ASCILITE 2025

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Factors influencing students' intentions toward generative AI tools: An ethics-trust-norms framework

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This study explores the factors influencing students' intention to use generative AI (Gen AI) tools, such as ChatGPT, based on an extended Technology Acceptance Model (TAM) that incorporates ethics, trust, and social norms. Going beyond the traditional models that emphasise usefulness and ease of use, this study highlights the growing influence of ethical beliefs, peer influence, and trust in driving adoption behaviour. A survey of 316 students at an international university in Bangladesh revealed that intention is strongly driven by perceived usefulness and ease of use, and intention is a strong predictor of actual usage. However, trust and ethical concerns exert more subtle effects such that trust directly influences usage and moderates the intention-action link, while ethical concerns do not directly predict behaviour but strengthen the intention-to-use connection. Structural equation modelling confirmed multiple mediation paths, highlighting the complexity of GenAI adoption in an educational setting. These results suggest that adoption decisions are not simply technical but are shaped by students' trust in the tool, social signals from peers, and the accuracy and quality of responses. The study offers practical guidance for educators and policymakers seeking to promote ethical GenAI adoption in higher education institutions.

Keywords: Generative AI, TAM, Ethics in AI use, Trust in AI systems, Social norms, ChatGPT, Bangladesh

Introduction

Generative artificial intelligence (Gen AI) tools such as ChatGPT, Gemini, and Copilot have quickly become everyday assistants for students in their academic activities. These tools respond to queries, provide solutions to problems, offer suggestions for essays, and deliver prompt feedback on code (Boyle, 2025). While this rapid support saves time and makes study sessions more effective, it also raises concerns about the ownership of the content generated by these tools. This may lead to concerns regarding academic integrity, plagiarism and intellectual property rights (Rane, 2024). Another issue is the quality of the output generated by these tools, including the fairness and accuracy of the information, and the amount of personal data disclosed with each prompt (Łodzikowski et al., 2024). Recent studies show that these tools increase motivation and improve academic grades (Lehmann et al., 2024). However, these studies also warn that overdependence on AI tools diminishes students' judgment and creativity and makes them overconfident in their abilities. This is further supported by a study where the university students demonstrated improved essay scores using ChatGPT, but no significant gains in knowledge transfer (Fan et al., 2025). In response to these complexities, responsible use of AI tools has emerged as a key research priority. Specifically, investigating the role of ethics, trust and normative practices of using AI tools can inform guidelines that balance academic integrity and student development.

Ethics, Trust, Norms, and the Technology Acceptance Model

The Technology Acceptance Model (TAM)(Davis, 1993) explains that people choose a new technology when they perceive it as useful for their tasks and find it easy to use. However, many scholars argue that usefulness and ease of use are not the sole factors influencing technology adoption, as modern tools can now write, draw, and even reason in ways that impact human values (Henriksen et al., 2024). Therefore, users also consider whether the tool behaves ethically, whether its responses are trustworthy, and whether its use is endorsed by peers and teachers (Mensah & Luo, 2021).

In this study, ethical belief refers to the basic judgment that the use of a generative AI tool does not violate principles of honesty or fairness (Mustofa et al., 2025). Trust refers to the confidence students have in the accuracy and relevance of the responses generated by AI (Foroughi et al., 2024). If trust is weak, intention declines even when the tool seems useful. Norms refer to the perceived social pressure to use or refrain from using a technology, influenced by peers, teachers, or institutional culture (Mustofa et al., 2025). The interconnected nature of ethics, trust, and norms in technology acceptance creates a complex framework where multiple factors interact to influence intention and use. Recent studies that integrate trust into the Technology Acceptance Model reveal that when a tool aligns with students' needs and existing workflows, it enhances user experiences and improves perceived trustworthiness (Uche et al., 2021). Also, AI users reported that competence influences their intention to use AI tools through the mediating effect of trust, with varying effects across different academic disciplines (Li et al., 2025). Additionally, the influence of social norms in the adoption of Gen AI has been observed in various studies, such as in the blended learning context (Hamad et al., 2024) and the engineering education discipline (Asag et al., 2024). These studies also show that when the peers and mentors openly endorse a technology, subjective norms significantly influence intention to use AI tools.

