5) and discussed below.

4.4. Benefits of AI adoption in higher education

4.4.1. Personalised learning

One benefit of AI in engineering education is the personalisation of learning pathways and the future directed learning (Almassaad et al., 2024). Some participants believe the inclusion of AI in engineering education will 'Provide insights into student performance trends' (Participant 55). This is because 'AI analyses student performance to improve teaching methods' (Participant 14), meaning, 'AI can provide personalized and adaptive learning experiences' (Participant 20). Other students believe that with AI, their learning experience will be more adaptive to their learning needs (Sánchez-Ruiz et al.). This perceived effectiveness of AI in personalising learning will likely drive its adoption.

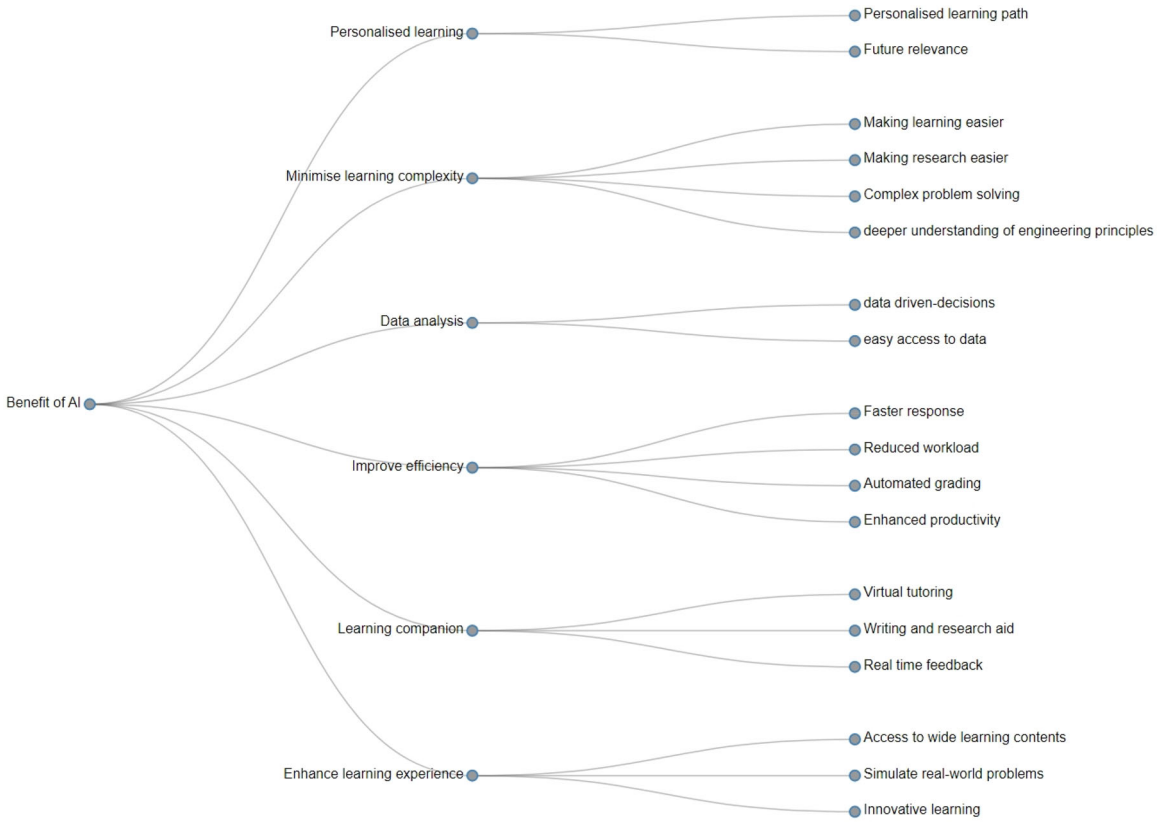

Figure 4. Popular themes on the benefits of using AI in engineering education.

