

Intentions to Use Artificial Intelligence: A Study on the University Students of Bangladesh

Mohammad Toriqul Islam Jony¹
Md. Minhaj Uddin²
Dr. Md. Sumon Hossain³

Abstract

The usage and development of artificial intelligence (AI) in higher education in Bangladesh have created new opportunities and difficulties. The internal architecture of higher education will undergo a significant shift in governance as a result of the use of AI in education. However, this study aims to investigate whether students of Bangladeshi universities have any plans to use various AI-related technologies. To get input, students were required to submit a survey on AI and intentions. The data were analyzed using Smart PLS 3 and the Statistical Package for Social Sciences (SPSS) version 24.0 considering the Unified Theory of Acceptance and Use of Technology (UTAUT), which served as the framework. We were able to successfully use a survey to validate our conceptual model and set of hypotheses by collecting data from 304 respondents. The results proved that the adoption of automated technologies, which have a strong correlation with collaboration, is positively connected to the antecedent variables, such as performance expectancy, social influence, and facilitating conditions. Additionally, this study has demonstrated that effort efficiency may not be as significant in forecasting a willingness to adopt new technology. The shortcomings of this study are: a global perspective is lacking, and the respondents don't have much expertise with AI. Researchers may carry out a longitudinal study with a larger sample size from universities in various nations. Additionally, it could include important model components and take into consideration various cultural contexts.

Keywords: Artificial Intelligence; UTAUT; Technology; University; Behavioral Intentions.

1.1 Introduction

Classroom education has progressed as advances in science have grown, from the traditional classroom teaching paradigm to the artificial intelligence (AI) virtual learning method. Many schools have also begun to use AI technology in recent times to organize and implement high-quality efficient education and perhaps teaching activities, such as image processing, speech recognition, natural language processing, augmented reality, and other technologies, which provide convenient conditions for promoting school modernization and improvement. However, AI fosters the growth of human learning, perception, emotion, and other intelligence by allowing machine systems to do human-like learning, perception, emotion, and other mental tasks (Zheng,

¹ Assistant Professor, Department of Management, Jatiya Kabi Kazi Nazrul Islam University

² Assistant Professor, Department of Accounting and Information Systems, Jatiya Kabi Kazi Nazrul Islam University.

³ Associate Professor, Department of Accounting and Information Systems, University of Rajshahi.

2020). This development has inspired educational solutions that take into account concerns such as AI-assisted teaching and AI-assisted learning. According to the present study, research on AI in education is concentrating on system innovations such as intelligent tutoring systems, with the bulk of current studies focusing on higher education (Zawacki-Richter et al. 2019). Besides the educational systems were radically altered during this COVID-19 pandemic. The need for AI is more understood in this dilemma. Schools, colleges, and universities all across the world have been closed down. Digital or online learning has become a feasible option for sustaining the educational system's goal as a result of changing learning situations. Trainers, academics, and students have all been caught off guard. While educational institution closures throughout the world have had a substantial influence on students' learning, E-learning has swiftly gained popularity as a means of dealing with the present crisis, and many schools and higher education institutions now use it for regular sessions. (Kashive, Powale&Kashive, 2020). Therefore, many researchers are looking towards digital innovations and upcoming technologies such as AI to help the education system not only to support this crisis but also to bring a revolutionary change in the learning circumstances of the world in the future (Bouktif& Manzoor, 2021). AI is projected to have an enormous effect on education as well, transforming how faculty teach by giving new tools. Offering tailored instruction improved access to information, and advocating for more inclusive education, can completely change how students learn. There are countless opportunities (UNESCO MGIEP, 2018). Though AI has substantial benefits, it also has some downfalls. Teachers employing remote teaching techniques are unable to regulate students in real-time, and students have a great degree of freedom, resulting in students' inability to focus on listening and teachers' inability to understand students' learning status in a timely fashion. (Wang, 2021). According to a study by (McGovern et al., 2018), AI adoption in Bangladesh and the rest of the world is slow, citing a lack of skill, growing privacy concerns, ongoing maintenance, integration capabilities, and limited demonstrated applications as factors. Applications of AI, however, have boosted Bangladesh's societal prospects. Adoption at the right time can substantially aid her distinctive growth, but neglect might have negative consequences. However, there appears to be a discrepancy between Bangladesh's concerns about AI's relevance and ramifications (Wahid-Uz-Zaman, 2019).