In educational settings, scholars suggest that generative AI should be used under clear guidelines and student-centred policies. In this regard, UNESCO (2023) calls for the implementation of age limits, privacy protections, and necessary teacher training for responsible use of AI. Policies on the ethical use of AI shape trust and responsible usage more profoundly than the technology itself (Barus et al., 2025). **Figure** 1 illustrates the conceptual research model, showing the relationships between Perceived Ease of Use, Perceived Usefulness, Ethical Consideration, Trust, and Subjective Norms as predictors of Intention to Use and Actual Use of generative AI. By incorporating trust, ethical considerations, and social norms as contextual variables into the framework, this study aims to measure the adoption and responsible use of generative AI tools in education.

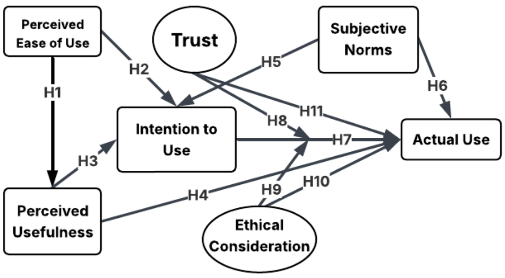

Figure 1 Ethics-Trust-Norms Research Model

Research Method

This study employed a quantitative research method to investigate students' intentions and adoption of AI tools. A structured survey instrument was developed for data collection based on the technology acceptance model (Davis, 1993) and its extended frameworks. The model consists of seven constructs: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Trust (TR), Ethical Consideration (EC), Subjective Norms (SN), Intention to Use (ITU), and Actual Use (AU). Each construct was measured using multiple items adapted from validated prior research. A 5-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5) was used to assess participant responses. Initially, the instrument included 23 items. After expert review and analysis of the data from pilot testing, one item has been removed to improve the reliability of the model. The proposed model, shown in **Figure 1**, consists of eleven hypotheses (H1–H11), focusing on both direct and moderating effects.

Research Context and Participants

This study was conducted at an international engineering university in Bangladesh. A convenience sampling method was used to collect the responses from 316 students of different nationalities, including local students and those from developing countries in Africa and Asia, which added rich cultural diversity to the sample. The research design and methodology for this study were approved by the Committee for Advanced Studies and Research (CASR) at the Islamic University of Technology (Ref. No. CASR/57/2025/01/Proc/001). Participation was voluntary and informed consent, confidentiality, and anonymity were maintained throughout the data collection process. **Table 1** presents the demographic details of the study participants.

Table 1
Demographic information of the students

Demographic Info	Category	Counts	% of Total	Cumulative %
Gender	Female	130	41.1%	41.1%
	Male	18 6	58.9%	100.0%
Student Status	Domestic	160	50.6%	50.6%
	International	156	49.4%	100.0%

Data analysis and results

The item loadings are presented in **Figure 2,** which shows the PLS results for the structural model, including item loadings for all constructs and the path coefficients between them. The Cronbach's alpha, composite reliability (CR) and average variance extracted (AVE) values shown in **Table 2** were used to assess the reliability of the model. All constructs met or exceeded the recommended threshold value of 0.70 for composite reliability and 0.50 for AVE (Hair Jr et al., 2021). Item loadings were all above the recommended threshold value of 0.60. Although the Cronbach's alpha values for Trust (0.667) and Ethical Consideration (0.670) are slightly below the threshold value, these values remain acceptable in exploratory research, especially when supported by CR (*rho_a, rho_c*) and sufficient item loadings and overall model validity (Hair Jr et al., 2021).

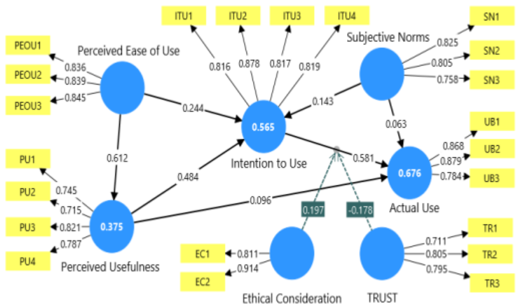

Figure 2 Results of PLS Algorithm analysis for the structural model

Table 2
Reliability and Convergent validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
Perceived Ease of Use (PEOU)	0.792	0.797	0.878	0.706
Perceived Usefulness (PU)	0.769	0.778	0.851	0.590
Ethical Consideration (EC)	0.670	0.730	0.854	0.746
Trust (TR)	0.667	0.684	0.815	0.595
Subjective Norms (SN)	0.713	0.720	0.839	0.635
Intention to Use (ITU)	0.852	0.853	0.900	0.694
Actual Use (AU)	0.800	0.818	0.882	0.714

Testing Hypotheses

Following the guidelines of Hair et al. (2021), the proposed model was evaluated by estimating standardised path coefficients (*β*), *t-values* obtained through a bootstrapping procedure with 5,000 resamples, and corresponding effect sizes (f^2). **Table 3** presents the path coefficients for all relationships within the model structure.

