Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Unpacking Drivers that Influence Behavioral Intention to Use AI among Private University Students in Bangladesh: Using UTAUT2 Model Approach

Asma Akter Faria [1], Faria Akter [2]
[1] *Lecturer, Southeast Business School, Southeast University, Bangladesh*
[2] *Lecturer, Southeast Business School, Southeast University, Bangladesh*

ARTICLE INFO

Received: 26 Dec 2024

Revised: 14 Feb 2025

Accepted: 22 Feb 2025

ABSTRACT

This study identifies the primary determinants influencing private university students' behavioral intention to use AI for studies and assignments. The study also explains the percentage of behavioral intention. For this purpose, this study surveyed 181 private university students in Bangladesh. The conceptual model for this study was developed using the UTAUT2 model. Using PLS-SEM, this study found that hedonic motivation (0.36), effort expectancy (0.16), performance expectancy (0.16), and social influence (0.13) are the drivers that significantly influence students' behavioral intention to use AI. Habit and facilitating conditions do not significantly affect students' behavioral intention to use AI for their studies and preparing assignments. The strongest driver among all is hedonic motivation, and the least influential driver is habit. The study's findings on Bangladeshi students will influence AI technology developers to tailor their tools to the preferences of both Bangladeshi and South Asian students.

Keywords: Artificial Intelligence (AI), students, studies, private universities, Bangladesh.

INTRODUCTION

This study discusses artificial intelligence in higher education. The use of AI has changed the learning and studying experience of many students. Students are adapting to AI technology as their teaching assistant rapidly, as they are adopting this technology in many other areas of life. Some factors are working as key agents to their adaptation behavior. This study tries to unpack those drivers of AI adoption, which will help AI technology developers and marketers to better understand users' minds.

The term artificial intelligence means simulation of human intelligence by machines or computer systems. In the education sector, AI is utilized to streamline administrative processes, support learning, and enhance access to digital materials (Lestariningrum, 2024). AI technology such as predictive modeling, intelligent analytics, assistive technology, automated content analysis, and image analysis applied in education can help solve important educational problems and ensure quality education (Salas-Pilco and Yang, 2022). AI enables personalized learning, where students can learn at their pace and according to their learning styles, potentially improving academic performance (Bhutoria, 2022).

Some of the popular AI tools used by the students in recent times are ChatGPT, DeepSeek, Grammarly, Microsoft Copilot, QuillBot, Canva Magic Write, Slidesgo, etc. Among these, ChatGPT is the most used AI tool by students. ChatGPT is considered the torchbearer of generative AI with transformative potential for educational landscapes (OpenAI, 2023). ChatGPT is a form of generative artificial intelligence (AI) that can have conversations like a real person and can answer student questions right away, making it a valuable asset in education (Foroughi et al., 2023; Strzelecki, 2023). Much research has been conducted solely on the use and acceptance of ChatGPT—Lai et al. (2024), Bahadur et al. (2024), Sobaih et al. (2024), Romero-Rodríguez et al. (2023), Habibi et al. (2023), Menon and Shilpa (2023), Strzelecki (2023), and Acosta-Enriquez et al. (2024). Many researchers ignored the overall user experience of all the popular open AI technology in higher education. This study attempted to fill this research gap. For that

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

purpose, this study did not focus on only one AI technology; rather, it surveyed the adoption of any AI technology that students find useful for learning, i.e., ChatGPT, Grammarly, Canva, and Slidesgo.

The use of AI is still in its early stage in Bangladesh. The biggest reason behind this is lack of adequate infrastructure. In remote areas, digital equipment to access AI is unavailable. In Bangladesh, AI is only popular among the students who live in urban areas. As the use of AI is not yet widespread throughout the country, the research studies about the adaptation of AI are also very few.

Very little research has been done on the context of AI technology adoption in the Bangladesh education sector. Among the few research studies based on Bangladesh, the following are some prominent ones: Sultana and Faruk (2024) and Karu & Hoque (2024). This study covered this research gap by surveying Bangladeshi private university students.

This study surveyed undergraduates of private universities to find out the factors affecting the intention of the students to use AI technology in completing their course-related study and assignments. This study used the "Unified Theory of Acceptance and Use of Technology 2" (UTAUT2) model by Venkatesh et al. (2012) for evaluating the factors affecting the behavioral intention of the students to use AI.

OBJECTIVES

The objectives of the study are to:

1. Identify the primary determinants that influence private university students' behavioral intention to use AI for studies and assignments.

2. Analyze the extent to which these determinants influence students' behavioral intention to use AI for studies and assignments.

Research Question

In this context, the primary research questions of this study are

RQ 1: What are the primary determinants that influence private university students' behavioral intention to use AI for studies and assignments?

RQ 2: Which determinant significantly influences students' behavioral intention to use AI for studies and assignments?

RQ 3: Which determinant insignificantly influences students' behavioral intention to use AI for studies and assignments?

LITERATURE REVIEW

A review of literature is significant in finding existing knowledge in subject areas and identifying research gap that augment further research. This section therefore, tried to accumulate key highlights or findings of previous research which paved the way for conducting this study by finding out prominent research gaps.

Major highlights of the previous literature have been presented in tabular form below:

Sl. No.	Authors	Objectives	Key Highlights/Findings
1	Lai et al. (2024)	Determine the motivators and barriers that affect the intention of using ChatGPT for assessment support among Hong Kong undergraduates.	The study found that performance and effort expectancy have a positive effect on behavioral intention to use ChatGPT. However, social influence has been found to be statistically insignificant.
2	Dang (2020)	Find out whether college students intend to use artificial intelligence (AI) in their education.	The findings show that college students' intentions to use AI are highly influenced by perceived ease of use and perceived usefulness.

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

3	Duy et al. (2024)	Determine the factors affecting students' use of artificial intelligence (AI) in their education.	According to the study, perceived ease of use and usefulness are the most significant factors that affect students' intention to use AI in learning.
4	Lestariningrum et al. (2024)	Examine how students' use of AI affects their academic performance.	According to this study, students' academic performance is positively and significantly impacted by the employment of AI in the classroom, with technology engagement acting as a key mediating factor.
5	Han et al. (2025)	Explore the adoption and use of AI technologies among Chinese undergraduate accounting students.	The findings reveal that social influence significantly affects both behavioral intention and actual use, with behavioral intention serving as a partial mediator of the relationship between social influence and actual use.
6	Bahadur et al. (2024)	Examine the factors influencing students' intention to use ChatGPT using the UTAUT2 model.	The study revealed that habit, learning value, and social influence were positively affecting students' intention to use ChatGPT. However, effort expectancy, hedonic motivation, facilitating conditions, and performance expectancy were found to be insignificant.
7	Sobaih et al. (2024)	Identify the adoption and usage of ChatGPT by students in Saudi Arabian (SA) higher education is investigated in this study.	The results indicate that behavioral intention and actual use of ChatGPT are significantly impacted by performance expectancy, social influence, and effort expectancy. However, it was discovered that there was no and little correlation between the facilitating condition and behavioral intention and actual use of ChatGPT.
7	Wu et al. (2022)	Discover the factors of the willingness to accept AI-Assisted Learning Environments.	It was found that effort expectancy, performance expectancy, and social influence were all positively related to college students' willingness to accept AI-Assisted Learning Environments.
8	Buabbas et al. (2023)	Find out how medical students perceive AI.	The study found that the majority of the students had positive perceptions of AI.
9	Gansser and Reich (2021)	Suggest an extension of UTAUT2 to find out the impact of AI on behavioral intention and use of AI.	According to the study, all the constructs of the UTAUT2 model except safety contribute significantly to the behavioral intention and use of AI.
10	Romero-Rodríguez et al. (2023)	Identify the use of ChatGPT by students at University.	Performance expectancy, hedonic motivation, and habit were significant that influenced the behavioral intention to use ChatGPT.
11	Habibi et al. (2023)	Determine if ChatGPT is accepted and used in higher education.	The strongest predictor of behavioral intention to use ChatGPT was found to be facilitating conditions. Behavioral intention was the most important determinant for ChatGPT use. However, effort expectancy did not have a substantial impact on behavioral intention.
12	Menon and Shilpa (2023)	Investigate the factors influencing students' intention to use OpenAI's ChatGPT.	It was observed that the four factors of UTAUT are significant to identify users' interaction and engagement with ChatGPT.
13	Strzelecki (2023)	Examine the factors that influence students'	Results show that habit has the greatest influence on behavioral intention, followed by

