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Assessing Zoomers Readiness for Artificial Intelligence Adoption in Higher Academic Institutions in Bangladesh: A PLS-SEM Approach

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Abstract
The purpose of the study is to examine the Zoomers readiness to adopt AI in Bangladeshi higher educational institutions by employing the extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework where Zoomers attitudes toward AI are considered as a mediating factor. A structured questionnaire was distributed to 400 respondents using a convenience sampling method, resulting in 335 valid responses for data analysis. PLS-SEM was utilized to examine the measurement and structural model, with data analysis conducted using SmartPLS 4.1.1.8. The findings reveal that effort expectancy positively influences both behavioural intention ($\beta = 0.211$, $p < .001$) and attitudes toward AI ($\beta = 0.443$, $p < .001$) with attitude serving as the strongest predictor of behavioural intention ($\beta = 0.600$, $p < .001$). While performance expectancy ($\beta = 0.166$, $p = .010$) and facilitating conditions ($\beta = 0.117$, $p = .038$) significantly enhance attitudes but do not directly predict behavioural intention. Social influence is found to be insignificant for both attitude and behavioural intention. Moreover, attitude significantly mediates the effects of performance expectancy, effort expectancy, and facilitating conditions on behavioural intention. These findings extend UTAUT framework by emphasizing the role of attitude as a pivotal factor in the adoption of AI. They also offer practical implications for creating accessible, supportive, and learner-centred AI environments in Bangladeshi higher education. Future research could consider other variables like trust in AI, ethical issues in media sharing, and comparisons of generational differences across various education levels in Bangladesh.

Keywords: Artificial Intelligence, Zoomers, UTAUT, Behavioural Intention, Attitude, PLS-SEM, Higher Education, Bangladesh.

1. Introduction

Artificial Intelligence (AI) is increasingly renovating higher education by changing how students learn, search for information, write academic work, receive feedback, and prepare for future careers (Sharma & Singh, 2024). In universities, AI-based tools such as chatbots, intelligent tutoring systems, automated writing assistants, plagiarism detection systems, learning analytics, and personalized learning platforms are becoming part of academic life (Soeffner, 2023). UNESCO has emphasized that generative AI can support teaching, learning, curriculum design, and research, but it also requires proper regulation, ethical use, data privacy protection, and institutional preparedness (Miao & Holmes, 2023). How students will make effective use of AI tools depends on their perceptions of usefulness, ease of use, social acceptance, and institutional support. It is important for universities, policymakers, educators, and tech developers to understand students' readiness and their willingness, ability, confidence, and perceived support regarding using technology. Readiness describes students' choice, capacity, assurance, and perceived facilitation to use AI tools for academic tasks (Falebita & Kok, 2025).

Digital transformation is happening in Bangladesh and it is reflected in the draft National AI Policy 2026–2030 where the importance of AI and computational thinking skills for students is underlined. However, low device ownership, poor connectivity, low preparedness in institutions and gaps in technological literacy are challenges to AI readiness in higher education (Ali et al., 2024). Without the right digital infrastructure and guidance, the adoption of AI could be inequitable, benefiting only those with better access and skills. A recent study by Jony et al. (2023) reveals that while Bangladeshi university students are open to using AI, their understanding of the technology is quite limited. Bangladesh is slowly adopting AI in education, but this is still in early stages (Y. Ali et al., 2024). Bangladesh ranked 75th in overall government AI readiness among all countries, according to the Oxford-Insights (2024) assessment.

Zoomers (also known as Generation Z) are the first generation to grow up with the internet, smartphones and social media and therefore show readiness for AI adoption because of their skilfulness in technology, education level and open-mindedness to innovation (Erkul, 2023). They are adept at using technology and have some familiarity with AI quite early (Ali et al., 2024). Zoomers are cited as digital natives, with distinctive attitudes toward the adoption of AI (Slepian et al., 2023), and born between 1997 and 2012. Academicians should effectively utilize AI while preserving the integrity of the learning process. This understanding of the generational gap in AI provides educators with insight into the ways they can incorporate it into their curriculum. This will make sure that Gen Z can integrate these technologies in a professional and academic environment (Ali et al., 2024).

In an earlier investigation, the predictors of UTAUT model were used to measure the intention to use AI among university students and found that the performance expectancy, social influence and facilitating conditions positively influenced AI (Yakubu et al., 2025; Joshi, 2025; Ali et al., 2024; Tian et al., 2024; Sharma & Singh, 2024b; Talla et al., 2023; Sridharlakshmi, 2020; Ahmmed et al., 2021b; Chatterjee & Bhattacharjee, 2020). However, effort expectancy was found to be negative (Jony et al., 2023). Utilizing the UTAUT model, it seeks to uncover factors influencing Zoomers' acceptance of AI in academia. The results aim to assist institutions in developing effective AI policies and training, while also guiding policymakers in preparing the youth for an AI-enhanced future.

The goal of the study is to measure the association between UTAUT determinants on ZBI; to evaluate the relationship between UTAUT determinants on ZAT; to assess the effect of ZAT on their ZBI; and to evaluate the mediating role of ZAT in the relationships between UTAUT determinants and ZBI to adopt AI in Bangladesh.

The remainder of the paper is structured as follows. The research hypotheses about the link between UTAUT determinants, specifically, performance expectancy, effort expectancy, social influence and facilitating conditions on ZBI and ZAT, and the mediation effect of ZAT on the link are developed in the next section, which also provides a review of the pertinent literature. This is followed by research methodology, including data gathering techniques and analytical methods including measurement and structural model analysis utilizing PLS-SEM. The results of the hypotheses test are presented in the next section, along with a discussion of the main conclusions about the relationship between UTAUT determinants and the ZBI with mediating ZAT. The study concludes with recommendations for further research based on its shortcomings.

2. Theoretical Background and Hypothesis Development

2.1 UTAUT Model

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al. (2003), serves as a valuable framework for evaluating the readiness of Zoomers to utilize AI in higher education in Bangladesh. It identifies four UTAUT determinants like, performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) affects this readiness. It is important to highlight that these four constructs are directly related to this study because they can explain how students are evaluating AI before accepting it for academic use. The above framework highlights that Zoomers acceptance of AI is influenced by academics, perceived ease of use, friends & teacher influence and institutional support system. The study employed the UTAUT model, but did not examine the moderators (age, gender, experience, and voluntariness). We will delineate the constructs individually and subsequently formulate the hypotheses and the model. Figure- 1 summarizes proposed framework of the research.