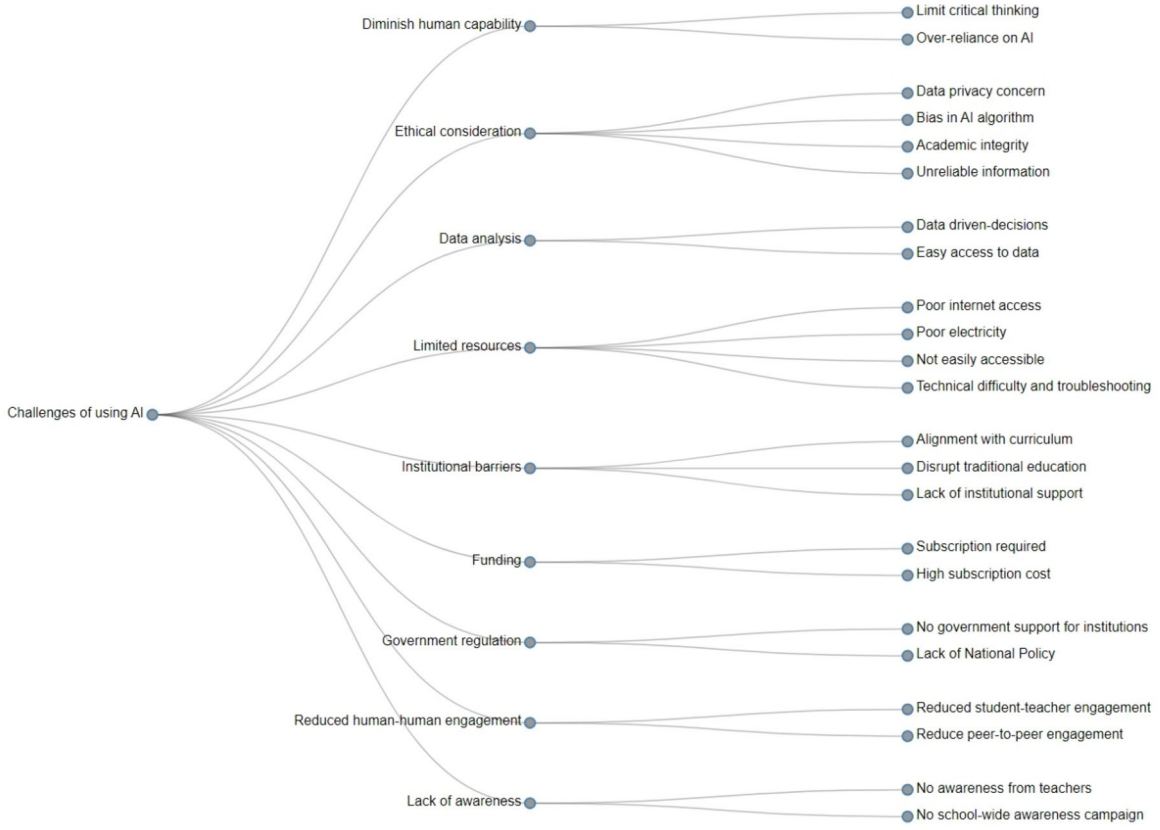

Figure 5. Popular themes on the challenges of using AI in engineering education.

4.4.2. Minimise learning complexity

AI in engineering education can minimise learning of complex concepts, unveiling deepening understanding of engineering concepts. Some participants stated, 'Students can gain a deeper understanding of engineering principles and develop problem-solving skills' (Participant 21). The perception that AI will make learning easier was found to be the most significant benefits stated by the participants. This perceived usefulness of AI can drive it adoption among engineering students as shown by the popular themes (Figure 4).

4.4.3. Data analysis

AI is perceived useful in performing data analysis. A participant stated, 'AI efficiently analyses large datasets, extracting valuable insights to inform decision-making and identify opportunities for improvement' (Participant 150). AI's role in simplifying data analysis which is at the core of engineering education will lead to its adoption.

4.4.4. Improve efficiency

The improved efficiency and speed of AI in carrying out task is a major factor that will likely drive its acceptance among engineering students. One participant stated, 'AI has so many benefits that can be summarised in the speed at which it generates study materials' (Participant 54).

4.4.5. Learning companion

Some students highlight the benefit of AI as a learning companion. One student mentioned, AI 'helps students in their studies and serves as a reading companion' (Participant 54), while another student mentioned that AI 'benefits students by providing academic response to their questions' (Participant 93). These responses suggests that AI will likely be widely accepted among students as a learning companion. This enhancement of collaborative learning shows the perceived usefulness of AI in transforming education and will likely drive its adoption (Tossell et al., 2024).