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

		acceptance of ChatGPT in higher education.	performance expectancy and hedonic motivation.
14	Acosta-Enriquez et al. (2024)	Investigate college students' attitudes about the use of ChatGPT in academic activities.	The findings of this study revealed a significant relationship between factors identified and attitudes toward using the ChatGPT.
15	Von Garrel and Mayer (2023)	Find out the use of ChatGPT and AI-based tools among the students in Germany.	It was identified that students in Germany incorporate AI-based tools in various ways into their studies.
16	Milicevic et al. (2024)	Explore students' intention to use AI in education.	Performance expectancy, effort expectancy, and social influence significantly affect students' intention to use AI in education.
17	Grassini et al. (2024)	Determine the factors influencing ChatGPT adoption and utilization among the Norwegian university students.	The results showed that performance expectancy has the highest impact on behavioral intention, followed by habit.
18	Sultana and Faruk (2024)	Investigate the impact of artificial intelligence (AI) on learners' sustainability in Bangladeshi higher education.	The findings indicate that AI-driven concepts significantly contribute to enhancing educational sustainability.
19	Rahman et al. (2023)	Explore students' intention to use ChatGPT.	The results suggest that perceived usefulness, ease of use, and informativeness can predict students' behavioral intention to use AI.
20	Karu & Hoque (2024)	Analyze the ChatGPT experiences of Bangladeshi undergraduate students pursuing English language and literature.	The study highlighted both positive and negative experiences with ChatGPT by the students.
21	Niloy et al. (2024)	Identify the factors affecting student use of ChatGPT.	The study found a strong positive relationship between students' intention to use ChatGPT and their actual use.
22	Mahmud et al. (2024)	Identify factors that influence the attitudes of university students toward using ChatGPT.	It was found that the intention to use ChatGPT is affected by the attitudes of the students towards it.

By reviewing previous studies, it is evident that a limited study in Bangladesh has been made on identifying the use of AI by the students. This created a knowledge gap in this area. Therefore, this study will identify the factors and their relative importance in adopting AI for assistance in studies and assignments.

Research Model

The hypothesis for this study has been developed keeping previous literature in consideration. The UTAUT2 model has been used by many researchers (Bervell et al., 2022; De Blanes Sebastián et al., 2022; Yin et al., 2023; Gansser and Reich, 2022; Aswani et al., 2018; Frank and George, 2023; Tavares et al., 2018) in finding out the behavioral intention and use of AI. Therefore, this study incorporates the UTAUT2 model developed by Venkatesh et al. (2012), which may predict correlations for the dimensions addressed in this study. To predict the endogenous variable "Behavioral Intention," the study included seven constructs from Venkatesh et al. (2012), eliminating the construct "Price" from the original model. The study also eliminated the effect of control variables such as age, gender, and experience of the real UTAUT2 model. The rationale for incorporating the constructs as well as the relevance of the hypothesis developed for the study is presented below:

Effort Expectancy: Effort expectancy can be referred to as the ease with which a system can be used even if having little previous experience with it (Venkatesh et al., 2003). Liebenberg et al. (2018) used effort expectancy to find out the extent to which AI is used by the users. Therefore, propose the following hypothesis:

H1: Effort expectancy has a positive effect on students' behavioral intention to use AI for study and assignment support.

Facilitating Conditions: Facilitating conditions can be referred to as the extent to which an individual's belief in technical and organizational settings leads to the acceptance of a new information system (Venkatesh et al., 2003). If necessary, technology and resources are available, it becomes easier for the students to learn and use AI. In light of this, we propose the following hypothesis:

H2: Facilitating conditions has a positive effect on students' behavioral intention to use AI for study and assignment support.

Habit

Habit is defined as the degree to which people tend to perform activities automatically as a result of learning (Limayem et al., 2007). Habit has been found to be a significant predictor of behavioral intention and technology use in the research study conducted by Tamilmani et al. (2019). If anything makes people's lives easy, then people become habituated to using it. Therefore, the following hypothesis was developed:

H3: Habit has a positive effect on students' behavioral intention to use AI for study and assignment support.

Hedonic Motivation

The satisfaction or pleasure that comes from using a technology is known as hedonic motivation, and it has been demonstrated to be a significant factor in deciding the adoption and use of that technology (Brown and Venkatesh 2005). Understanding hedonic motivation for technology use is based on the notion that excitement naturally motivates people and makes them more likely to accept and use new things (De Blanes Sebastián et al., 2022). Hence, we suggest the following hypothesis:

H4: Hedonic motivation has a positive effect on students' behavioral intention to use AI for study and assignment support.

Performance expectancy:

Performance expectancy can be explained as the extent to which a person thinks that using a certain system will aid him or her to improve performance (Venkatesh et al. 2003). Liu et al. (2019) and Liand Zhao (2021) also used performance expectancy in finding out the degree of AI use. Thus, we put forward the following hypothesis:

H5: Performance Expectancy has a positive effect on students' behavioral intention to use AI for study and assignment support.

Social Influence:

Social influence is the level at which a person feels obligated to use the system because significant others do (Venkatesh et al. 2003). According to Lai et al. (2024), social influence refers to the extent to which individuals perceive that those who are important to them believe they should use AI to support their study. Rocha et al. (2024) highlighted that social influence can play an important role in adopting any technology. Alvi (2021) in his study, also used social influence to find out AI use. Thus, the following hypothesis was proposed:

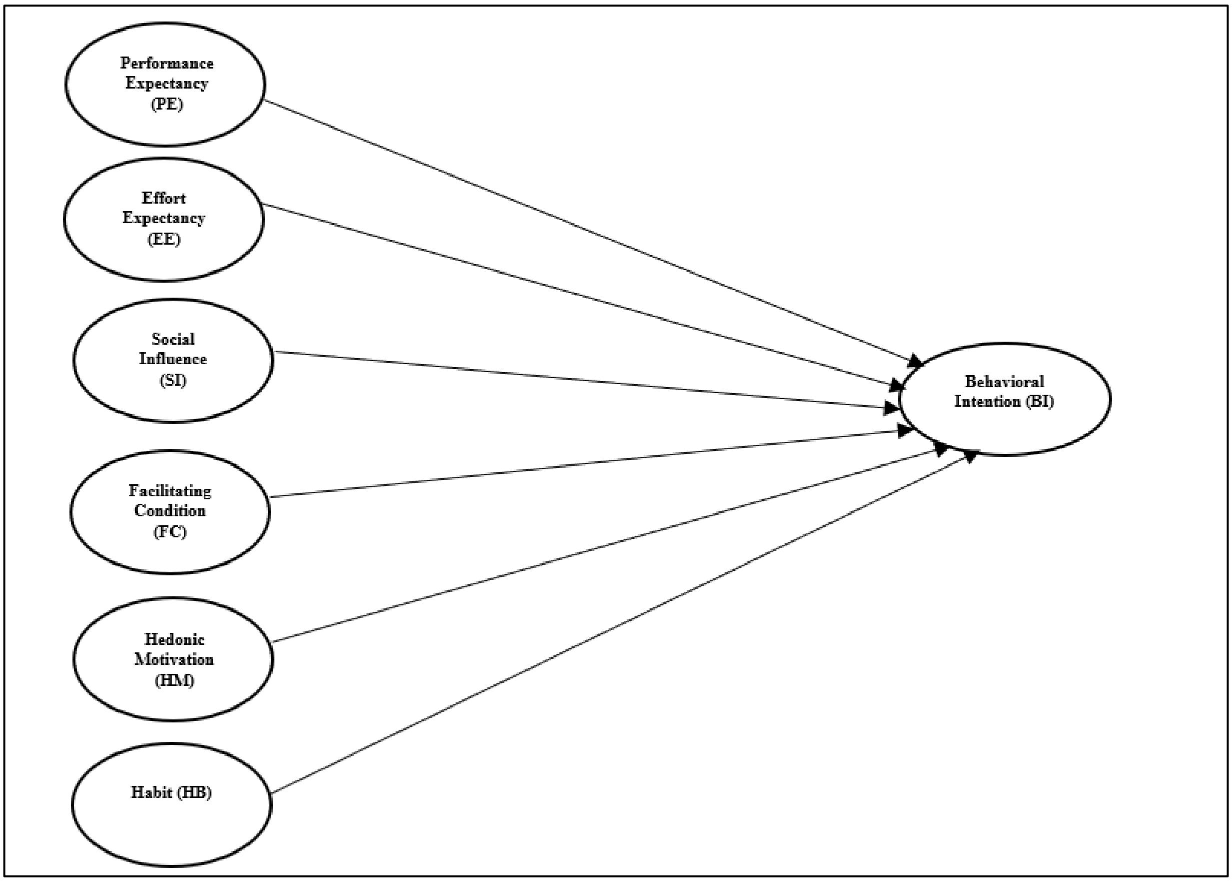
H6: Social influence has a positive effect on students' behavioral intention to use AI for study and assignment support.

Behavioral intention (BI): Behavioral intention is the readiness of a human being to adopt things. It refers to an individual's willingness to use a specific technology for a specific purpose (Venkatesh et al., 2003). Behavioral intention to use the system is found to be associated with the use of ChatGPT for assessment support in the study conducted by Lai et al. (2024). In the model, it is the only endogenous variable. The model of UTAUT2 of this study is shown in figure 1.

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Figure 1: Conceptual model of behavioral intention of to use AI by private university students



METHODS

Data Source

Using survey data, this study investigates the behavioral intention of Bangladeshi students attending private universities to use AI. Both primary and secondary data sources were considered to conduct this study. Secondary data was collected mainly from online sources such as articles, journals, conference papers, books, and websites. This helped to enrich the background of this research, identifying the research gap. Primary data was gathered from five private universities through self-administered survey forms with structured questionnaires based on the measurement items on a five-point Likert scale during the period from January 2025 to February 2025. The questionnaire comprises two sections: the first section is designed to gather demographic information, including sex, age, education year, and university, to provide a comprehensive understanding of the participants.

The second section focuses on evaluating the factors influencing the adoption of AI by private university students in Bangladesh using a five-point Likert scale from 1 to 5 (1 = strongly agree to 5 = strongly disagree) encompassing key constructs such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Condition (FC), Hedonic Motivation (HM), Habit (HB), and Behavioral Intention (BI). Similar questionnaires have been extensively used for evaluating technology adoption (Aswani et al., 2018; Frank and George, 2023; Tavares et al., 2017; Handayani, 2023; Sharma et al., 2022; Kumar and Bervell, 2019). The items used to measure the constructs are provided in Appendix A.

Sample

The study used the purposive sampling method to collect data from respondents. A power analysis for 7 constructs was performed using G*Power version 3.1 (Faul, 2007) for sample size calculation in structural equation modeling (SEM). The result showed the required sample size for the study should include a minimum of 103 samples to detect a statistically significant difference.

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

A total of 250 questionnaires were distributed, of which 193 were returned, resulting in a response rate of 77.2%. Among these, 12 respondents shared that they don't use AI, leaving 181 responses suitable for final analysis.

Data Analysis

Microsoft Excel and SPSS 25 were used in data cleaning and demographic analysis. The partial least squares path modeling to structural equation modeling (PLS-SEM) is appropriate for understanding cause-and-effect relationships between variables (Hair et al., 2011) in a hypothesized model (Ringle et al., 2015), for which Smart PLS 4 has been used to run the model.

The minimum and maximum value of each answer was checked using descriptive statistics in SPSS. The frequencies in the dataset showed no missing value. Then data cleaning was performed to identify and omit the responses of unengaged respondents. The data with an SD of less than 0.25 were removed as per the guidelines of Collier, J. E. (2020). The analysis found that 2.76% of the data was less than 0.25, which was the data of 5 respondents. After deleting the data, the study got 176 data for analysis.

Table 1 shows the demographic analysis of the study. The data of the sex group suggests that the study had more male (58%) respondents than female (42%). The majority (65.9%) of the students fall within the 18-21 age group, indicating that most respondents are in the early stages of their undergraduate studies. Only 1.7% fall within the 26–29 age group, indicating that fewer older students participated. First-year students make up the largest category in the study, accounting for more than half (51.7%) of the responses. This distribution implies that as students advanced in their academic years, participation declined. The respondents came from five private universities in Dhaka, Bangladesh. The two universities with the largest representations (26.1%) are East-West University and Independent University, Bangladesh. The remainder of the sample was constructed with assistance from Southeast University, Daffodil International University, and Green University of Bangladesh. To conclude, it can be highlighted that the private universities are only from Dhaka, for which the result depicts urban scenarios.

Table 1: Demographic Analysis

Demographic Items	Categories	Frequency	Percentage
Gender	Female	74	42%
	Male	102	58%
Age	18-21	116	65.9%
	22-25	57	32.4%
	26-29	3	1.7%
Education Year	1 Year	91	51.7%
	2 Year	47	26.7%
	3 Year	21	11.9%
	4 Year	17	9.7%
Universities	Southeast University	38	21.6%
	East West University	46	26.1%
	Independent University, Bangladesh	46	26.1%
	Daffodil International University	30	17%
	Green University of Bangladesh	16	9.1%

RESULTS

For survey-based research, it is important to find out if the dataset is free from collinearity and common method bias. Checking for collinearity makes sure that the individual variables are not highly correlated, which makes it easy to find out individual effects. A dataset that is free from common method bias ensures that the data is valid and not overstated, which leads to correct and error-free findings.