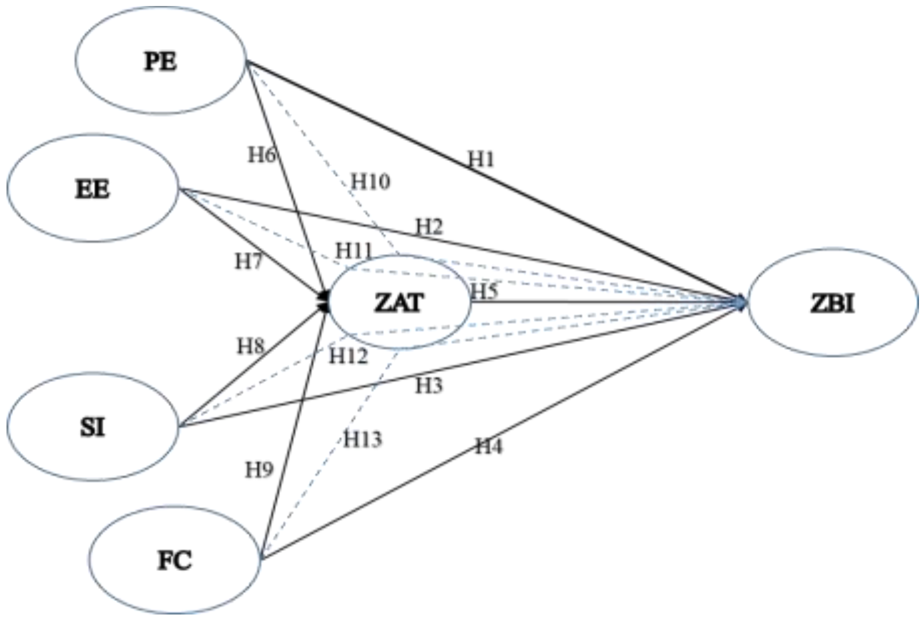

Figure -1: Hypothesized Model

2.2 Explanation of the Variables

Performance expectancy (PE) is a belief that AI will help them to perform better their academic performance. Students, for instance, may have the expectation that AI can help them prepare assignments, be a source of reading summaries, improve their writing skills, synthesis ideas for them, translate academic texts into a language they understand and provide support with research tasks (Alshammari et al., 2026). If students relate that AI has instrumental value with respect to achieving better performance outcomes, they are expected to be more likely willing to accept AI (Rehman et al., 2025). Effort expectancy (EE) is defined as the degree of usability of the system (Venkatesh et al., 2003). Another related determinant is social influence (SI) which has significant impact on Zoomers adoption of AI in higher education, which is influenced by the attitudes of teachers and peers as well as institutional culture (Rehman et al., 2025). If AI is embraced socially and academically, Zoomers are likely to increased openness to adopt AI technologies. Facilitating conditions (FC) include basic resources and support systems needed for the introduction of AI in higher education such as internet access, digital devices, preparation to AI literacy and institutional policy (Jony et al., 2023). Zoomers behavioural Intention (ZBI) is the intentional plans of individuals either to perform in a specific future behaviour or not to perform in any way like Khan et al. (2024).

2.3 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) by Ajzen (1991), states that human behaviour is determined by the intention, and this behaviour is indeed influenced very much in psychological and social processes. Therefore, TPB is relevant in this study since it predicts the adoption of AI in higher education among Zoomers not only through access to AI tools but also through control beliefs regarding perceived behavioural influences by social norms around using AI and perceived self-efficacy for effective use of AI. (Ngo et al., 2025). TPB is relevant for this study as it elucidates the mediating role of attitude in the context of the UTAUT model. While UTAUT focuses on factors like performance expectancy and social influence, TPB demonstrates how these factors influence students' readiness to adopt AI by first shaping their attitudes (Lakulu et al., 2025).

2.4 Link between UTAUT Dimensions and Zoomers Behavioural Intention (ZBI)

2.4.1 PE and ZBI

Prior studies highlight the significant influence of performance expectancy on the adoption of AI technologies in higher education. Koteczki & Eisinger, (2025) emphasize that perceived usefulness positively impacts Zoomers intentions to use AI. Also, Sergeeva et al. (2025) identify performance expectancy as a key predictor for generative AI adoption among students. In Bangladesh, Akter et al. (2026) confirm that performance expectancy affects stakeholders' attitudes and intentions towards AI adoption in universities. Thus, we propose the following hypothesis:

H1: PE positively influences ZBI to adopt AI.

2.4.2 EE and ZBI

Research indicates that EE is crucial for promoting AI adoption in industries such as higher education, hospitality, and online retail business (Chatterjee & Bhattacharjee, 2020; Pillai & Sivathanu, 2020; Kasilingam, 2020). Jony et al. (2023) found a negative correlation between BI and EE regarding the use of AI. Koteczki & Eisinger, (2025) found that perceived ease of use had a positive role in AI acceptance among Generation Z university students, although its influence may work through attitude rather than only as a direct effect. Therefore, following hypothesis is proposed to test:

H2: EE positively influences ZBI to adopt AI.

2.4.3 SI and ZBI

Earlier study found that SI serves as a significant determinant of UTAUT framework (Zheng et al., 2021). Through the application of UTAUT variables, (Abbad, 2021) determined that social influence does not exert a favourable effect on students regarding e-learning. Ali et al. (2024) & Jony et al. (2023) found that social influence did not positively impact AI adoption intention among Bangladeshi students, while Akter et al. (2026) found that social influence directly influenced attitude and behavioural intention toward AI adoption in Bangladeshi universities. Therefore, following hypothesis is proposed to test:

H3: SI positively influences ZBI to adopt AI.

2.4.4 FC and ZBI

In the original UTAUT model, facilitating conditions are directly related to actual technology use; however, later studies often examine their effect on behavioural intention, especially in educational technology and AI adoption contexts. In Bangladesh, Akter et al. (2026) found that facilitating conditions directly influence stakeholders' attitudes and behavioural intention toward AI adoption in higher education. Ali et al. (2024) also found that facilitating conditions positively impact AI adoption intention among Bangladeshi students. Another study conducted by Chatterjee & Bhattacharjee (2020) and further supported by Jony et al. (2023) found a positive correlation between BI and FC in academic settings. Accordingly, the subsequent hypothesis is proposed:

H4: FC positively influences ZBI to adopt AI.

2.5 Link between ZAT and ZBI

Zoomers' psychological acceptance of AI significantly affects its adoption. While students may have access to AI tools, their intention to use them is influenced by their attitudes. While a favorable perception acknowledges AI helps in improving productivity and supporting learning, negative aspects comprise of fears around plagiarism, misinformation and ethical concerns. Strzelecki (2024) found that students' willingness to use ChatGPT is influenced by their positive perceptions. Similarly, Babu et al. (2024) linked Zoomers characteristics to their adoption of ChatGPT, indicating that favourable views can enhance usage tendencies. Acosta-Enriquez et al. (2024) further emphasized that Zoomers interactions with AI are shaped by their knowledge, concerns, attitudes, and ethical perceptions, suggesting that addressing ethical concerns can bolster positive behavioural intentions towards AI tools. Thus, we propose the following hypothesis:

H5: ZAT have a positive influence on ZBI to adopt AI

2.6 Link between UTAUT Dimensions and Zoomers Attitudes (ZAT)

2.6.1 PE and ZAT

Performance expectancy has a strong impact on technology adoption. Research by Venkatesh et al. (2003) and Davis (1989) showed that users are more inclined to accept technology when they perceive it as beneficial. Similarly, Zoomers are more likely to adopt AI when they believe it can improve their academic performance. This relationship is also supported by studies from Chan and Lee (2023) and Acosta-Enriquez et al. (2024). Thus, we propose the following hypothesis:

H6: PE positively influences ZAT to adopt AI.