4.4.6. Enhance learning experience

AI is perceived useful in widening access to learning contents. One participant mentioned, 'AI is important as it helps learners get information on a wide range of content' (Participant 103). The simulation of real-world problems is also highlighted as a benefit by another participant; 'AI-powered simulations help students practice real-world engineering problems' (Participant 12). Another student believes that AI can also enhance their problem-solving skills as 'students can gain a deeper understanding of engineering principles and develop problem-solving skills' (Participant 20). These perceived enhancements of learning will likely lead to its acceptance among students.

4.5. Challenges of AI adoption in higher education

The participants responses to the challenges of using AI are highlighted in this section. Figure 5 shows the complexities of incorporating AI into engineering education.

4.5.1. Institutional barriers

One major concern raised by some students is the institutional barriers, from the support of the university governing body to the difficulty in integrating and aligning AI with the traditional curriculum. One student mentioned, 'Challenges include ensuring AI tools align with curriculum standards as well as the limited availability of AI-trained educators' (Participant 72). Another student stated the challenge to be 'difficulty balancing AI integration with traditional teaching methods' (Participant 80). These concerns raised by students suggest the need for institutions to have frameworks and strategies for AI integration.

4.5.2. Ethical consideration

Ethical considerations from data privacy concerns, to bias in AI algorithm and academic integrity were highlighted as potential challenges for integrating AI in engineering education. As stated by a student, a

challenge is the 'ethical considerations in AI usage. Plagiarism is a serious concern as well as lack of originality' (Participant 62). The responses pertaining to the ethical implications of AI were low in comparison with other challenges highlighted. This suggests that the students are either not concerned with ethical issues or are not enlightened on the various ethical issues associated with the use of AI. For AI to be widely accepted, ethical issues have to be addressed, and the students must be aware those issues and how to responsibly use AI (Almassaad et al., 2024).

4.5.3. Limited resources

A major concern raised by most students in utilising AI as a tool in engineering education is the poor internet access and poor electricity leading to reduced accessibility. One student mentioned, 'Challenges might involve poor network connection' (Participant 74). This is particularly the case of developing countries with limited access to electricity and internet. Considering that the respondents are from Nigeria, it is expected that the issue of limited access is raised. This may not be the case for students in developed countries where such limitations do not exist. For AI to be widely accessible in developing countries, there must be reliable power and internet access.

4.5.4. Diminished human capability

The most significant challenges identified in the survey is the cognitive impairment of users as a result of over-reliance on AI tools. Most of the respondents believe that the use of AI is a risk that both students and educators could become overly dependent on technology. This dependence might reduce critical thinking and problem-solving skills, as students may rely too much on AI to provide answers and solutions. A student stated that 'this dependence might reduce critical thinking and problem-solving skills, as students may rely too much on AI to provide answers and solutions' (Participant 150). Another student believes, 'there will be no intellectual abilities and urge for rigorous research work' (Participant 145). For AI to be widely accepted, strategies must be developed to enhance the students' cognitive abilities. It is not very clear, why many respondents highlight the potential decline in critical thinking as a major concern in using AI in education. This could be widely believed, cultural or an indication that more needs to be done to develop strategies for enhancing critical thinking when AI is used in education. In any case, this suggests efforts must be made in preserving the learnings of some core fundamental engineering principles that has led to the development of AI (Qadir, 2023).

4.5.5. Funding

The second most significant challenge in adopting AI in education identified by the students is the high subscription cost for accessing AI tools (Almassaad et al., 2024). One student stated, 'it requires subscription which some students can't afford' (Participant 59). Another student mentioned, 'the major challenge I face is high cost of AI subscription' (Participant 108). The maintenance cost was also highlighted as challenges for using AI, 'high initial implementation costs and requires continuous maintenance and updates' (Participant 146). These responses from students the wide adoption of AI in engineering education would require the offsetting or reducing the subscription cost for students especially those in developing countries. Institution that are adopting AI needs funding and sustainable management strategy to maximise its benefits (Ali et al., 2025).