For this purpose, Harman's single-factor test has been conducted using SPSS. This test identifies if any single factor dominates the variance in the dataset. The findings revealed that the first factor only captures 33.45%, which is less

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

than the 50% threshold value of the variances (Podsakoff et al., 2003). It means that the dataset of this study is free of common method bias (CMB).

To check potential collinearity issues, the variance inflation factor (VIF) value has been evaluated in this study. A VIF value of 5 and higher indicates a collinearity problem (Hair et al., 2022); a VIF value higher than 3.3 indicates common method bias (Mason and Perreault, 1991) and VIF values less than 3.33 indicates the model can be considered free from common method bias (Kock, 2015). **Table 4-1** shows the VIF of the inner model, which has values less than 3.33, thus indicating the model is free from common method bias.

Hence, collinearity or common method bias is not a serious issue in this structural model.

The Measurement Model

The study specified the relationship between constructs and their indicators, which is the outer model, after developing the research model according to the suggestion of Hair et al. (2014). After that, an evaluation of the constructs and their indicators has been conducted, which is part of the measurement model. The measurement model confirms the validity and reliability of the measurements chosen for the study. **Table 2** and **Table 3** display the results of the measurement model, which include factor loadings, composite reliability (rho_a), Cronbach's alpha, and average variance extracted (AVE).

Table 2: Factor Loadings

Latent Variables	Indicators	Factor Loadings
Behavioral Intention	BI1	0.859
	BI2	0.836
	BI3	0.751
Effort Expectancy	EE1	0.778
	EE2	0.678
	EE3	0.754
	EE4	0.823
Facilitating Condition	FC1	0.835
	FC2	0.856
	FC3	0.783
	FC4	0.621
Habit	HB1	0.769
	HB2	0.926
	HB3	0.783
Hedonic Motivation	HM1	0.861
	HM2	0.844
	HM3	0.863
Performance Expectancy	PE1	0.806
	PE2	0.745
	PE3	0.826
Social Influence	SI1	0.849
	SI2	0.861
	SI3	0.822

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Hair et al. (2022) recommended that factor loadings ideally exceed 0.7, with a minimum threshold of 0.5 considered acceptable. The factor loadings in **Table 2** show all the indicators exceed 0.7, indicating a strong correlation between indicators and constructs, except EE2 and FC4, which are also within the minimum threshold, indicating they still contribute to the measurement of the constructs.

Hinton (2004) stated that Cronbach's alpha and composite reliability values of (≥ 0.90) indicate excellent reliability, 0.70 and 0.90 indicate high reliability, 0.50 and 0.70 indicate moderate reliability and less than (< 0.50) indicate low reliability. **Table 3** shows that Cronbach's alpha and composite reliability for all the constructs have values within the range of 0.70 and 0.90. The values of Cronbach's alpha suggest the items within each construct are measuring the same underlying concept consistently. Whereas, composite reliability values of the constructs confirm a high level of reliability, indicating that the measurement model produces consistent results.

Table 3: Relaiblity and Validity

Latent Variables	Cronbach's alpha	Composite reliability (rho_a)	Average variance extracted (AVE)
Behavioral Intention	0.75	0.76	0.67
Effort Expectancy	0.76	0.75	0.59
Facilitating Condition	0.78	0.81	0.61
Habit	0.78	0.85	0.69
Hedonic Motivation	0.82	0.82	0.73
Performance Expectancy	0.70	0.71	0.63
Social Influence	0.80	0.80	0.71

According to Hair (2011), the average variance extracted (AVE) for each variable should be equal to or greater than 0.5, which suggests that the construct explains more than 50% of the variance of its related indicators (Bhattacherjee and Premkumar, 2004). **Table 3** shows that the AVE of each construct is higher than the threshold value, which means each construct explains at least 50% of the variance of its related indicators, confirming that the indicators share a common underlying construct.

Discriminant Validity

Discriminant validity checks that the constructs are significantly different from each other. The discriminant validity of the constructs was determined through the HTMT ratio, Fornell-Larcker criterion, and cross-loadings. The measurements of discriminant validity are presented in **Tables 3-1, 3-2, and 3-3.**

The standard threshold recommended by Nitzl (2016) for the HTMT ratio indicates that all values should be below 0.90, whereas values below 0.90 confirm discriminant validity between two constructs (Henseler et al., 2015). **Table 3-1** shows the HTMT ratio, which shows that all values were below the threshold of 0.90, confirming discriminant validity between the constructs. There is no notable overlap or repetition among the constructs; each one is distinct and captures another aspect of the study model.

Table 3-1: HTMT Ratio

	Behavioral Intention	Effort Expectancy	Facilitating Condition	Habit	Hedonic Motivation	Performance Expectancy	Social Influence
Behavioral Intention							
Effort Expectancy	0.734						
Facilitating Condition	0.612	0.865					
Habit	0.179	0.181	0.235				
Hedonic Motivation	0.815	0.716	0.557	0.141			

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Performance Expectancy	0.738	0.712	0.584	0.15	0.764		
Social Influence	0.573	0.523	0.463	0.203	0.551	0.501	

To compare the correlations between constructs and the square root of the average variance extracted for that construct, the Fornell and Larcker (1981) criterion is used. The results in **Table 3-2** based on the Fornell and Larcker criterion show all the values on the diagonals were greater than the corresponding row and column values, which indicates the model fulfills the requirements for discriminant validity. Hence, discriminant validity is established for the model, signifying each construct in the model is unique and does not overlap.

Table 3-2: Fornell–Larcker criterion

	Behavioral Intention	Effort Expectancy	Facilitating Condition	Habit	Hedonic Motivation	Performance Expectancy	Social Influence
Behavioral Intention	0.817						
Effort Expectancy	0.556	0.76					
Facilitating Condition	0.476	0.67	0.779				
Habit	0.139	0.112	0.176	0.829			
Hedonic Motivation	0.642	0.56	0.45	0.108	0.856		
Performance Expectancy	0.54	0.52	0.428	0.115	0.578	0.793	
Social Influence	0.451	0.407	0.357	0.155	0.449	0.381	0.844

Cross-loadings are used to assess discriminant validity, justifying that each indicator measures only its own construct. The loading value of the construct should be greater than all the loadings in the other constructs (Hair et al., 2022). The results in **Table 3-3** show that the cross-loading value for an indicator in a given construct was greater than the loading value for another construct. This indicates that each indicator is correctly assigned to its intended construct.