2.6.2 EE and ZAT

Effort expectancy positively influences users' attitudes toward technology. Davis (1989) and Venkatesh et al. (2003) showed that technologies perceived as easy to use are more likely to be accepted. Similarly, user-friendly AI tools such as ChatGPT and writing assistants can encourage favorable attitudes among Zoomers, a relationship also supported by Strzelecki (2024).Therefore, we propose the following hypothesis:

H7: EE positively influences ZAT to adopt AI.

2.6.3 SI and ZAT

Consistent with the UTAUT model, social influence plays an important role in technology acceptance. Among Zoomers, perceptions of AI are often shaped by peer practices and academic norms. Chan and Lee (2023) found that although Zoomers show strong interest in generative AI for learning, their acceptance is also influenced by ethical concerns and institutional support, indicating that encouragement from teachers and peers can strengthen positive attitudes toward AI adoption. Thus, we propose the following hypothesis:

H8: SI positively influences ZAT to adopt AI.

2.6.4 FC and ZAT

Facilitating conditions, such as institutional resources and technical support, play an important role in shaping technology use in higher education (Venkatesh et al., 2003). In the context of AI, universities therefore need to provide an environment that supports responsible and effective adoption. Recent studies further confirm the relevance of UTAUT in higher education, showing that both contextual support and user-related factors influence AI acceptance (Xue et al., 2024; Acosta-Enriquez et al., 2024). Accordingly, the following hypothesis is proposed:

H9: FC positively influences ZAT to adopt AI.

2.7Relationship between UTAUT Dimensions and ZBI: The Mediating role of ZAT

2.7.1 PE, ZAT, and ZBI

UTAUT identifies performance expectancy (PE) as an important predictor of technology acceptance, consistent with Davis's (1989) concept of perceived usefulness. Individuals are more likely to adopt a technology when they believe it can improve their performance. Recent studies in higher education also show that students' acceptance of AI is influenced by its perceived academic usefulness and performance benefits (Emon & Khan, 2025). In this study, PE is expected to influence Zoomers' behavioural intention (ZBI) indirectly through their attitude toward AI (ZAT). When Zoomers perceive AI as beneficial for their academic performance, they are more likely to develop a positive attitude toward its use, which can subsequently strengthen their intention to adopt AI. Therefore, we propose the following hypothesis:

H10: ZAT mediates the connection between PE and ZBI in adopting AI.

2.7.2 EE, ZAT and ZBI

Effort expectancy (EE) reflects the perceived ease of using AI tools and is expected to shape Zoomers' attitudes toward AI. This aligns with Davis's (1989) concept of perceived ease of use, which suggests that individuals are more inclined to adopt a technology when they find it simple and user-friendly. Recent evidence also indicates that effort expectancy positively influences students' behavioural intention to use AI in academic contexts, particularly in developing countries (Rana et al., 2024). However, perceived ease of use may not directly translate into adoption unless it first contributes to a favorable attitude toward the technology (Emon & Khan, 2025). Therefore, EE is expected to influence Zoomers' behavioural intention (ZBI) indirectly through their attitude toward AI (ZAT). Therefore, we propose the following hypothesis:

H11: ZAT mediates the connection between EE and ZBI in adopting AI.

2.7.3 SI, ZAT and ZBI

Within the UTAUT framework, social influence (SI) is considered an important factor shaping individuals' intention to adopt technology, which is also consistent with the Theory of Planned Behaviour (TPB). In the context of generative AI, Gen Z students generally recognize its potential benefits for learning, although their views may also be influenced by ethical concerns and academic regulations (Rana et al., 2024). Support and encouragement from teachers, peers, and other important social groups may therefore help students develop a more positive attitude toward AI. In turn, this favorable attitude can strengthen their intention to adopt and use AI technologies. Thus, we propose the following hypothesis:
H12: ZAT mediates the connection between SI and ZBI in adopting AI.

2.7.4 FC, ZAT and ZBI

Facilitating conditions (FC) refer to the organizational and technical resources available to support technology use (Venkatesh et al., 2003). When institutions provide adequate infrastructure, guidance, and technical assistance, users are more likely to develop a favorable attitude toward new technologies, including AI (Mohamed et al., 2022). Similar findings in educational contexts indicate that facilitating conditions can significantly influence AI acceptance among students (Acosta-Enriquez et al., 2024; Rana et al., 2024). Therefore, supportive conditions are expected to strengthen Zoomers' behavioral intention (ZBI) indirectly by fostering a more positive attitude toward AI (ZAT). Thus, we propose the following hypothesis:
H12: ZAT mediates the connection between FC and ZBI in adopting AI.

3Methodology

3.1 Participants and Procedure

This study utilized exploratory research to evaluate the readiness of Zoomers for AI adoption in higher education in Bangladesh. It involved collecting data from students at both public and private universities. Using SmartPLS 4.1.1.8, the research investigates the dimensions of the UTAUT framework, as well as Zoomers attitudes toward AI, and their behavioural intentions through a structured questionnaire. The survey assesses performance expectancy, effort expectancy, social influence, and facilitating conditions using a five-point Likert scale. A purposive sampling technique employed to target specific respondents. In a total, 400 questionnaires were distributed via Google Form, resulting in 335 completed questionnaires that were deemed suitable for analysis after a careful review. The questionnaire is divided into several sections, including demographics, UTAUT dimensions, ZAT, and ZBI sections.
Table 1 presents the demographic and academic characteristics of the 335 respondents. Among them, 230 (68.65%) were male and 105 (31.35%) were female. Regarding institutional affiliation, 200 respondents (59.70%) were enrolled in public universities, while 135 (40.30%) were from private universities. Most respondents were undergraduate students (64.18%), followed by graduate (23.88%) and postgraduate students (11.94%). In terms of academic discipline, Business Studies represented the largest group (50.75%), followed by Science (25.37%) and Arts (23.88%). The respondents also showed a high level of exposure to AI tools. A total of 318 students (94.93%) reported using tools such as ChatGPT, Gemini, or Copilot for academic purposes, while only 17 (5.07%) had not used such tools.