Furthermore, fostering students' desire to understand AI would be an essential educational aim in this setting. A well-designed curriculum typically encourages pupils to learn more about the subject. Investigating students' desire to learn as a measure of the curriculum's impact may help to guarantee that students continue to study more about AI. This study attempts to use artificial intelligence to correlate students' classroom conduct with engagement in class, as well as to accurately assess their active involvement in class. A unique technique based on feature fusion will be developed to assess the proper classroom management for this aim.

1.2 Related Literature

In their study, Li et al. (2021) stated that adding artificial intelligence to the classroom can encourage interactive learning and the development of intelligent institutions. Another study was carried out by Nayal et al. (2021) to see if artificial intelligence (AI) and machine learning (ML) are adequate for dealing with COVID-19 effects. The finding revealed that "lack of central and state norms and standards," as well as "lack of data security and privacy," are the two most significant barriers to AI –ML deployment in the agriculture supply chain. Furthermore, AI-ML in the ASC allows for more precise prediction, which decreases uncertainty. The outcome of a scholarly investigation by Chatterjee et al. (2020) suggested that employees' behavioral intent to use an AI-integrated CRM system at their place of employment is directly impacted by perceived utility and simplicity of use. Furthermore, two intermediate factors: the hedonic attitude (HA) and utilitarian attitude (UTA); have an impact on workers' behavioral intention to utilize an AI-integrated CRM system. Another study by Kashive, Powale, and Kashive (2020) found that attitudes and satisfaction levels influencing the inclination to use the e-learning module fluctuated by gender and learner type. During the COVID-19 epidemic, Barton (2020) used machine learning to describe the influence of AI in academia and faraway schooling options. According to the research, students, instructors, schools, and universities faced distinct problems when remote learning was adopted soon following the closure of educational facilities. The research looked at AI techniques that are thought to be more successful in remote education, as well as the problems that may arise. Another study, performed by Alam (2020), suggested that AI will undoubtedly change India's educational environment, generating massive disruptions in traditional pedagogy. However, several crucial constraints have thwarted the adoption of artificial intelligence in the educational process in India. A Markov approach to decision-making has been implemented by Dwivedi et al. (2020) to assess the value of AI in academic information systems to follow the successful execution of strategies for instruction during a crisis. According to the study, students had trouble interacting with existing online teaching materials, which affected their academic achievement. According to a subsequent study by Gourari et al. (2020), a thorough and informed investigation of student, teacher, scientific, and educational electronic environments is essential regarding correctly creating and implementing artificial intelligence technology. Fuzzy thinking is employed by Sun et al. (2020) to describe how AI might help students at Southeast University in China improve their digital learning systems. Because digital learning systems could sustain instructional continuity in a way that was comparable to that of traditional classrooms, the majority of students were excited about them. The teachers used upbeat energy in the classroom to assist children deal with the mental stress brought on by the quarantine. To investigate the opinions of primary school teachers in Indonesia on online learning, Aliyyah et al. (2020) used data analysis and machine learning. Insufficient resources, frequent false positives, a breakdown in communication, and lower levels of student engagement were among the reasons given by 77.6% of primary school teachers as to why remote learning was difficult. Faculty

were only able to convey to students the essential components of the subject matter due to the limited availability of online learning tools and technologies. According to Zaman (2019), the effective use of AI would depend on people, processes, and technology. People will adopt AI more quickly if they recognize the advantages, accept the technology, comprehend it, and use it objectively. Kandlhofer et al. (2016) predict that in the future, AI will take a more prominent role in education, from pre-kindergarten to higher education, with potential subjects including reasoning learning, expert systems, supervised learning, decision trees, and neural networks. The development of artificial intelligence has opened up a wide range of new opportunities while also drawing attention to important elements of the existing higher education teaching and learning processes.

The above evidence strongly suggests that many studies have been conducted in the field of AI, but there is a clear gap that, according to the best of my knowledge, none of them has examined the student's intention to use AI in Bangladesh. So, this study is thus an attempt to expose the crucial issue identified above.

1.3 Conceptual Framework and Hypotheses Development

Conceptual Framework

Our theoretical basis was the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT, a cohesive causal model, was generated to clarify and foresee how students in an assortment of fields would begin to utilize technology (Dowdy, 2020; Sumak& Sorgo, 2016). In several prior studies, the validity and reliability of UTAUT have been empirically confirmed. The UTAUT is based on the specific notions of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, and it integrates eight technological acceptance models. These models aid in identifying the factors that affect how well people adopt technology (Venkatesh et al., 2003). These four important criteria were the initial ones we used for our inquiry. Following are discussions of the key constructs and ensuing hypotheses based on the model and study areas.