4.5.6. Government regulation

The lack of government support for institutions is also highlighted as a major barrier to its adoption in educational institutions. One student stated that,

> it well makes learning a lot easier and also more interesting to learn with AI tools, but the challenges are time and lean financial or no support from the Government to help institutions access these tools readily for students and thus must be addressed urgently

(Participant 24). For AI to be widely accepted in academic institutions there has to a top-bottom support from the government that covers policies and incentives.

4.5.7. Reduced human-human engagement

Another challenge mentioned in adopting AI is the reduced student-to-teacher engagement, 'Over-reliance on AI may reduce teacher-student engagement' (Participant 14). and reduced peer-to-peer engagement during learning, as simply put by another student, 'Challenges include risk of reducing human interaction in education' (Participant 148). For AI to be widely accepted, there must be strategies that promote the human elements of learning and how to preserve the human interaction during learning (Almassaad et al., 2024).

4.5.8. Lack of awareness

The lack of awareness of AI also emerged as the third most significant challenge identified by the respondents. One student stated, 'we have to make it popular amongst the students and then make available the resources and time to learn more in it' (Participant 49) and another student mentioned, 'they are not readily used here or popular but with awareness and also available resources will lead the educational sector' (Participant 52). The creation of the awareness of the role of AI in engineering education is critical for its wide adoption among students (Kelly et al., 2023). This implies adequate preparation needs to be in place to train the future engineers on how they can harness the potential of AI in addressing global problems (Ali et al., 2025).

In summary, the students believe that AI has the potential to diminish human critical thinking skills, the lack of funding to subscribe for AI tools and the lack of awareness of the role of AI in education are the major challenges to its wide adoption in engineering education.

4.6. Discussion of the TAM analysis results

This research explores the perception of engineers on the impact of AI in engineering education, focusing on five hypotheses; (H1: AT –> BI), (H2: PEU –> AT), (H3: PEU –> PU), (H4: PU –>AT) and (H5: PU –> BI). Engineering students recognise that AI adoption has a potential to solve complex problem, personalise learning, increasing efficiency and solving global problem. However, other wider impacts of AI adoption such as overreliance on AI, ethics, data privacy and institutional barriers needs to be addressed.

Among the five hypotheses tested, four (H2, H3, H4, and H5) have been supported by the analysis, while one (H1) has not been supported. The results shows that engineering students are more likely to use AI as part of their learning toolbox, if they believe it will be useful to them. This preceding reveals the role of intuitive AI system designs in improving its usefulness and consequently its adoption or intention to use.

The engineering students demonstrated a strong intention to use AI, but their attitude towards the use of AI was not influenced by the perceived usefulness and perceived use of it. The reason for the statistically insignificant relationship between the engineering students' attitude to using AI and their intention to use it could also be attributed to the benefits of AI being overshadowed by the challenges highlighted, as shown in the qualitative analysis. Attitude towards using AI mediates the effects of perceived usefulness and the perceived ease of use on students' intention to use AI in engineering education (Min; Zou & Huang, 2023). For instance, 30% of students believed the use or over-reliance on AI will limit their critical thinking (Chan & Hu, 2023) and 29% mentioned the lack of supportive environment and lean resources as one of the challenges they face in using AI. These resulted in the negative attitude towards using AI. It is important to point out that the negative attitude could also be due to the lack of support from their institutions on the use of AI tools in engineering education. This minimises the participants perception of its usefulness. Similar findings appear in studies on AI hesitancy (Tossell et al., 2024), suggesting that even when users recognise a technology's value, unresolved concerns can weaken adoption intent. Also, the lack of awareness of AI in education by a small number (14%) resulted in their negative attitude towards its use. Science and engineering students have reported high awareness of the knowledge of AI tools (Kelly et al., 2023).

An interesting point in the challenges highlighted by the engineering students on using AI is the perception that AI will reduce their critical thinking. It is not clear whether there is a cultural underlying factor resulting to this conclusion especially considering the students are from a certain demographic, or

this is peculiar to the experience of engineering students, or an indication that more needs to be done to development strategies for enhancing critical thinking when AI is used in education. The limitation of critical thinking has also been highlighted by a study that assess the perception of students from a developing country (Chan, C. K. Y & Hu, W., 2023). In any case, this suggests efforts must be made in preserving the learnings of some core fundamental engineering principles that even led to the development of AI (Qadir, 2023).