Table 1: Respondents' Profile

	Frequency	**Percentage**
Gender		
Male	230	68.65%
Female	105	31.35%
Total	335	100%
Academic Institution		
Public University	200	59.70%
Private University	135	40.30%
Total	335	100%
Level of Study		
Undergraduate	215	64.18%
Graduate	80	23.88%
Post graduate	40	11.9%
Total	335	100%
Field of Study		
Arts	80	23.88%
Science	85	25.37%
Business Studies	170	50.75%
Total	335	100.0%
AI Tool Usage		
Yes	318	94.93%
No	17	5.07%

Total	335	100.0%

Source: Field Survey

3.2 Measurement

To enhance validity and reliability, we utilised measurement scales from established sources. A 5-item performance expectancy scale were derived from Chatterjee & Bhattacharjee (2020); Venkatesh et al., (2003). Item such as “smart educational content can be prepared using AI technology” was utilized”. A 5-item effort expectancy scale were derived from Chatterjee & Bhattacharjee (2020); Falebita & Kok (2025). Such as "AI technology is difficult to learn". A 5-item facilitating conditions scale were derived from Chatterjee & Bhattacharjee (2020). Item such as “My University sponsor any AI related learning opportunity”. A 5-item social influence scale were derived from Ng et al. (2024); Venkatesh et al., (2003). Item such as “My teachers, seniors, or mentors influence me to use AI tools”. A 5-item Zoomers attitudes scale were derived from Chatterjee & Bhattacharjee (2020); Venkatesh et al., (2003). Item such as “AI technology is useful for teaching-learning activities”. Finally, a 5 items Zoomers’ behavioural intention derived from Chatterjee & Bhattacharjee (2020); Venkatesh et al., (2003). Item such as “I believe AI technology is very easy to learn by beginner”.

4.0 Results

4.1 Measurement Model

The measurement model was evaluated to ensure the reliability and validity of the study constructs by examining internal consistency, convergent validity, and discriminant validity.

The standardised factor loadings of all items on their corresponding constructs were analysed. Hair et al. (2021) established a threshold of 0.70 to signify adequate item reliability, and the item values in this study exceed this criterion. Figure 2 illustrates the loading from the measurement model.

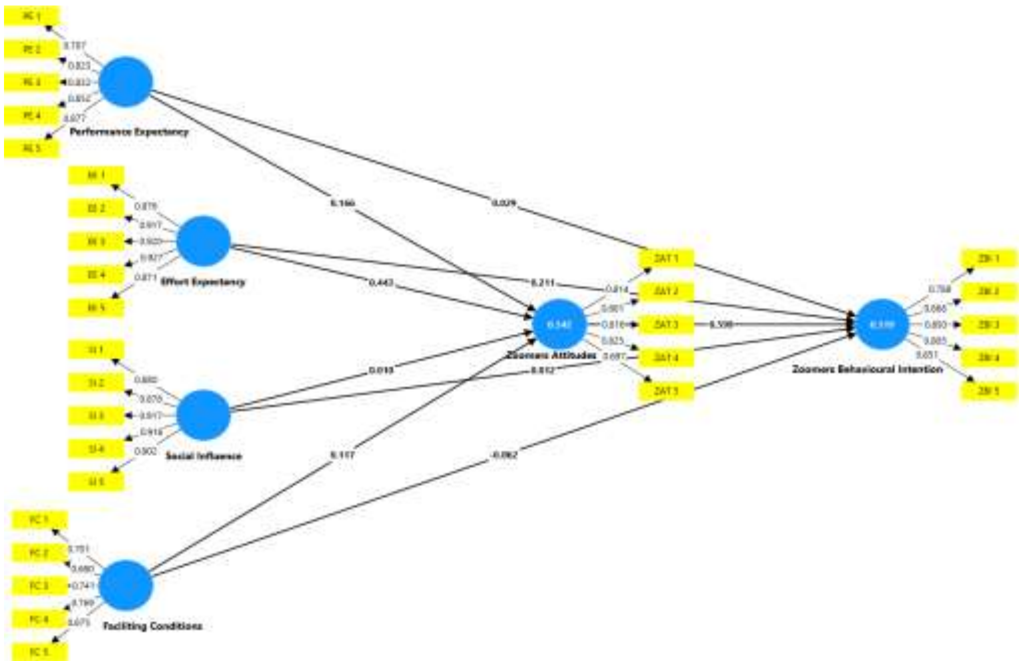

Figure 2: Measurement Model (Source: Authors’ calculation)

Table 2: Factor loading, reliability, and AVE assessment

Construct	Loading	CA (α)	CR (rho_a)	AVE
Performance Expectancy		0.877	0.879	0.673
PE_1	0.707			
PE_2	0.823			
PE_3	0.832			
PE_4	0.852			
PE_5	0.877			
Effort Expectancy		0.943	0.948	0.815
EE_1	0.876			
EE_2	0.917			

EE_3	0.920			
EE_4	0.927			
EE_5	0.871			
Social Influence		0.943	0.983	0.808
SI_1	0.880			
SI_2	0.878			
SI_3	0.917			
SI_4	0.916			
SI_5	0.902			
Facilitating Conditions		0.780	0.795	0.513
FC_1	0.701			
FC_2	0.690			
FC_3	0.741			
FC_4	0.769			
FC_5	0.675			
Zoomers Attitudes		0.850	0.855	0.627
ZAT_1	0.814			
ZAT_2	0.801			
ZAT_3	0.816			
ZAT_4	0.825			
ZAT_5	0.697			
Zoomers Behavioural Intention		0.897	0.898	0.709
ZBI_1	0.788			
ZBI_2	0.868			
ZBI_3	0.893			
ZBI_4	0.805			
ZBI_5	0.851			

Notes: CA-Cronbach's Alpha, CR-Composite reliability and AVE-Average variance extracted

Then the internal consistency reliability was measured using two indicators, namely the Composite reliability with a threshold of 0.70 and below 0.95 and Cronbach's Alpha with a threshold of > 0.70 (Nunnally & Bernstein, 1994; Hair et al., 2021). Results indicate that all constructs pass the threshold values, showing satisfactory internal consistency without redundancy (refer to Table 2). Finally, the Average Variance Extracted (AVE) was used to test for convergent validity. An AVE of 0.50 or higher means that the construct explains more than half of the variance of its indicators (Fornell & Larcker, 1981). All constructs used in the study have AVE values greater than 0.50 (refer to Table 2). The discriminant validity was evaluated with two approaches, namely the Heterotrait-Monotrait Ratio (HTMT) and the Fornell-Larcker Criterion. At the beginning, HTMT values below 0.90 indicate adequate discriminant validity (Hair et al., 2021). The HTMT values ranged from 0.091 to 0.796 and none exceeded the conservative threshold of 0.90, indicating adequate empirical distinctiveness of the constructs (refer to Table 3).