Table 3
Path coefficients.

Hypo No.	**Relationship**	**Std.(β)**	**Std.error**	**T value**	**P values**	**Decision**	**F-square**
H1	PEOU → PU	0.612	0.043	14.096***	0.000	Supported	0.600
H2	PEOU → ITU	0.244	0.053	4.614***	0.000	Supported	0.123
…	…	…	…	…	…	…	…
H11	TR → AU	0.155	0.048	3.242***	0.001	Supported	0.040
			Moderator				
H8	TR × ITU → AU	-0.178	0.037	4.774	0.000	Supported	0.098
H9	EC × ITU → AU	0.197	0.048	4.115***	0.000	Supported	0.103
			Mediation				
H2, H7	PEOU → ITU → AU	0.172	0.034	5.209***	0.000	Partial mediation	
H1, H3	PEOU → PU → ITU	0.296	0.036	8.240***	0.000	Partial mediation	
H3, H7	PU → ITU → AU	0.281	0.038	7.404***	0.000	Full mediation	
H5, H7	SN → ITU → AU	0.083	0.027	3.035**	0.002	Full mediation	
H1, H4	PEOU → PU → AU	0.059	0.033	1.782	0.075	No	
H1, H3, H7	PEOU → PU → ITU → AU	0.172	0.026	6.554***	0.000	Partial mediation	

The results show significant direct effects for H1, H2, H3, H5, H7, and H11. Moderation analysis reveals that TR negatively moderates the ITU–AU link (H8: β = –0.178, $p < 0.001$), whereas EC positively moderates it (H9: β = 0.197, $p < 0.001$). Mediation analysis supports partial mediation in the paths PEOU → ITU → AU and PEOU → PU → ITU, full mediation in PU → ITU → AU and SN → ITU → AU, and a significant indirect path from PEOU to AU via PU and ITU (β = 0.172, $p < 0.001$), while the direct path from PEOU to AU via PU alone is not significant. These findings highlight the pivotal roles of perceived ease of use, perceived usefulness, and intention, while suggesting that ethics and trust exert more nuanced indirect effects.

Gender and Student Status Differences in the Adoption of Generative AI

Independent-samples *t-tests* were conducted to assess whether gender or student status shapes students' ethic-trust-norms regarding their intention and the adoption of AI use. Table 4 shows that male and female students reported nearly identical mean scores across all variables; none of the tests were significant ($p > .05$). By contrast, Table 4 reveals status-based differences: domestic students report higher perceived usefulness, $t\ (314) = 2.58,\ p = .010,\ \Delta M = 0.83$; greater ease of use, $t\ (314) = 3.13,\ p = .002,\ \Delta M = 0.81$; and stronger intention to use, $t\ (314) = 3.13,\ p = .002,\ \Delta M = 1.07$. However, social norms, trust, or ethical concerns did not differ significantly between them. In sum, gender does not influence attitudes toward AI, whereas domestic students perceive the tools as more valuable, easier to use, and are more inclined to adopt them.

Table 4
Independent Samples T-Test Results by Gender and Student Status

	Variable	t	p	Mean Diff	Decision.		Variable	t	p	Mean Diff	Decision.
Gender	SN	0.088	.930	0.027	No	Student Status	SN	0.583	.560	0.179	No
	PU	-0.726	.469	-0.238	No		PU	2.583	.010	0.826	Yes
	PEOU	-1.896	.059	-0.505	Marginal		PEOU	3.129	.002	0.813	Yes
	Trust	-0.112	.911	-0.030	No		Trust	-1.204	.230	-0.317	No
	ITU	-1.314	.190	-0.460	No		ITU	3.132	.002	1.067	Yes
	EC	-0.676	.499	-0.140	No		EC	-1.523	.129	-0.309	No

Discussion and implications

The proposed model in this study explores the behavioural intention and use of generative AI tools among engineering students and how they are impacted by trust-ethics-norms. Perceived Ease of Use significantly influences Perceived Usefulness (β = 0.612), and Usefulness remains a strong driver of intention (β = 0.484). This result is consistent with recent studies showing that ease of use and perceived intelligence increase usefulness (Balaskas et al., 2025). The findings confirmed that Intention to Use is the strongest predictor of Actual Use, which aligns with earlier literature where intention was a key factor in explaining digital behaviour, especially when access to technology was not a limiting factor (Setälä et al., 2025).