Table 3-3: Cross-Loadings

	Behavioral Intention	Effort Expectancy	Facilitating Condition	Habit	Hedonic Motivation	Performance Expectancy	Social Influence
BI1	0.859	0.486	0.43	0.104	0.572	0.517	0.447
BI2	0.836	0.474	0.37	0.101	0.529	0.406	0.341
BI3	0.751	0.398	0.361	0.141	0.466	0.39	0.303
EE1	0.439	0.778	0.522	0.067	0.505	0.336	0.357
EE2	0.44	0.678	0.377	0.116	0.323	0.457	0.293
EE3	0.381	0.754	0.556	-0.007	0.407	0.367	0.275
EE4	0.421	0.823	0.586	0.152	0.462	0.412	0.303
FC1	0.396	0.608	0.835	0.207	0.379	0.341	0.315
FC2	0.412	0.566	0.856	0.138	0.376	0.311	0.233
FC3	0.392	0.522	0.783	0.111	0.382	0.374	0.291
FC4	0.261	0.359	0.621	0.076	0.243	0.322	0.291
HB1	0.088	0.172	0.235	0.769	0.075	0.054	0.147
HB2	0.147	0.058	0.124	0.926	0.104	0.11	0.121

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

HB3	0.099	0.078	0.106	0.783	0.087	0.114	0.13
HM1	0.55	0.405	0.355	0.137	0.861	0.558	0.424
HM2	0.516	0.587	0.421	0.117	0.844	0.472	0.356
HM3	0.58	0.455	0.382	0.029	0.863	0.455	0.372
PE1	0.417	0.484	0.44	0.06	0.475	0.806	0.292
PE2	0.414	0.36	0.227	0.07	0.455	0.745	0.295
PE3	0.453	0.394	0.351	0.14	0.447	0.826	0.319
SI1	0.396	0.213	0.214	0.167	0.346	0.355	0.849
SI2	0.402	0.454	0.36	0.111	0.451	0.365	0.861
SI3	0.339	0.366	0.335	0.113	0.332	0.233	0.822

Based on the analysis presented in **Tables 3-1, 3-2, and 3-3**, it can be concluded that all the constructs satisfy the discriminant validity criteria and do not exhibit any issue with discriminant validity.

Structural Model

A structural model is used to investigate the degree of relationship between endogenous and exogenous variables. The proposed correlations are examined in the structural model using collinearity (VIF), effect size f^2 and Q^2 estimation, R^2 values, model fit, path coefficients (β), t-statistics, and p values. The structural model and path coefficient are displayed in **Tables 4-1 and 4-2.**

Table 4-1: Structural Model

	VIF	Effect Size (f^2)	Q^2	R^2
Effort Expectancy -> Behavioral Intention	2.25	0.02	0.313	0.510
Facilitating Condition -> Behavioral Intention	1.90	0.01		
Habit -> Behavioral Intention	1.04	0.00		
Hedonic Motivation -> Behavioral Intention	1.84	0.15		
Performance Expectancy -> Behavioral Intention	1.67	0.03		
Social Influence -> Behavioral Intention	1.35	0.02		

Table 4-1 shows VIF, effect size f^2, Q^2 and R^2. The effect size (f^2) is used to understand the impact of exogenous constructs on endogenous constructs of the model. It measures the change in the R^2 value when an exogenous construct is deleted from the model. The evaluation is done to identify if the deleted construct has any significant effect on the endogenous constructs. f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively (Hair et al., 2022). Values of less than 0.02 indicate that there is no effect (Sarstedt et al., 2021). **Table 4-1** shows, that Effort Expectancy (0.02), Performance Expectancy (0.03), and Social Influence (0.02) have small effects, indicating the constructs still matter for the model. Hedonic Motivation (0.15) has a medium effect, indicating a stronger motivator of students' intention to use AI. Facilitating Condition (0.01) and Habit (0.00) do not affect behavioral intention to use AI meaning they do not play a major role in influencing student's intention to use AI.

In the measurement model of the endogenous variables, Q^2 is significant for precisely predicting indicator data points. Significance is achieved if Q^2 estimation is above zero (Geisser, 1974). From **Table 4-1**, it can be seen that the Q^2 value of the endogenous construct behavioral intention is 0.313, which is considerably above zero, suggesting that the model has strong predictive power for behavioral intention, meaning it effectively explains and predicts this construct based on the given data.

R^2 (coefficient of determination) measures how well exogenous variables explain the variance in an endogenous variable. According to Hair et al. (2014), R2 values range from 0.25, 0.5, and 0.7 as thresholds indicating weak,

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

adequate, and strong results. **Table 4-1** shows that the R^2 value of behavioral intention (0.510) indicates adequate explanation power, suggesting the model has adequate ability to predict this construct.

For this study, model fit indices such as Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI) were measured, which indicates how well a hypothesized model structure fits into the data (Henseler et al., 2014). The SRMR values below 0.1 or 0.09 confirm the PLS model's fit (Hair et al., 2022), and NFI values from 0 and 1 are considered a good fit (Ringle et al., 2015). The SRMR value found for the model was 0.071 and the NFI value was 0.713. Both indices meet thresholds confirming acceptable model fit. This also indicates that the hypothesized model represents observed data and is suitable for further analysis.

Path Coefficient of Structural Model

Using bootstrapping, the structural model was examined with Smart PLS 4 (Ringle et al., 2015) to get measurable outcomes for the validation of hypotheses. The study's hypotheses were tested using bootstrapping with 5000 re-samplings (Hair et al., 2014). **Figure 2** shows the research model expressing the path co-efficients and p values for each path.

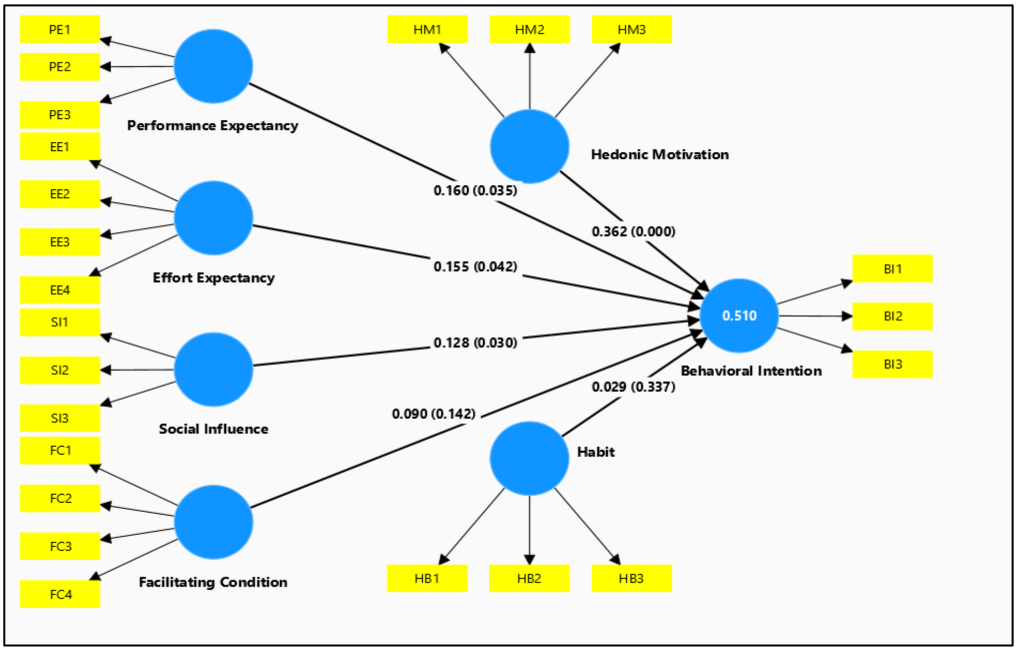


Table 4-2 states the path coefficient of the structural model for the behavioral intention to use AI by private university students in Bangladesh. The study found that Effort Expectancy (β = 0.16, t = 1.72, and p= 0.04), Performance Expectancy (β= 0.16, t = 1.82, and p=0.03), Social Influence (β =0.13, t = 1.89, and p=0.03) and Hedonic Motivation (β = 0.36, t = 4.09, and p=0.000) have significant effect on the Behavioral intention to use AI. Therefore, H1, H4, H5, and H6 hypotheses are supported. Facilitating Condition (β = 0.09, t = 1.07, and p=0.14) and Habit (β = 0.03, t = 0.42, and p=0.34) did not have any statistically significant influence on behavioral intention to use AI. Hence, H2 and H3 are not supported.

Table 4-2: Path Coefficient of Structural Model

Hypothesis	Relationship	Path Coefficient	Standard deviation (STDEV)	T statistics	P values	Decisions
H1	Effort Expectancy ->Behavioral Intention	0.16	0.09	1.72	0.04	Accepted

H2	Facilitating Condition -> Behavioral Intention	0.09	0.08	1.07	0.14	Rejected
H3	Habit -> Behavioral Intention	0.03	0.07	0.42	0.34	Rejected
H4	Hedonic Motivation -> Behavioral Intention	0.36	0.09	4.09	0.00	Accepted
H5	Performance Expectancy -> Behavioral Intention	0.16	0.09	1.82	0.03	Accepted
H6	Social Influence -> Behavioral Intention	0.13	0.07	1.89	0.03	Accepted

DISCUSSION

This study used the UTAUT2 model and six independent variables to estimate the behavioral intention to use AI by private university students in Bangladesh. The independent latent variables are effort expectancy, facilitating condition, habit, hedonic motivation, performance expectancy, and social influence. Out of six endogenous variables, effort expectancy, hedonic motivation, performance expectancy, and social influence have been statistically significant in influencing the behavioral intention to use AI, whereas facilitating condition, habit have been statistically insignificant in influencing the behavioral intention to use AI.

One of the key findings of the study reflects that hedonic motivation is the strongest (0.36) driver of behavioral intention, which indicates that students' hedonic motivation to use AI is significant in determining their behavioral intention to use AI. Hedonic motivation was also found to be statistically significant by the studies of Gansser and Reich (2021), Romero-Rodríguez et al. (2023), Strzelecki (2023). This suggests that students are more likely to use AI when they find it enjoyable and entertaining. The enjoyment factor compels students to integrate AI into their studies and assignments.

Effort expectancy (0.16) and performance expectancy (0.16) are both equally important, following hedonic motivation in terms of relative weightage. Many researchers also found the significance of effort expectancy (Sobaih et al., 2024; Lai et al., 2024; Wu et al., 2022; Gansser and Reich, 2021; Menon and Shilpa, 2023; Milicevic et al., 2024) and performance expectancy (Milicevic et al., 2024; Grassini et al., 2024; Sobaih et al., 2024; Wu et al., 2022; Lai et al., 2024; Strzelecki, 2023; Gansser and Reich, 2021; Romero-Rodríguez et al., 2023; Menon and Shilpa 2023). The significance of effort expectancy suggests that ease of use increases students' intention to use AI. Similarly, the significance of performance expectancy reflects that students would like to use AI if they found it can increase their performance in studies and assignments.

Social Influence (0.13) was also found to be one of the influencing factors of AI use by the students. This finding is supported by the results of (Han et al., 2025; Bahadur et al., 2024; Wu et al., 2022; Sobaih et al., 2024; Wu et al., 2022; Gansser and Reich, 2021; Menon and Shilpa, 2023; Milicevic et al., 2024). This indicates private university students are using AI in Bangladesh as they are observing their classmates, friends, and teachers are utilizing it.

Interestingly, contrary to previous studies' findings, facilitating condition (Gansser and Reich, 2021; Habibi et al., 2023; Menon and Shilpa, 2023; and habit (Bahadur et al., 2024; Gansser and Reich, 2021; Romero-Rodríguez et al., 2023; Strzelecki, 2023; Grassini et al., 2024) do not affect students' behavioral intention to use AI for their studies and preparing assignments. However, Bahadur et al. (2024), Sobaih et al. (2024) also found facilitating conditions do not affect students' use of AI which aligns with our results.

The lack of significance for facilitating conditions suggests that the availability of the resources does not strongly affect students' intention to use AI. Similarly, habit did not play a significant role, which indicates that prior experience in using AI does not drive students to use them. This could be the availability of enormous AI tools that

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

might get students to forget which one to use, thus losing interest. The evolving nature of AI requires users to learn newer versions of it, which requires users to learn it rather than rely on previous habits.

CONCLUSION

This study has examined the concerned variables extensively following the UTAUT2 model to answer the research questions satisfactorily.

1. Primary determinants that influence private university students' behavioral intention to use AI for studies and assignments are hedonic motivation, effort expectancy, performance expectancy, social influence, and facilitating conditions.

2. Hedonic motivation, effort expectancy, performance expectancy, and social influence—these determinants affect students' behavioral intention to use AI for studies and assignments significantly. Among these, hedonic motivation has the strongest (0.36) influence on behavioral intention.

3. Facilitating conditions and habits are found to be insignificant in influencing students' behavioral intention to use AI for studies and assignments. Though insignificant, it can be considered as a determinant of the study. Whereas, this study found habit has no effect (0.00) on behavioral intention.

In Bangladesh, AI tools that offer enjoyable and engaging experiences can encourage students to incorporate them into their studies and assignment preparation. User-friendly, simple yet effective AI tools can encourage students to utilize AI. In order to prevent the unethical use of AI, universities can organize training sessions and establish policies that can guide students on the ethical use of AI. Furthermore, enhancing IT infrastructure can provide students with the necessary resources and access to fully benefit from AI.

IMPLICATIONS

Given the lack of research on this topic in Bangladesh, this study will add to the existing body of knowledge by presenting the most recent situation regarding students' intentions to use AI in their studies and assignment preparation. The determinants identified in this study will aid the developers and marketers of AI technology. The findings of this study will guide them to develop AI related to academic areas according to the necessity and usage pattern of the students. Based on these, authorities in Bangladesh can solve the problems related to the use of AI in Bangladesh. The findings may also be used by university authorities to create guidelines, host lectures, and hold workshops to encourage and control the ethical use of AI. The findings of this study will complement existing AI adoption literature and assist universities with establishing policies and strategies that will promote a better learning environment in Bangladesh.

LIMITATIONS AND FUTURE DIRECTION

Like any other study, this study was also challenged by some limitations. One of the major limitations of this study was that the respondents were from five private universities only, which are located in the capital city of Bangladesh. All the respondents of this study were from undergraduate programs at different universities, which is another limitation of the present study. A study conducted on the students of both private and public universities of Bangladesh located in urban and rural areas could have given a comprehensive picture of the behavioral intention of the students. Moreover, respondents from undergraduate and graduate programs could have added some valuable insight to the findings.

Prospects for further research may include an analysis based on time intervals to check how usage patterns change according to changes in the period. Future researchers can also consider moderating or mediating effects for the model to understand how variables change due to those effects. The impact of AI on students' performance can be evaluated by future researchers as well.

CONFLICT OF INTEREST

There was no potential conflict of interest stated by the authors.