Table 3: HTMT-List

	Social Influence	Facilitating Conditions	ZBI	ZAT	Performance Expectancy	Effort Expectancy
SI						
FC	0.262					
ZBI	0.091	0.250				
ZAT	0.140	0.408	0.796			
PE	0.324	0.639	0.313	0.436		
EE	0.144	0.370	0.558	0.593	0.347	

Notes: ZAT-Zoomers attitudes and ZBI-Zoomers behavioural intention

According to the Fornell-Larcker Criterion, the square root of the AVE of each construct must be greater than the highest correlation of its validity with other constructs (Hair et al., 2021). The AVE had more correlation with other constructs as the findings indicate (refer to Table 4). Therefore, all the constructs have positive levels of discriminant validity.

Table-4: Fornell and Larcker Criterion

	AVE	Social Influence	Facilitating Conditions	ZBI	Zoomers Attitudes	Performance Expectancy	Effort Expectancy
SI	0.808	**0.899**					
FC	0.513	-0.247	**0.716**				
ZBI	0.709	-0.095	0.251	**0.842**			
ZAT	0.627	-0.136	0.373	0.698	**0.792**		
PE	0.673	-0.307	0.630	0.280	0.378	**0.820**	
EE	0.815	-0.150	0.348	0.517	0.535	0.318	**0.903**

Notes: AVE-Average variance extracted

4.2 Structural Model

The Variance Inflation Factor (VIF) values for the structural model range from 1.112 to 1.797, all below the threshold of 5.0, indicating no critical collinearity among the predictor constructs. Hence, the model meets the collinearity assessment criterion and is suitable for further evaluation of the hypothesized relationships (Hair et al., 2021).

Table 5: Collinearity Statistics

VIF	
Performance Expectancy --> ZBI	1.797
Effort Expectancy --> ZBI	1.459
Social Influence --> ZBI	1.112
Facilitating Conditions --> ZBI	1.755
Zoomers Attitudes --> ZBI	1.519
Performance Expectancy --> ZAT	1.755
Effort Expectancy --> ZAT	1.162
Social Influence --> ZAT	1.112
Facilitating Conditions --> ZAT	1.734

Notes: ZAT-Zoomers attitudes and ZBI-Zoomers behavioural intention

The proposed associations were tested with the bootstrapping approach in PLS-SEM. The sample coefficient (β) indicates the direction and strength of each structural relationship, followed by t-statistics and p-values to support this assessment statistically. Statistically significant relationships are denoted with $p < 0.05$ at the 5% significance level (Hair et al., 2021). Table 6 summarizes the use of the route coefficient value to test hypotheses. H2 evaluates that effort expectancy significantly influenced ZBI to adopt AI in higher education ($\beta = 0.211$, $t = 4.364$, $p < 0.001$). H2 is accepted. In contrast, performance expectancy did not show a significant direct effect ($\beta = 0.028$, $t = 0.465$ $p = 0.642$), thus H1 is rejected. Similarly, SI and FC had no significant impact on ZBI (SI: $\beta = 0.012$, $t = 0.249$, $p = 0.795$; FC: $\beta = -0.062$, $t = 0.255$, $p = 0.255$), leading to the rejection of H3 and H4. However, H5 is accepted ($\beta = 0.600$, $t = 11.546$, $p < 0.001$), suggesting that ZAT exerted a strong positive effect on ZBI.

Table 6: Direct effect

		β	σ	t	p	Decision
H1	Performance Expectancy → ZBI	0.028	0.061	0.465	0.642	Rejected
H2	Effort Expectancy → ZBI	0.211	0.048	4.364	<0.001	**Accepted**
H3	Social Influence → ZBI	0.012	0.046	0.259	0.795	Rejected
H4	Facilitating conditions → ZBI	−0.062	0.054	1.138	0.255	Rejected
H5	Zoomers Attitudes → ZBI	0.600	0.052	11.546	<0.001	**Accepted**
H6	Performance Expectancy → ZAT	0.166	0.064	2.592	0.010	**Accepted**
H7	Effort Expectancy → ZAT	0.443	0.049	9.074	<0.001	**Accepted**
H8	Social Influence → ZAT	0.010	0.049	0.213	0.832	Rejected
H9	Facilitating conditions → ZAT	0.117	0.056	2.077	0.038	**Accepted**

Notes: ZAT-Zoomers attitudes and ZBI-Zoomers behavioural intention

The hypothesis H6, which posits that performance expectancy has a positive effect on ZAT ($\beta = 0.166$, $t = 2.592$, $p = 0.010$) has been accepted. Then, H7 is also accepted ($\beta = 0.443$, $t = 9.074$, $p < 0.001$), indicating that effort expectancy exhibited an even stronger positive relationship with ZAT. In contrast, SI did not significantly predict ZAT (β = 0.010, t = 0.213, p = 0.832), H8 is rejected. Again, facilitating conditions has positive impact on ZAT (β = 0.117, t = 2.077, p = 0.038), H9 is accepted.

Table 7: Indirect effect

		β	σ	t	p	Decision
H10	PE → ZAT → ZBI	0.100		2.489	0.013	**Accepted**
H11	EE → ZAT → ZBI	0.265		6.978	<0.001	**Accepted**
H12	SI → ZAT → ZBI	0.006		0.213	0.831	Rejected
H13	FC → ZAT → ZBI	0.070		2.031	0.042	**Accepted**

Notes: ZAT-Zoomers attitudes, ZBI-Zoomers behavioural intention, PE-Performance expectancy, EE-Effort expectancy, SI-Social influence, and FC-Facilitating conditions,

Table 7 represents the indirect effect of performance expectancy on ZBI through ZAT is positive and statistically significant (β = 0.100, t = 2.489, p = 0.013). Therefore, H10 is accepted. Then. H11 is accepted (β = 0.265, t = 6.978, p < 0.001), indicating that effort expectancy on ZBI through ZAT has highly significant. In contrast, H12 is rejected (β = 0.006, t = 0.213, p = 0.831), indicating that social influence on ZBI through ZAT is statistically insignificant. Finally, facilitating conditions has significant indirect effect on ZBI through ZAT (β = 0.070, t = 2.031, p = 0.042), H13 is accepted. Figure 3 displays the research framework according to the analysis, which includes the path coefficients.