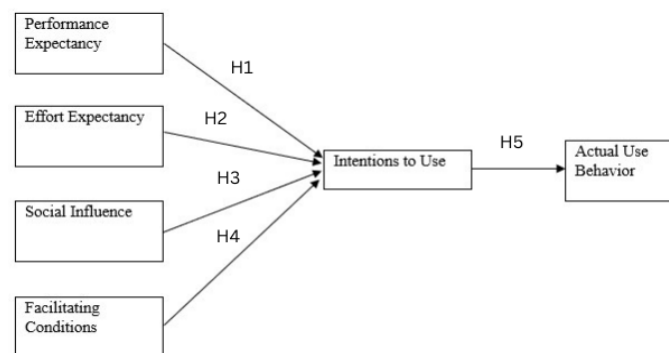


Figure: Conceptual Framework of the Study.

1.3.1 Performance Expectancy (PE)

Performance expectancy (PE) refers to the perceived value of adopting a system and the conviction that doing so would improve one's performance at work (Venkatesh et al., 2003). Because users frequently want to foresee the extent of advantages to be received from a given technology, It has repeatedly been noted by several studies (Dwivedi et al., 2019) that it is the most relevant driver of behavioral intention (BI) for technology use. Prior investigations (Brown et al., 2010, Hong et al., 2011, Wang et al., 2014, and Pullen et al., 2015) have shown that there is a significant correlation between performance expectancy and the use of technology. It seems sensible to extrapolate this relationship to AI-enabled products. According to studies (Ransbotham et al., 2018; Duan et al., 2021), AI is associated with enhanced efficiency, which may be interpreted as an attachment to performance expectancy. Information technology research models only have a little amount of empirical data to support this link. Performance expectations and intention to use technology did not significantly correlate, according to Cao et al. (2021). According to Chatterjee et al. (2021), utilizing AI-enabled technologies to improve performance was connected with performance expectancy. The following hypothesis was formulated in light of the review above:

H1: Performance expectancy positively influences the student's intention to use artificial intelligence.

1.3.2 Effort Expectancy

Effort expectancy (EE) is a dependable gauge of technology adoption. It is referred to as the ease of system usage, according to Venkatesh et al. (2003). EE is regarded to be a highly crucial variable since it supports individuals to figure out how much activity is required to use a certain technology., as previously discovered (Magsamen-Conrad, Upadhyaya, Joa, & Dowd, 2015; Oliveira, Thomas, Baptista, & Campos, 2016). Its effect on user intention is thus anticipated to be large and positive. In light of these debates, the accompanying hypothesis is created.

H2: EE positively influences students' intention to use AI.

1.3.3 Social Influence (SI)

Social influence (SI), as defined by Venkatesh et al. (2003), is the degree to which individual judges that "vital people" think they should approve the use of a new system. The influence of SI (friends, family, coworkers, and peers) on the adoption of behaviors at the individual level has been studied in many research (Shen, Ho, Ly, & Kuo, 2019; Wu & Chen, 2017). SI is a strong predictor of action and intention, according to studies by academics like Pavlou and Fygenson (2006), Lu et al. (2005), and Rogers (1995). The study's premise is that teachers who receive encouraging feedback from their social networks are more likely to have a strong BI to use ICTs. The discussions raised above generate the following hypothesis:

H3: Social influence has a positive impact on the student's intention to use AI.

1.3.4 Facilitating conditions

Venkatesh et al. (2003) defined facilitating conditions as the degree to which the user thinks that there are enough resources and support options available for using technology in enterprises. The organizational and technological support provided to students to enable them to adopt and use online tools with artificial intelligence (AI) in their assignments is referred to in this study as enabling conditions. A recently completed meta-analysis of the UTAUT model showed pleasant conditions can also contribute to the expansion of a positive attitude toward technology (Dwivedi et al., 2019). Supporting the usage of AI and being willing to behave has a favorable association. (Chatterjee and Bhattacharjee, 2020; Jain et al., 2022; Alam et al., 2018). As a result, we come up with the following hypothesis:

H4: Facilitating conditions have a positive influence on the student's intention to use AI.

1.3.5 Intention to use (IU) and actual usage behavior (AUB)

Intention to use (IU) technology refers to a user's plans to embrace and employ a certain tool (Venkatesh & Brown, 2001; Venkatesh et al., 2003). It is thus believed to have the greatest impact on how they will utilize technology (Jaradat & