Engineering Students' Adoption of Generative AI: The Role of Social Influence and Cognitive Processes

Mazen Abdulwahab Asag, Md Abdullah Al Mamun, Mahbub Hasan
Islamic University of Technology

Generative AI, such as ChatGPT, Google Gemini, Bing CoPilot, and similar models, bring changes in how students interact and search for knowledge online. Researchers are increasingly interested in exploring the factors that influence this change in student interaction with generative AI. This study examines the factors that influence students' intention to use generative AI in the context of a Bangladeshi engineering university. As part of a larger study, this research reports initial findings from pilot data. Based on the Unified Theory of Acceptance and Use of Technology (UTAUT), the study examines the role of social influences and cognitive processes in AI adoption of students. Using a quantitative research approach, the study reveals that factors such as social influence, student image, job relevance and perceived usefulness significantly influence students' intention to use generative AI. While male and female students have similar attitudes towards the use of generative AI, local students significantly differ from international students in perceived usefulness, perceived ease of use, and result demonstrability of generative AI tools. These observations can guide educational institutions to integrate generative AI models in the learning environment and offer more interactive and personalised learning experiences for students.

Keywords: Generative AI, engineering students, social influence, UTAUT, ChatGPT, Bangladesh

Introduction

Generative artificial intelligence (AI) brought a rapid paradigm shift in educational settings in terms of how students interact, learn, and search for information on the Internet. It offers students the benefits of improved interaction and efficient learning strategies. Research showed that generative AI tools can enhance motivation and learning outcomes (Deng & Yu, 2023) and can significantly impact the academic performances of students (Tanvir et al., 2023). Generative AI offers personalised learning support, assistance in writing and brainstorming, and guidance in research and data analysis (Chan & Hu, 2023). On the contrary, Generative AI lacks in building an emotional connection with its users (Annuš, 2023). In the context of Bangladesh, Naher et al. (2023) found both positive and negative aspects of its use. On one hand, it offers personalised learning experiences and saves time, on the other hand, it decreases the creativity of the learners and often misleads them with incomplete information. Hasan et al. (2024) highlight the risks of using AI in the learning process, focusing specifically on the reduced creativity of the learners.

Despite increasing research on generative AI in education, there is still a lack of understanding of the factors that influence students' attitudes to accept and use these tools in their learning process. In Bangladesh, the role of social influences and cognitive processes in the adoption and use of generative AI among engineering students is unexplored and requires further investigation. This gap underscores the necessity for more extensive research into the distinct socio-cognitive dynamics that influence the adoption of generative AI among students.

Social influences, cognitive processes and UTAUT framework

The Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003) extends and modifies the widely used Technology Acceptance Model (TAM). UTAUT is a robust and adaptable model that can be applied to a wider range of technological contexts. While other models focus on limited aspects of technology adoption, UTAUT offers a broader perspective for understanding students' technology adoption. Particularly in the current study context, the ability to incorporate social influence and cognitive processes in the UTAUT model makes it suitable for studying generative AI adoption among students.

UTAUT framework explains that user behaviours and intentions to adopt new technology are influenced by performance expectancy (perceived usefulness) and effort expectancy (perceived ease of use). The model also emphasises that social influences (subjective norm and image) and facilitating conditions (supportive infrastructure) are two additional key constructs that shape the behaviour and intention to adopt new technologies. Venkatesh et al. (2003) further argued that the adoption and usage of new technology can be driven by social influences and cognitive processes of a learner in academic settings. Social influence significantly impacts student's technology adoption when they see their peer and instructors using it effectively (Davis & Venkatesh, 2004). Especially in collaborative learning settings it strongly influences technology adoption (Venkatesh, 2022). Venkatesh et al. (2003) refer to social influence as the subjective norms and the desire to improve the image among others. Subjective norms are defined as the perceived social pressure to engage or not engage in a particular action (Farooq et al., 2017). Image refers to the use of a particular technology to improve the status or reputation of a learner within a peer group. Performance expectancy i.e., the belief that AI will improve outcomes is also important for the students. They value AI for its direct benefit in learning such as task automation and reduced cognitive load (Naseri & Abdullah, 2024). Shah et al. (2021) showed that cognitive processes, specifically perceived ease of use, influence the intentions and interactions of users with new technologies. Within the broader theoretical understanding of the technology acceptance framework, cognitive processes also include job relevance, result demonstrability, and output quality of new technologies (Camilleri, 2024). Job relevance and output quality relate to performance expectancy, while result demonstrability relates to effort expectancy (Oye et al., 2014).

Table 1
Focus of the study within the UTAUT framework

Focus of the study	Constructs under investigation	UTAUT elements
Social Influences	Subjective norm Learner Image	Social Influences and Facilitating Conditions
Cognitive Processes	Perceived Usefulness Output Quality Job Relevance	Performance Expectancy
	Perceived Ease of Use Result Demonstrability	Effort Expectancy

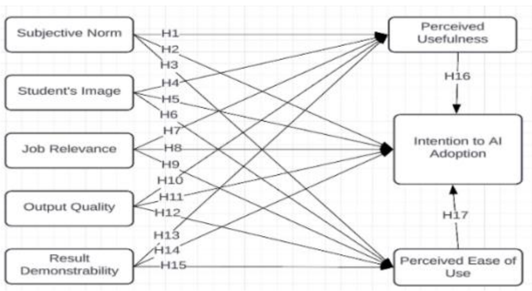

Figure 1 The research model of the current study

Table 1 illustrates how the focus of the current study is framed within the UTAUT theoretical framework. Figure 1 depicts the relationships between factors stemming from social influences and cognitive processes and how they affect the perceived usefulness and perceived ease of use of generative AI. Based on the UTAUT theory, these factors collectively define the performance and effort expectancy of the students, which ultimately influence their intention to adopt generative AI in the learning process.

Research contexts and participants

This study collects data from an international engineering university in Bangladesh using a purposive sampling technique. Further, a convenience sampling technique has been utilised to get data from 109 participants from both local and international students. The international students mostly come from developing countries of different ethnicities across Africa and Asia. Before data collection, students were required to provide informed consent, indicating that their participation was voluntary, and that they could withdraw at any stage. The anonymity of the students was ensured throughout the process. The consent and responses of the students were collected using a Google Form, and the online survey questionnaire ensured the participation of students from diverse backgrounds. This study adopted a quantitative research approach for data analysis. Table 2 shows the demographic information of the participants.

Table 2
Demographic information of the students

Demographic Info (N = 109)	**Category**	**Counts**	**% of Total**	**Cumulative %**
Gender	Female	43	39.4 %	39.4 %
	Male	66	60.6 %	100.0 %
Student Status	Domestic	46	42.2 %	42.2 %
	International	63	57.8 %	100.0 %

Data analysis and results

Table 3 presents the descriptive statistics of all eight constructs of the model shown in Figure 1**.** The skewness and kurtosis values are within the recommended range, indicating the normality of the data.

Table 3
Descriptive analysis of the variables

Factors	***M***	***SD***	***SE***	**Min**	**Max**	**Skewness**	**Kurtosis**
Subjective Norm (SN)	14.4	3.11	0.298	6	20	-0.513	0.0817
Perceived Usefulness (PU)	15.9	3.24	0.310	6	20	-0.980	0.9167
Perceived Ease of Use (PEU)	11.8	2.62	0.251	3	15	-1.061	1.2986
Student Image (SI)	18.1	4.13	0.395	8	25	-0.179	-0.6619
Results Demonstrability (RD)	11.6	2.27	0.217	5	15	-0.715	0.3394
Output Quality (OQ)	10.8	2.55	0.244	4	15	-0.486	0.0631
Job Relevance (JR)	11.5	2.49	0.238	3	15	-0.780	0.6682
Intention to AI Adoption (IAA)	15.8	3.35	0.321	6	20	-0.938	0.5484

Predicting student intention to AI adoption

Table 4
Model Fit Measures

				Overall Model Fit			
Model	**Dependent Variable**	***R***	***R²***	***F***	***df1***	***df2***	***p***
1	Perceived usefulness	0.747	0.558	26.0	5	103	< .001
2	Perceived ease of use	0.743	0.552	25.4	5	103	< .001
3	Intention to AI Adoption	0.810	0.657	27.6	7	101	< .001

Table 4 shows that subjective norm, student image, job relevance, result demonstrability, and output quality (Figure 1) explained a significant proportion of variance in perceived usefulness, $R^2 = 0.558$, $F\ (5, 103) = 26.0$, $p < .001$ and in perceived ease of use $R^2 = 0.552$, $F\ (5, 103) = 25.4$, $p < .001$. Also, perceived usefulness, perceived ease of use and all other variables in the model accounted for 65.7% of the variances in intention to adopt generative AI, $R^2 = 0.657$, $F\ (7, 101) = 26.0$, $p < .001$. These findings indicate that students are more inclined to adopt generative AI in their learning if they perceive it as useful, believe it improves their image, can observe tangible results, and find it relevant to their job.

Table 5
Model coefficient and predictor variables

Model coefficient	**Predictor**	***β***	***SE***	***t***	***p***
Model 1 Coefficient	*Intercept*	2.140	1.244	1.720	0.088
Perceived usefulness	Subjective Norm	0.330	0.086	3.835	0 .000***
	Student Image	0.092	0.070	1.321	0.189
	Results demonstrability	0.262	0.137	1.901	0.060
	Output Quality	-0.014	0.124	-0.110	0.913
	Job Relevance	0.389	0.138	2.809	0.006**

Model 2 Coefficient Perceived ease of use.	*Intercept*	0.949	1.010	0.935	0.352
	Subjective Norm	0.209	0.070	2.970	0.004**
	Student Image	-0.032	0.057	-0.554	0.581
	Results demonstrability	0.338	0.112	3.008	0.003**
	Output Quality	0.337	0.101	3.322	0.000***
	Job Relevance	0.080	0.113	0.706	0.482
Model 3 Coefficient Intention to AI adoption	*Intercept*	0.391	1.165	0.336	0.737
	Subjective Norm	0.034	0.086	0.389	0.698
	Perceived usefulness	0.236	0.094	2.493	0.014*
	Perceived ease of use	0.089	0.116	0.774	0.441
	Student Image	0.146	0.066	2.224	0.028*
	Results demonstrability	0.329	0.133	2.470	0.015*
	Output Quality	-0.115	0.121	-0.947	0.346
	Job Relevance	0.430	0.132	3.247	0.002**

*Significant at $p < .05$; **Significant at $p < .01$; ***Significant at $p < .001$

Specifically, Table 5 shows that subjective norm significantly predicted perceived usefulness, $\beta = .330$, $t\ (103) = 3.835$, $p < .001$ and perceived ease of use, $\beta = .209$, $t\ (103) = 2.970$, $p < .01$; job relevance significantly predicted perceived usefulness, $\beta = .389$, $t\ (103) = 2.809$, $p < .01$ and intention to AI adoption, $\beta = .430$, $t\ (101) = 3.247$, $p < .01$; result demonstrability significantly predicted perceived use of use, $\beta = .338$, $t\ (103) = 3.008$, $p < .01$ and intention to AI adoption, $\beta = .329$, $t\ (101) = 2.470$, $p < .05$; output quality significantly predicted perceived ease of use, $\beta = .337$, $t\ (103) = 3.322$, $p < .001$ and student image significantly predicted students' intention to AI adoption, $\beta = .147$, $t\ (101) = 2.224$, $p < .05$. Also, perceived usefulness significantly predicted students' intention to AI adoption, $\beta = .236$, $t\ (101) = 2.493$, $p < .05$.

How do student status and gender influence AI adoption?

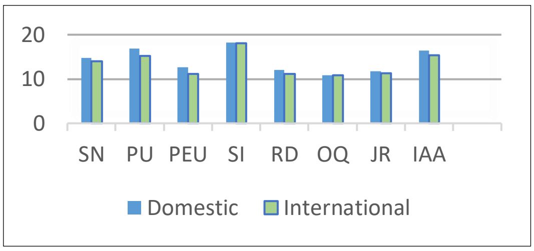

Figure 2 Domestic and international

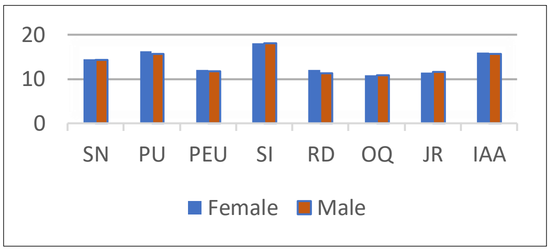

Figure 3 Female and male students

The study used an independent sample t-test to examine the effect of students' status and gender disparities on different variables of the model as well as on their intention to adopt AI in the learning process. Figure 2 and Figure 3 show the mean differences between the domestic-international and female-male students in terms of the different variables shown in Figure 1. When comparing domestic and international students, it is found that domestic students showed higher levels of acceptance of the adoption of generative AI. In the case of gender, it appears that both male and female students have similar attitudes to all the variables of the model. The independent-sample *t-test* showed no significant difference between female and male students in their intention to adopt generative AI or in any other variables. However, domestic and international students differ significantly in perceived usefulness, $t\ (107) = 2.662$, $p < .01$, $d = .516$; in perceived ease of use, $t\ (107) = 2.992$, $p < .01$, $d = .580$; and in result demonstrability, $t\ (107) = 2.119$, $p < .05$, $d = .410$. Domestic students rated these variables higher than their international counterparts, indicating that they perceive generative AI tools as more valuable, user-friendly, and beneficial.

Discussion and implications

The proposed model in this study, based on the framework of the Unified Theory of Acceptance and Use of Technology (UTAUT), showed excellent predictability ($R^2 = 0.657$) explaining 65.7% of the variances in students' behavioural intentions towards adopting generative AI tools. The finding is supported by a previous study which established that perceived usefulness and perceived ease of use are strong predictors of technology adoption (Venkatesh et al., 2003). Particularly, social influences such as subjective norms and the approval of peers and teachers play a significant role in educational settings to influence student intention to adopt the new technology (Li, 2023). Similarly, when students find that adopting new technology enhances their future job prospects and increases the tangible benefits, students are more likely to recognise its value and usefulness and show an inclination to adopt it (Alyoussef, 2021). The findings of this study confirmed that the use of generative AI affects students' self-image and the perception of others. A recent study argued that the impact of student image ties into the broader construct of social influence within the UTAUT framework (Strzelecki, 2024). All these factors of social influences and cognitive processes highlight the improvement in the performance and effort expectancy of the students and influence their intention to adopt generative AI in the learning process.

While considering the role of demographic variables, this study found a significant difference between domestic and international students regarding perceived usefulness, perceived ease of use, and result demonstrability of the generative AI. It is reported that international students often face additional challenges like language barriers and cultural differences that may negatively impact their perceptions and adoption of new technologies (Wang et al., 2023). Domestic students might find it easier to perceive the usefulness and ease of use of generative AI tools because they are more familiar with the educational context and have better access to support systems. On the other hand, this study showed no statistically significant difference in the intention to adopt generative AI between male and female students. This finding suggests that gender may not play a significant role in the adoption of generative tools in educational settings. This result is in line with the findings of the recent literature where the benefits of AI and its perceived ease of use, regardless of gender, significantly influence student intention to adopt AI technologies (Fuchs, 2023). Historically, gender differences have always drawn attention in the study of technology adoption. Venkatesh and Morris (2000) found that men were influenced by performance-related factors (e.g., usefulness), while women were affected by social and affective aspects (e.g., social influence and ease of use). However, these gaps are narrowing for the younger generations and with increased access to technology. As generative AI becomes more integrated into education, gender-based disparities may further diminish. The findings of the current study confirm that perceived usefulness and ease of use are found to be the primary factors influencing the adoption of AI, dismissing any potential gender differences among the students (Li, 2023). In brief, educational interventions aiming to enhance AI adoption among students should focus on increasing the perceived usefulness and ease of use of generative AI, rather than emphasising traditional gender differences, as they are less relevant in technology use. To ensure equity in technology adoption in education, universities could implement policies to provide free or subsidized access to AI tools. Students from minority ethnic groups or least-developed countries may have lower levels of digital literacy. To promote inclusivity and equal access, universities can offer tailored support programs and ensure that all students, regardless of background, can engage with and benefit from AI technologies.

Conclusion and future research directions

The strong predictability of the proposed model in the current study highlights its effectiveness in identifying the key factors that influence the adoption of generative AI in educational settings. As generative AI continues to evolve, understanding these factors is important for creating effective learning environments. Specifically, factors such as perceived usefulness, ease of use, and social influence are found to be more critical determinants of technology adoption in academic settings than any other factors like gender differences. In an engineering field where practicality is given more importance over theoretical knowledge, students will embrace AI technologies when they find them beneficial in practical use. Future research can combine quantitative and qualitative data to further understand students' interactions with generative AI. Also, the incorporation of Activity Theory into UTAUT will help researchers understand the broader sociocultural context, including institutional and cultural factors related to AI adoption. The researchers can benchmark generative AI against other emerging technologies, such as adaptive learning platforms or intelligent tutoring systems. This comparison would help researchers understand whether the role of social influence and cognitive processes is unique to AI adoption or consistent across other technologies. Finally, this study acknowledges its limitation about the use of a small dataset to explore the factors that influence the students’ adoption of generative AI.

The larger dataset from the ongoing research study may potentially uncover more dimensions and provide deeper insights into the student's intention to use generative AI technologies.

References

Alyoussef, I. Y. (2021). Factors Influencing Students' Acceptance of M-Learning in Higher Education: An Application and Extension of the UTAUT Model. *Electronics*, *10*(24), Article 24. https://doi.org/10.3390/electronics10243171

Annuš, N. (2023). Chatbots in education: The impact of artificial intelligence based ChatGPT on teachers and students. *International Journal of Advanced Natural Sciences and Engineering Researches*, *7*(4), 366–370. https://doi.org/10.59287/ijanser.739

Camilleri, M. A. (2024). Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework. *Technological Forecasting and Social Change*, *201*, 123247. https://doi.org/10.1016/j.techfore.2024.123247

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, *20*(1), 43. https://doi.org/10.1186/s41239-023-00411-8

Davis, F. D., & Venkatesh, V. (2004). Toward preprototype user acceptance testing of new information systems: Implications for software project management. *IEEE Transactions on Engineering Management*, *51*(1), 31–46. IEEE Transactions on Engineering Management. https://doi.org/10.1109/TEM.2003.822468

Deng, X., & Yu, Z. (2023). A meta-analysis and systematic review of the effect of chatbot technology use in sustainable education. *Sustainability*, *15*(4), 2940. https://doi.org/10.3390/su15042940

Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017). Acceptance and use of lecture capture system (LCS) in executive business studies: Extending UTAUT2. *Interactive Technology and Smart Education*, *14*(4), 329–348. https://doi.org/10.1108/ITSE-06-2016-0015

Fuchs, K. (2023). Exploring the opportunities and challenges of NLP models in higher education: Is Chat GPT a blessing or a curse? *Frontiers in Education*, *8*. https://doi.org/10.3389/feduc.2023.1166682

Hasan, N., Polin, J. A., Ahmmed, M. R., Sakib, M. M., Jahin, M. F., & Rahman, M. M. (2024). A novel approach to analyzing the impact of AI, ChatGPT, and chatbot on education using machine learning algorithms. *Bulletin of Electrical Engineering and Informatics*, *13*(4), Article 4. https://doi.org/10.11591/eei.v13i4.7158

Li, K. (2023). Determinants of College Students' Actual Use of AI-Based Systems: An Extension of the Technology Acceptance Model. *Sustainability*, *15*(6), Article 6. https://doi.org/10.3390/su15065221

Naher, J., Maruf, M. H., Bakht, S. T., & Sadaf, S. S. (2023). A Survey to Understand the experience of ChatGPT Usage among Engineering University Students in Bangladesh. *Technium: Romanian Journal of Applied Sciences and Technology*, *15*, 1–8. https://doi.org/10.47577/technium.v15i.9660

Naseri, R. N. N., & Abdullah, M. S. (2024). Understanding AI Technology Adoption in Educational Settings: A Review of Theoretical Frameworks and their Applications. *Information Management and Business Review*, *16*(3(I)), 174–181. https://doi.org/10.22610/imbr.v16i3(I).3963

Oye, N. D., Iahad, N. A., & Rahim, N. Ab. (2014). The history of UTAUT model and its impact on ICT acceptance and usage by academicians. *Education and Information Technologies*, *19*(1), 251–270. https://doi.org/10.1007/s10639-012-9189-9

Shah, S. N. A., Khan, A. U., Khan, B. U., Khan, T., & Xuehe, Z. (2021). Framework for teachers' acceptance of information and communication technology in Pakistan: Application of the extended UTAUT model. *Journal of Public Affairs*, *21*(1), e2090.

Strzelecki, A. (2024). Students' Acceptance of ChatGPT in Higher Education: An Extended Unified Theory of Acceptance and Use of Technology. *Innovative Higher Education*, *49*(2), 223–245. https://doi.org/10.1007/s10755-023-09686-1

Tanvir, K., Islam, M., Sezan, S., Sanad, Z., & Ataur, A.-J. (2023). Impact of ChatGPT on Academic Performance among Bangladeshi Undergraduate Students. *International Journal of Research In Science & Engineering*, 18–28. https://doi.org/10.55529/ijrise.35.18.28

Venkatesh, V. (2022). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1), 641–652. https://doi.org/10.1007/s10479-020-03918-9

Venkatesh, V., & Morris, M. G. (2000). Why Don't Men Ever Stop to Ask for Directions? Gender, Social Influence, and Their Role in Technology Acceptance and Usage Behavior. *MIS Quarterly, Vol. 24, No. 1, Pp. 115-139, 2000*, *24*(1), 115–139.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.1201/9780849375477.ch230

Wang, T., Lund, B. D., Marengo, A., Pagano, A., Mannuru, N. R., Teel, Z. A., & Pange, J. (2023). Exploring the Potential Impact of Artificial Intelligence (AI) on International Students in Higher Education: Generative AI, Chatbots, Analytics, and International Student Success. *Applied Sciences*, *13*(11), Article 11. https://doi.org/10.3390/app13116716

Asag, M.A., Al Mamun, M.A. & Hasan, M. (2024). Engineering Students' Adoption of Generative AI: The Role of Social Influence and Cognitive Processes. In Cochrane, T., Narayan, V., Bone, E., Deneen, C., Saligari, M., Tregloan, K., Vanderburg, R. (Eds.), *Navigating the Terrain: Emerging frontiers in learning spaces, pedagogies, and technologies*. Proceedings ASCILITE 2024. Melbourne (pp. 483-489). https://doi.org/10.14742/apubs.2024.1217