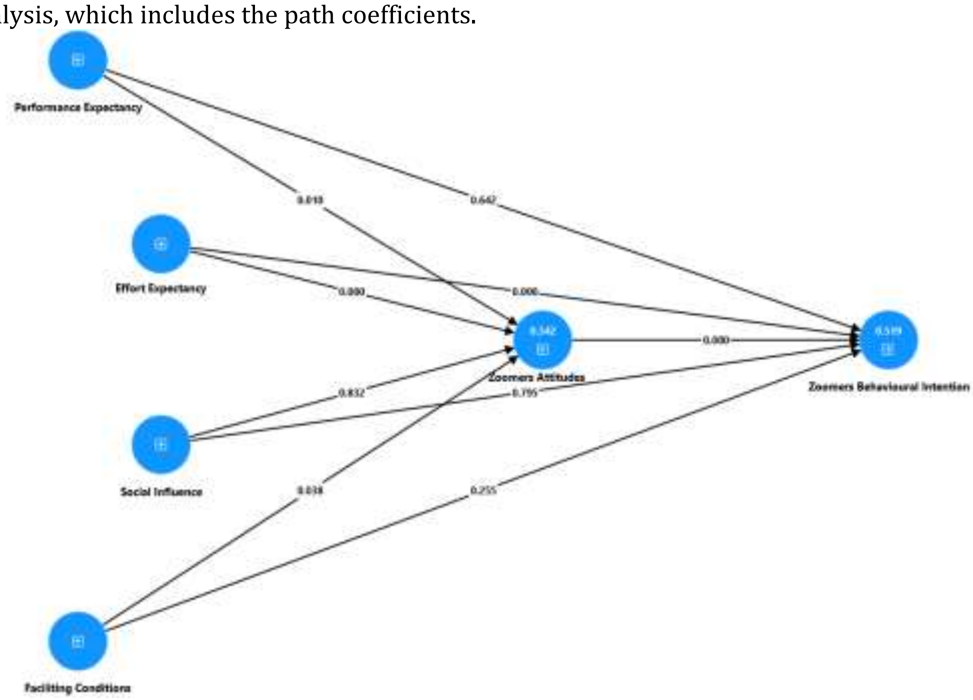

Figure 3: Tested (Structural) Model

5. Discussion

The study aimed to investigate the determinants of AI acceptance among Zoomers based on UTAUT framework in higher education in Bangladesh. The study found that effort expectancy significantly impacts ZBI, showing that Zoomers are more likely to adopt AI when they find it easy to use (β = 0.211, p < .001). This aligns with the UTAUT model and consistent with recent research (Kibria et al., 2026; Yakubu et al., 2025). EE is the strongest predictor of ZAT (β = 0.443, p < .001) and has a substantial indirect effect on ZBI through ZAT (β = 0.265, p < .001), indicating complementary partial mediation. Thus, Zoomers' intention to embrace AI is directly strengthened by its simplicity of use, which also fosters a positive mindset that further increases behavioural intention. This pattern strongly aligns with recent extended-UTAUT research that highlights the mediation effect of attitude in university students' adoption of generative AI. In contrast, Performance expectancy had a positive but non-significant direct effect on ZBI to adopt AI (β = 0.028, p = .642), indicating that mere recognition of AI's academic benefits is insufficient. This differs from recent studies, where it was a key predictor of generative AI adoption (Strzelecki, 2024; Yakubu et al., 2025). However, PE significantly influenced ZAT toward AI (β = 0.166, p = .010) and had an indirect effect on ZBI (β = 0.100, p = .013), emphasizing that attitude mediates the relationship between perceived performance benefits and adoption intention. Consequently, for Zoomers, recognizing the use of AI is essential in cultivating a positive disposition to promote its acceptance.

Again, social influence showed insignificant effect on either ZBI (β = 0.012, p = .795) or their ZAT toward AI (β = 0.010, p = .832). This finding departs from the conventional UTAUT proposition that social influence can shape behavioral intention (Venkatesh et al., 2003) and from some recent studies reporting a significant role of social influence in students' adoption intentions (Yakubu et al., 2025). Also, the indirect effect was insignificant ($\beta = 0.006$, $p = .831$), indicating that attitude does not mediate this relationship. Zoomers' AI adoption appears to be more self-directed and experience-based than socially driven, with personal perceptions of usability and attitude outweighing normative pressures. Once more, facilitating conditions showed statistically insignificant direct relationship with ZBI ($\beta = -0.062$, $p = .255$). This finding aligns with recent research indicating that facilitating conditions may have limited direct effects on students' intention to use generative AI (Yakubu et al., 2025), while other studies report positive effects, emphasizing the context-dependent nature of AI adoption (Kaya & Adıgüzel, 2025). FC positively influenced ZAT toward AI ($\beta = 0.117$, $p = .038$) and indirect effect on ZBI through ZAT was significant ($\beta = 0.070$, $p = .042$), highlighting that facilitating conditions influence intentions mainly via attitude rather than directly. Access to resources alone might not motivate Zoomers to adopt AI. Instead, creating supportive conditions that enhance confidence, convenience, and perceived preparedness can lead to more positive attitudes and stronger intentions to adopt these technologies. Importantly, ZAT toward AI adoption had a significant effect on ZBI ($\beta = 0.600$, $p < .001$). This finding aligns with recent research in higher education, which shows that positive attitudes toward generative AI significantly improve students' intentions to adopt these technologies (Zhao et al., 2024). When students view AI as beneficial, acceptable, and appropriate for academic use, they are more likely to develop stronger intentions to integrate it into their learning activities.

6. Conclusions and Future Directions

Drawing from the UTAUT framework encompassing performance expectancy, effort expectancy, and social influence, and facilitating conditions, AI adoption intention is more heavily influenced by effort expectancy and attitudes toward AI than by social influence or facilitating conditions. Specifically, effort expectancy directly impacts behavioural intention, while attitudes serve as the most significant predictor. Although performance expectancy and facilitating conditions do not directly predict behavioural intention, they significantly impact attitudes, affecting intention accordingly. Social influence was found to be insignificant in both direct and indirect pathways.

Next, the mediation findings suggest that Attitude plays a significant mediating role in the relationships between performance expectancy and ZBI, effort expectancy and ZBI, as well as facilitating conditions and ZBI. Notably, effort expectancy has both a direct and an indirect effect on ZBI through ZAT, demonstrating a complementary partial mediation effect. Practically, this implies the higher academic institutions in Bangladesh should provide user-friendly AI environment which are easily accessible and positively perceived by students. This means universities must also focus on AI literacy; offer hands-on training with AI tools, use easily accessible platforms; provide guidance from faculty members, and develop clear institutional policies for ethical and responsible uses of AI. Because positive attitudes are strong predictors of behavior intention, institutional interventions should do more than simply grant access to AI technologies; they also ought to transition students' understanding from mere accessibility to actual educational value-added, limitations and risks, and suitable academic usages.

The study has several limitations that should be acknowledged. First, the research focuses exclusively on Zoomers for deeper insight into the preferences and behaviors of younger users, future research could incorporate perceptions of Millennials, Gen X or others. Second, even though the suggested model was developed based on an extended UTAUT framework, other aspects outside of this study may influence AI adoption. Future studies may incorporate other constructs such as AI literacy, trust in AI, ethical issues on media sharing etc. Finally, this study is conducted through quantitative analysis only. Future studies may employ mixed-method approaches that integrate PLS-SEM with qualitative data, such as results from interviews or focus groups offering a deeper understanding of Zoomers attitudes toward the AI adoption.