One of the key contributions of this study is its integration of trust, ethical consideration, and subjective norms as contextual variables. *Subjective Norms (SN)* were found to significantly influence intention but did not directly impact actual use (Asag et al., 2024). The results also revealed that *Trust* had a significant direct influence on *Actual Use*, and negatively moderated the relationship between intention and use. This implies that for students who strongly trust GenAI, the need for conscious deliberation (i.e., intention) is reduced. They are more likely to act based on confidence and perceived reliability. Similar findings were observed among Malaysian undergraduates, where high trust reduced the weight of perceived usefulness and ease of use when deciding to adopt ChatGPT (Foroughi et al., 2024). Conversely, *Ethical Consideration* does not drive behaviour directly but positively moderates the step from intention to actual use. Evidence from a recent study shows that higher academic-integrity awareness strengthens the conversion of effort expectancy into GenAI usage (Bouteraa et al., 2024). Complementary findings in another study indicate that clear institutional policies on when and how GenAI may be used markedly reduce students' uncertainty and encourage them to act on their intentions within ethical boundaries (Johnston et al., 2024). Although the data were collected in Bangladesh, similar challenges are emerging across neighbouring and Australasian higher education contexts. Universities in Australia and New Zealand are developing GenAI policies to safeguard academic integrity and investing in digital skills and staff training. Meanwhile, debates on access, assessment, and responsible use are unfolding across South and Southeast Asia, suggesting that the findings hold broader regional relevance.

T-test analysis showed no statistically significant differences between genders in any factors, indicating that male and female students share similar views and attitudes toward generative AI. This is because both groups have grown up with wide access to technology, making them equally comfortable using new tools. Recent studies also show that in Gen Z populations, the gap between genders in technology adoption is narrowing, especially among younger students who are used to digital learning environments (Asag et al., 2024; Bagdi et al., 2023). However, significant statistical differences were found in student status, where domestic students showed stronger perceptions of, and greater intention to use, generative AI tools. This may be due to their familiarity with the local education system and language, which helps them better understand and use the new technologies. In contrast, international students may face language barriers, cultural differences, and limited access to support, which can affect their perceptions and willingness to adopt AI tools (Asag et al., 2024).

The findings of this study can be translated into several practical actions for higher education. Institutions can establish clear course-level policies that define acceptable GenAI use and promote academic integrity. Short workshops can help students build trust in generative AI and encourage responsible adoption by teaching effective prompt design that produces reliable outputs. Staff and students should also be encouraged to openly model acceptable GenAI practices to reinforce social norms. Finally, targeted guidance for international students can address gaps in clarity and accessibility, ensuring more equitable engagement with GenAI tools.

Conclusion and Future Research Directions

The incorporation of ethics, trust, and norms into the TAM model clarifies students' intentions and their use of generative AI in higher education. Perceived ease of use and perceived usefulness remain key factors influencing intention, but they function within a broader system. Trust in a tool's reliability, ethical alignment with academic values, and social cues from peers and institutions all shape behaviour. Trust directly encourages the use of generative AI but weakens the link between intention and use under conditions of uncertainty. Ethical considerations do not directly predict use but strengthen the intention–use relationship, suggesting that internalised ethics promote responsible engagement.

This study has several limitations. Responses were obtained from a convenience sample at a single international engineering university in Bangladesh, which restricts the generalisability of the findings beyond the engineering context. Cultural and linguistic diversity within the sample may also affect perceptions. In addition, self-reported data can introduce response bias, and the cross-sectional design limits causal inferences. Future research could employ a mixed-method design to examine how intentions translate into classroom practice. Sociocultural perspectives, such as activity theory, may further clarify how policy, norms, and culture influence acceptance. Comparative studies across different educational technologies and cultural settings could also determine whether trust and social influence are context-specific or more broadly applicable. Finally, larger and more diverse samples across disciplines would help assess transferability and explore connections to digital well-being and the satisfaction of basic psychological needs.

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