As expected, PU and PEU directly affect engineering students' intention to use AI in education, and it was also not surprising to find that PEU directly influence the PU (Ali et al., 2025) (Kleine et al., 2025). However, other external factors such as ethics, cost, institution acceptance and sustainability that emerged as themes also reduces the PU of AI in engineering education. These factors have been seen to minimise PU and PE, which will hinder AI adoption *(*Kleine et al., 2025*;* Zou & Huang, 2023). This disconnects between PEU's theoretical importance and real-world constraints mirrors findings from developing economies, where infrastructure gaps weaken technology adoption (Chan & Hu, 2023). Educational institutions need to provide strategy interventions to drive the adoption of AI in engineering.

Some of the findings presented here collaborated with existing findings in literatures. In summary, these findings reveal that to drive the adoption of AI in engineering education, it is imperative to promotes it perceived usefulness and address the factors mitigating its usefulness.

4.7. Recommendations

4.7.1. Intervention strategies to enhance engineering students' attitude toward the use of AI

While most engineering students recognize that AI has a potential to solve complex problems, personalize learning, increase efficiency and solve global problems, this does not translate to their intention to use AI. Therefore, students should be trained and supported by institutions to use AI, which will enhance their attitude towards the technology. Since the findings show that PU strongly influences the intention to use AI, there is a need for more sensitization on the usefulness of AI in engineering education to drive its adoption.

4.7.2. Intervention strategies to mitigate ethical consideration, cost, privacy issues, security and sustainability of AI in engineering education

The wider external factors identified that could impact the adoption of AI need to be addressed. Engineering institutions must be willing to support AI adoption and develop strategies to mitigate the potential negative impacts such as data privacy issues and job losses.

AI Literacy for Students (Kelly et al., 2023) Despite the perceived usefulness of AI, its lack of awareness indicate that student need to be taught how to apply AI in their education. Institution needs to develop learning activities that build student skills in using AI into engineering curricula.

5. Conclusion

This research explores the factors that drive the adoption of AI in engineering education using quantitative and qualitative methods to measure and assess the PU, PEU, AT and IU of engineering students, through the TAM construct.

The results from the quantitative analysis demonstrate that perceived usefulness and perceived ease of use have a statistically significant relationship with intention to use AI amongst engineering students. Moreover, perceived ease of use strongly influences the perceived usefulness of AI technologies among the students. However, the effect of engineers' attitude on their intention to use AI was not statistically significant. The implies that their attitude to AI's mediated perceived usefulness and perceived ease of use can lead to AI adoption. Through qualitative analysis, the PU of AI in personalised learning, solving complex problems, increasing efficiency and solving global problem were highlighted. However, it was noted that wider adoption of AI would be achieved when there are strategies to address the potential reduction in critical thinking, lack of resources and institutional support, lack of awareness and ethical issues.

However, while some of the results in these finding can be generalised, it is important to further explore the perception of students in the role of AI on their critical thinking ability. This implies that, to drive AI adoption in education, students need to be taught on how to use AI to enhance their critical thinking. Moreover, stakeholders in engineering education needs to dedicate more effort in developing strategies that would mitigate concerns regarding the adoption of AI.

5.1. Research limitations

While this research provides insights on the perception of engineering students in adoption of AI in education, several limitations should be acknowledged. Firstly, the use of 150 out of 40,000 participants may limit the generalisations of the findings to the wider population. Having the participants from a developing country could also influence the perspectives reported. This could explain why resources and access to technology emerged as a theme. Engineering students have also identified ethics, bias and AI algorithm accuracy as significant barriers to their adoption. Further studies can compare the perspective of engineering students from developing and developed countries to identify the barriers to AI adoption.

Secondly, since engineering students are generally technologically savvy, they are more likely to report non-technical barriers such as institutional acceptance, accessibility, financial resources as barriers to AI adoption in education. It will be interesting to understand what the barriers would be, when there are minimal external limitations on the use of AI in education. More empirical studies that go beyond understanding the students' perceptions can unveil deeper insights into the factors that limits its adoption.

Disclosure statement

The authors declare no competing interests, financial or otherwise, related to this research. All relevant information has been disclosed according to journal requirements.

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