References

1. Abbad, M. M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. Educational Information Technologies, 26(6), 7205-7224.
2. Acosta-Enriquez, B. G., Ramos Farroñan, E. V., Villena Zapata, L. I., Mogollon Garcia, F. S., Rabanal-León, H. C., Morales Angaspilco, J. E., & Saldaña Bocanegra, J. C. (2024). Acceptance of artificial intelligence in university contexts: A conceptual analysis based on UTAUT2 theory. Heliyon, 10(19), e38315. doi:10.1016/j.heliyon.2024.e38315
3. Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. doi:10.1016/0749-5978(91)90020-T
4. Akter, N., Chowdhury, M. S., Sadique, M. S., Hasan, M. M., & Moral, I. H. (2026). Bridging the gap: Factors influencing AI adoption in higher education institutions in Bangladesh. Research and Practice in Technology Enhanced Learning, 22, Article 006. doi:10.58459/rptel.2027.22006
5. Ali, M. M., Wafik, H. M. A., Mahbub, S., & Das, J. (2024). Gen Z and Generative AI: Shaping the future of learning and creativity. Cognizance Journal of Multidisciplinary Studies, 4(10), 1–18. https://doi.org/10.47760/cognizance.2024.v04i10.001

6. Ali, Y., Neogy, T. K., & Akter, K. (2024). Determinants of AI adoption intent among Bangladeshi students: An extended UTAUT model analysis. NEXG AI Review of America, 5(1), 19–38.
7. Alshammari, S. H., Krishna, S., & Alghamdi, B. A. (2026). The mediating role of engagement in the relationship between performance expectancy, effort expectancy, and students' behavioral intention to use ChatGPT. Acta Psychologica, 263, 106270.
8. Babu, M. A., Yusuf, K. M., Eni, L. N., Jaman, S. M. S., & Sharmin, M. R. (2024). ChatGPT and generation 'Z': A study on the usage rates of ChatGPT. Social Sciences & Humanities Open, 10, 101163. https://doi.org/10.1016/j.ssaho.2024.101163
9. Baharin, N. a. T. (2025). Exploring the adoption of Generative Artificial Intelligence by TVET Students: A UTAUT analysis of perceptions, benefits, and implementation challenges. Journal of Information Systems Engineering & Management, 10(19s), 429–437. https://doi.org/10.52783/jisem.v10i19s.3052
10. Chan, C. K. Y., & Lee, K. K. W. (2023). The AI generation gap: Are Gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and millennial generation teachers? Smart Learning Environments, 10, Article 60. doi:10.1186/s40561-023-00269-3
11. Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: a quantitative analysis using structural equation modelling. Education and Information Technologies, 25(5), 3443–3463. https://doi.org/10.1007/s10639-020-10159-7
12. Chemlal Y, Azzouazi M (2024) A Methodology for Evaluating and Reporting the Integration of Artifcial Intelligence for Sustainability in Higher Education: New Insights and Opportunities. In Engineering Applications of Artificial Intelligence (pp. 113– 130). Cham: Springer Nature Switzerland.
13. Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th Ed.). SAGE Publications.
14. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. doi:10.2307/249008
15. Deming, C., Kothapalli, K. R. V., Mohammed, R., Pasam, P., Natakam, V. M., & Karanam, R. K. (2023). Sustainable Digitization: How U.S. Tech Leaders are Shaping the Global Future. Digitalization & Sustainability Review, 3(1), 35- 47. https://upright.pub/index.php/dsr/article/view/153.
16. Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., et al. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. International Journal of Information Management, 71, 102642.
17. Emon MMH and Khan T, (2025). The Mediating Role of Attitude towards the Technology in Shaping Artificial Intelligence Usage among Professionals. 17 Telematics and Informatics Reports 100188 <https://doi.org/10.1016/j.teler.2025.100188
18. Erkul, E. (2023, October 20). Council Post: Gen Z will shape the age of AI. Forbes. https://www.forbes.com/councils/forbestechcouncil/2023/10/20/gen-z-will-shape-the-age-of-ai/
19. Fadziso, T., Mohammed, R., Kothapalli, K. R. V., Mohammed, M. A., Karanam, R. K. (2022). Deep Learning Approaches for Signal and Image Processing: State-of-the-Art and Future Directions. Silicon Valley Tech Review, 1(1), 14-34.
20. Falebita, O. S., & Kok, P. J. (2024). Artificial Intelligence Tools Usage: A structural equation modeling of undergraduates' technological readiness, Self-Efficacy and attitudes. Journal for STEM Education Research. https://doi.org/10.1007/s41979-024-00132-1
21. Falebita, O. S., & Kok, P. J. (2025). Artificial intelligence tools usage: A structural equation modeling of undergraduates' technological readiness, self-efficacy, and attitudes. Journal for STEM Education Research, 8(2), 257-282.
22. Government AI Readiness Index - Oxford Insights. (2025, January 7). Oxford Insights. https://oxfordinsights.com/ai-readiness/ai-readiness-index/
23. Government of Bangladesh. (2026). Bangladesh National Artificial Intelligence Policy 2026–2030 [Draft v2.0].
24. Gunasinghe, A., Hamid, J. A., Khatibi, A., & Azam, S. F. (2019). The adequacy of UTAUT-3 in interpreting academician's adoption to e-Learning in higher education environments. Interactive Technology and Smart Education, 17(1), 86–106. https://doi.org/10.1108/itse-05-2019-0020
25. Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Partial Least Squares Structural Equation Modeling (PLS-SEM) using R. In Classroom companion: business. https://doi.org/10.1007/978-3-030-80519-7
26. Howlader, M. H., Tohan, M. M., Zaman, S., Chanda, S. K., Guo, J., & Rahman, M. A. (2025). Factors influencing the acceptance and usage of ChatGPT as an emerging learning tool among higher education students in Bangladesh: A structural equation modeling. Cogent Education, 12(1), 2504224.