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

REFRENCES

[1] Acosta-Enriquez, B. G., Ballesteros, M. a. A., Jordan, O. H., Roca, C. L., & Tirado, K. S. (2024). Analysis of college students' attitudes toward the use of ChatGPT in their academic activities: effect of intent to use, verification of information and responsible use. BMC Psychology, 12(1). https://doi.org/10.1186/s40359-024-01764-z
[2] Alvi, I. (2021). College students' reception of social networking tools for learning in India: an extended UTAUT model. Smart Learning Environments, 8(1). https://doi.org/10.1186/s40561-021-00164-9
[3] Aswani, R., Ilavarasan, P. V., Kar, A. K., & Vijayan, S. (2018). Adoption of public WiFi using UTAUT2: An exploration in an emerging economy. Procedia Computer Science, 132, 297–306. https://doi.org/10.1016/j.procs.2018.05.180
[4] Bervell, B. B., Kumar, J. A., Arkorful, V., Agyapong, E. M., & Osman, S. (2021). Remodelling the role of facilitating conditions for Google Classroom acceptance: A revision of UTAUT2. Australasian Journal of Educational Technology, 115–135. https://doi.org/10.14742/ajet.7178
[5] Bhattacherjee, N., & Premkumar, N. (2004). Understanding Changes in Belief and Attitude toward Information Technology Usage: A Theoretical Model and Longitudinal Test. MIS Quarterly, 28(2), 229. https://doi.org/10.2307/25148634
[6] Brown, N., & Venkatesh, N. (2005). Model of adoption of technology in households: A baseline model test and extension incorporating household life cycle. MIS Quarterly, 29(3), 399. https://doi.org/10.2307/25148690
[7] Buabbas, A. J., Miskin, B., Alnaqi, A. A., Ayed, A. K., Shehab, A. A., Syed-Abdul, S., & Uddin, M. (2023). Investigating Students' Perceptions towards Artificial Intelligence in Medical Education. Healthcare, 11(9), 1298. https://doi.org/10.3390/healthcare11091298
[9] C, S. B. G., Bhandari, P., Gurung, S. K., Srivastava, E., Ojha, D., & Dhungana, B. R. (2024b). Examining the role of social influence, learning value and habit on students' intention to use ChatGPT: the moderating effect of information accuracy in the UTAUT2 model. Cogent Education, 11(1). https://doi.org/10.1080/2331186x.2024.2403287
[10] Collier, J. E. (2020). Applied Structural Equation Modeling using AMOS: Basic to Advanced Techniques. Retrieved from https://www.bookdepository.com/Applied-Structural-Equation-Modeling-using-AMOS-Joel-E-Collier/9780367863296
[11] Dang, H. L. (2020, December 23). An analysis of the factors affecting intention to use artificial intelligence technology in learning: a case study of Hanoi students. Retrieved from https://ajmi.stamford.edu/index.php/ajmi/article/view/183
[13] De Blanes Sebastián, M. G., Guede, J. R. S., & Antonovica, A. (2022b). Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.993935
[14] Duy, N. B. P., Phuong, T. N. M., Chau, V. N. M., Nhi, N. V. H., Khuyen, V. T. M., & Giang, N. T. P. (2024). AI-assisted learning: an empirical study on student application behavior. Multidisciplinary Science Journal, 7(6), 2025275. https://doi.org/10.31893/multiscience.2025275
[15] Eneizan, B., Mohammed, A. G., Alnoor, A., Alabboodi, A. S., & Enaizan, O. (2019). Customer acceptance of mobile marketing in Jordan: An extended UTAUT2 model with trust and risk factors. International Journal of Engineering Business Management, 11. https://doi.org/10.1177/1847979019889484
[16] Faul, F., Erdfelder, E., Lang, A., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. Behavior Research Methods, 39(2), 175–191. https://doi.org/10.3758/bf03193146
[17] Frank, M. P., & George, G. (2023). Pilot Study on Adoption and Usage of AI in Food Processing Industry by UTAUT2. In Studies in systems, decision and control (pp. 191–205). https://doi.org/10.1007/978-3-031-28314-7_17
[18] Gansser, O. A., & Reich, C. S. (2021). A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. Technology in Society, 65, 101535. https://doi.org/10.1016/j.techsoc.2021.101535
[19] Grassini, S., Aasen, M. L., & Møgelvang, A. (2024). Understanding University Students' Acceptance of ChatGPT: Insights from the UTAUT2 Model. Applied Artificial Intelligence, 38(1). https://doi.org/10.1080/08839514.2024.2371168
[20] Habibi, A., Muhaimin, M., Danibao, B. K., Wibowo, Y. G., Wahyuni, S., & Octavia, A. (2023). ChatGPT in higher education learning: Acceptance and use. Computers and Education Artificial Intelligence, 5, 100190. https://doi.org/10.1016/j.caeai.2023.100190

[21] Hair, J. F. (2011). Multivariate Data Analysis: An Overview. In International Encyclopedia of Statistical Science (pp. 904–907). https://doi.org/10.1007/978-3-642-04898-2_395
[22] Hair, J. F., Jr, Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM). European Business Review, 26(2), 106–121. https://doi.org/10.1108/ebr-10-2013-0128
[23] Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: indeed a silver bullet. The Journal of Marketing Theory and Practice, 19(2), 139–152. https://doi.org/10.2753/mtp1069-6679190202
[24] Handayani, W. P. P. (2023). The UTAUT implementation model in defining the behavioral intention of mobile banking users. Jurnal Manajemen Bisnis, 14(2), 361–377. https://doi.org/10.18196/mb.v14i2.18649
[25] Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., . . . Calantone, R. J. (2014). Common beliefs and reality about PLS. Organizational Research Methods, 17(2), 182–209. https://doi.org/10.1177/1094428114526928
[26] Hinton, P. R. (2004). Statistics explained. Routledge eBooks. https://doi.org/10.4324/9780203496787
[27] Kock, N. (2015). Common method bias in PLS-SEM. International Journal of e-Collaboration, 11(4), 1–10. https://doi.org/10.4018/ijec.2015100101
[28] Kumar, J. A., & Bervell, B. (2019). Google Classroom for mobile learning in higher education: Modelling the initial perceptions of students. Education and Information Technologies, 24(2), 1793–1817. https://doi.org/10.1007/s10639-018-09858-z
[29] Lai, C. Y., Cheung, K. Y., Chan, C. S., & Law, K. K. (2024). Integrating the adapted UTAUT model with moral obligation, trust and perceived risk to predict ChatGPT adoption for assessment support: A survey with students. Computers and Education Artificial Intelligence, 6, 100246. https://doi.org/10.1016/j.caeai.2024.100246
[30] Lestariningrum, A., Ausat, A. M. A., Wanof, M. I., Pramono, S. A., & Syamsuri, S. (2024). The Impact of AI Use in Learning and Digital Material Accessibility on Students' Academic Achievement through Technology Engagement as A Mediating Variable : The Perspective of Theory of Planned Behaviour and UTAUT Theory. Jurnal Kependidikan Jurnal Hasil Penelitian Dan Kajian Kepustakaan Di Bidang Pendidikan Pengajaran Dan Pembelajaran, 10(4), 1317. https://doi.org/10.33394/jk.v10i4.12896
[31] Li, Y., & Zhao, M. (2021). A study on the Influencing Factors of continued Intention to use MOOCs: UTAUT model and CCC Moderating effect. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.528259
[32] Limayem, N., Hirt, N., & Cheung, N. (2007). How habit limits the predictive power of intention: the case of information Systems continuance. MIS Quarterly, 31(4), 705. https://doi.org/10.2307/25148817
[33] Liu, D., Maimaitijiang, R., Gu, J., Zhong, S., Zhou, M., Wu, Z., . . . Hao, Y. (2019). Using the Unified Theory of Acceptance and Use of Technology (UTAUT) to investigate the intention to use physical activity apps: Cross-Sectional Survey. JMIR Mhealth and Uhealth, 7(9), e13127. https://doi.org/10.2196/13127
[34] Mahmud, A., Sarower, A. H., Sohel, A., Assaduzzaman, M., & Bhuiyan, T. (2024). Adoption of ChatGPT by university students for academic purposes: Partial least square, artificial neural network, deep neural network and classification algorithms approach. Array, 21, 100339. https://doi.org/10.1016/j.array.2024.100339
[35] Mason, C. H., & Perreault, W. D. (1991). Collinearity, power, and interpretation of multiple regression analysis. Journal of Marketing Research, 28(3), 268. https://doi.org/10.2307/3172863
[36] Menon, D., & Shilpa, K. (2023). "Chatting with ChatGPT": Analyzing the factors influencing users' intention to Use the Open AI's ChatGPT using the UTAUT model. Heliyon, 9(11), e20962. https://doi.org/10.1016/j.heliyon.2023.e20962
[37] Milicevic, N., Kalas, B., Djokic, N., Malcic, B., & Djokic, I. (2024). Students' Intention toward Artificial Intelligence in the Context of Digital Transformation. Sustainability, 16(9), 3554. https://doi.org/10.3390/su16093554
[38] Niloy, A. C., Bari, M. A., Sultana, J., Chowdhury, R., Raisa, F. M., Islam, A., . . . Hossen, M. A. (2024). Why do students use ChatGPT? Answering through a triangulation approach. Computers and Education Artificial Intelligence, 6, 100208. https://doi.org/10.1016/j.caeai.2024.100208
[39] Nitzl, C. (2016). The use of partial least squares structural equation modelling (PLS-SEM) in management accounting research: Directions for future theory development. Journal of Accounting Literature, 37(1), 19–35. https://doi.org/10.1016/j.acclit.2016.09.003
[40] Rahman, M. S., Sabbir, M. M., Zhang, J., Moral, I. H., & Hossain, G. M. S. (2023). Examining students' intention to use ChatGPT: Does trust matter? Australasian Journal of Educational Technology, 51–71. https://doi.org/10.14742/ajet.8956

[41] Rocha, D. P., Bewersdorff, A., & Nerdel, C. (2024). Exploring Influences on ICT adoption in German Schools: A UTAUT-Based Structural Equation Model. Journal of Learning for Development, 11(2), 311–322. https://doi.org/10.56059/jl4d.v11i2.1116
[42] Romero-Rodríguez, J., Ramírez-Montoya, M., Buenestado-Fernández, M., & Lara-Lara, F. (2023). Use of ChaTGPT at university as a tool for complex thinking: students' perceived usefulness. Journal of New Approaches in Educational Research, 12(2), 323–339. https://doi.org/10.7821/naer.2023.7.1458
[43] Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In Springer eBooks (pp. 587–632). https://doi.org/10.1007/978-3-319-57413-4_15
[44] Sharma, A., Sanghvi, K., & Churi, P. (2022). The impact of Instagram on young Adult's social comparison, colourism and mental health: Indian perspective. International Journal of Information Management Data Insights, 2(1), 100057. https://doi.org/10.1016/j.jjimei.2022.100057
[45] Sobaih, A. E. E., Elshaer, I. A., & Hasanein, A. M. (2024). Examining students' acceptance and use of CHATGPT in Saudi Arabian higher education. European Journal of Investigation in Health Psychology and Education, 14(3), 709–721. https://doi.org/10.3390/ejihpe14030047
[46] Strzelecki, A. (2023). 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
[47] Sultana, R., & Faruk, M. (2024). Does artificial intelligence increase learners' sustainability in higher education: insights from Bangladesh. Journal of Data Information and Management, 6(2), 161–172. https://doi.org/10.1007/s42488-024-00121-4
[48] Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2018). Use of 'Habit' Is not a Habit in Understanding Individual Technology Adoption: A Review of UTAUT2 Based Empirical Studies. IFIP Advances in Information and Communication Technology, 277–294. https://doi.org/10.1007/978-3-030-04315-5_19
[49] Tavares, J., Goulão, A., & Oliveira, T. (2017). Electronic Health Record Portals adoption: Empirical model based on UTAUT2. Informatics for Health and Social Care, 43(2), 109–125. https://doi.org/10.1080/17538157.2017.1363759
[50] Venkatesh, N., Morris, N., Davis, N., & Davis, N. (2003). User acceptance of information Technology: toward a unified view. MIS Quarterly, 27(3), 425. https://doi.org/10.2307/30036540
[51] Venkatesh, N., Thong, N., & Xu, N. (2012). Consumer Acceptance and use of Information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157. https://doi.org/10.2307/41410412
[52] Von Garrel, J., & Mayer, J. (2023). Artificial Intelligence in studies—use of ChatGPT and AI-based tools among students in Germany. Humanities and Social Sciences Communications, 10(1). https://doi.org/10.1057/s41599-023-02304-7
[53] Wu, W., Zhang, B., Li, S., & Liu, H. (2022). Exploring factors of the willingness to accept AI-Assisted learning environments: an empirical investigation based on the UTAUT model and perceived risk theory. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.870777
[54] Yin, M., Han, B., Ryu, S., & Hua, M. (2023). Acceptance of generative AI in the creative industry: Examining the role of AI anxiety in the UTAUT2 model. In Lecture notes in computer science (pp. 288–310). https://doi.org/10.1007/978-3-031-48057-7_18
[55] Ikhsan, R. B., Prabowo, H. A. R. T. I. W. I., & Yuniarty, Y. (2021). Drivers of the mobile-learning management system's actual usage: Applying the utaut model. ICIC express letters. Part B, Applications: an international journal of research and surveys, 12(11), 1067-1074.
[56] Karu E. K. and Hoque M. A. (2024). User Experience of ChatGPT: Insights from Undergraduate English Language and Literature Students in Bangladesh, Studies in Self-Access Learning Journal, 15(3), 394–418. https://doi.org/10.37237/150305.
[57] Liebenberg, J., Benade, T., & Ellis, S. (2018). Acceptance of ICT: Applicability of the Unified Theory of Acceptance and Use of Technology (UTAUT) to South African students, The African Journal of Information Systems, 10(3).
[58] Ringle C. M., Wende S., and Becker J.M. (2015). SmartPLS. Available: http://www.smartpls.com.
[59] Podsakoff P. M., MacKenzie S. B., Lee, J.Y. and Podsakoff N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903.

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

[60] Hair J. F., Hult T., Ringle C. M., and Sarstedt M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM). Sage.
[61] Geisser S. (1974). A predictive approach to the random effect model. Biometrika, 61(1),101–107.
[62] Fornell C. and Larcker D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistic. Journal of Marketing Research, 18(3), 382, doi:10.2307/3150980.
[63] Henseler J., Ringle C. M. and Sarstedt M. (2014). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135, doi:10.1007/s11747-014-0403-8.
[64] Sarstedt M., Hult G. T. M., Ringle C. M. and Hair J. (2013). A primer on partial least squares structural equation modeling. https://www.amazon.com/Partial-Squares-Structural-Equation-Modeling/dp/1452217440.