27. Jony, M. T. I., Uddin, M. M., & Hossain, M. S. J. (2023). Intentions to Use Artificial Intelligence: A Study on the University Students of Bangladesh. Journal of Business Studies, 13(2), 19.
28. Joshi, H. (2025). Integrating trust and satisfaction into the UTAUT model to predict Chatbot adoption – A comparison between Gen-Z and Millennials. International Journal of Information Management Data Insights, 5(1), 100332. https://doi.org/10.1016/j.jjimei.2025.100332
29. Kasilingam, D. L. (2020). Understanding the attitude and intention to use Smartphone chatbots for shopping. Technology in society, 62, Article 101280.
30. Kaya, M. H., & Adıgüzel, T. (2025). Exploring the acceptance of ChatGPT in higher education: A comprehensive quantitative study of university students and faculty. Frontiers in Education, 10, 1652292. https://doi.org/10.3389/feduc.2025.1652292
31. Kelly S, Kaye SA, Oviedo-Trespalacios O (2023) What factors contribute to the acceptance of artifcial intelligence? A Systematic Rev Telematics Inf 77:101925
32. Khan, M. A., Popli, S., Purohit, H., & Syed, A. A. (2024). Social Networking Intent of the Zoomers: Evidence from Saudi Arabia. Global Business Review, 09721509241250231.
33. Khan, M. S. U., Hasan, M. F., Islam, M. S., & Hassan, S. T. (2021). Artificial intelligenc e in the banking sector of Bangladesh: Applicability and the challenges. Roundtable e discussion series-. Keynote Paper of Roundtable Discussion of BIBM, 6(2).
34. Kibria, M. G., Khanom, K., Sultana, J., & Chowdhury, F. P. (2026). Determinants of ChatGPT adoption in higher education: An empirical study on public and private university students in Bangladesh. Global Business Review. Advance online publication. https://doi.org/10.1177/09721509261443740
35. Lakulu, M. M., Izkair, A. S., Harfiez Abdul Muttalib, M. F., & Zainuddin, N. A. (2025). Understanding AI and Mobile Learning Adoption in Malaysian Universities: A UTAUT-Based Model. International Journal of Interactive Mobile Technologies, 19(11).
36. Lopez, S., Sarada, V., Praveen, R., Pandey, A., Khuntia, M., & Haralayya, B. (2024). Artificial intelligence Challenges and role for Sustainable education in India: problems and prospects. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.5031316
37. Madan R, Ashok M (2024) Making sense of AI benefts: a mixedmethod study in Canadian public administration. Inf Syst Front. https://doi.org/10.1007/s10796-024-10475-0
38. Miao, F., & Holmes, W. (2023). Guidance for generative AI in education and research. UNESCO.
39. Mohamed Riyath, M. I., Muhammed Rijah, U. L., & Rameez, A. (2022). Students' attitudes on the use of Zoom in higher educational institutes of Sri Lanka. Asian Association of Open Universities Journal, 17(1), 37-52.
40. Ng, D. T. K., Tan, C. W., & Leung, J. K. L. (2024). Empowering student self-regulated learning and science education through ChatGPT: A pioneering pilot study. British Journal of Educational Technology, 55(4), 1328-1353.
41. Ngo, T. T. A., Vo, T. T. A., & Phan, M. T. (2025). The psychology of AI adoption in education: University students' intentions to use Large Language Models for learning from a TAM and TPB perspective. Acta Psychologica, 261, 105789.
42. Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. International Journal of Contemporary Hospitality Management, 32(10), 3199–3226.
43. Qin, F., Li, K., & Yan, J. (2020). Understanding user trust in artificial intelligence-based educational systems: Evidence from China. British Journal of Educational Technology, 51(5), 1693–1710. https://doi.org/10.1111/bjet.12994
44. Rana, M. M., & Ahamed, M. R. (2024). Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework. Heliyon, 10, e37569. https://doi.org/10.1016/j.heliyon.2024.e37569
45. Rehman, A. U., Raza, M. A., & Abbas, N. (2025). Understanding AI adoption In education: the role of readiness, confidence, and social influence among Pakistani students. Innovation Journal of Social Sciences and Economic Review, 7(1), 64-78.
46. Saunders, M., Lewis, P., & Thornhill, A. (2019). Research methods for business students (8th ed.). Pearson.
47. Sharma, S., & Singh, G. (2024a). Adoption of artificial intelligence in higher education: an empirical study of the UTAUT model in Indian universities. International Journal of Systems Assurance Engineering and Management. https://doi.org/10.1007/s13198-024-02558-7
48. Slepian, R. C., Vincent, A. C., Patterson, H., & Furman, H. (2023). "Social media, wearables, telemedicine and digital health,"—A Gen Y and Z perspective. In Elsevier eBooks (pp. 524–544). https://doi.org/10.1016/b978-0-12-824010-6.00072-1
49. Slepian, R. C., Vincent, A. C., Patterson, H., & Furman, H. (2023). "Social media, wearables, telemedicine and digital health,"—A Gen Y and Z perspective. In Elsevier eBooks (pp. 524–544). https://doi.org/10.1016/b978-0-12-824010-6.00072-1
50. Soeffner, J. (2023). Meaning–thinking–AI. AI & Society, 39(5), 2213–2220. https://doi.org/10.1007/s00146-023-01709-x

51. Strzelecki, A. (2024). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. Innovative Higher Education, 49, 223–245. doi:10.1007/s10755-023-09686-1
52. Strzelecki, A. (2024). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. Innovative Higher Education, 49, 223–245.
53. Tian, W., Ge, J., Zhao, Y., & Zheng, X. (2024). AI Chatbots in Chinese higher education: adoption, perception, and influence among graduate students—an integrated analysis utilizing UTAUT and ECM models. Frontiers in Psychology, 15. https://doi.org/10.3389/fpsyg.2024.1268549
54. Why Gen Z is the most AI-Ready cohort — and what that means. (n.d.). https://recruiseindia.com/Why-GenZ-Is-the-Most-AI-Ready-Cohort-and-What-That-Means.
55. Xue, L., Rashid, A. M., & Ouyang, S. (2024). The Unified Theory of Acceptance and Use of Technology (UTAUT) in higher education: A systematic review. SAGE Open, 14(1). doi:10.1177/21582440241229570
56. Yakubu, M. N., David, N., & Abubakar, N. H. (2025). Students' behavioural intention to use content generative AI for learning and research: A UTAUT theoretical perspective. Education and Information Technologies, 30(13), 17969-17994.
57. Zawacki-Richter, O., Marín, V.I., Bond, M. et al. Systematic review of research on artificial intelligence applications in higher education – where are the educators?. Int J Educ Technol High Educ 16, 39 (2019). https://doi.org/10.1186/s41239-019-0171-0
58. Zheng, Y., Wang, Y., Liu, K. S. X., & Jiang, M. Y. C. (2024). Examining the moderating effect of motivation on technology acceptance of generative AI for English as a foreign language learning. Education and Information Technologies, 29(17), 23547-23575.
59. Zhao, Y., Li, Y., Xiao, Y., Chang, H., & Liu, B. (2024). Factors influencing the acceptance of ChatGPT in high education: An integrated model with PLS-SEM and fsQCA approach. SAGE Open, 14(4). https://doi.org/10.1177/21582440241289835
60. Zulfiker, M. S., Kabir, N., Biswas, A. A., Chakraborty, P., & Rahman, M. M. (2020). Predicting students' performance of the private universities of Bangladesh using machine learning approaches. International Journal of Advanced Computer Science and technology, 11(3), 672-679.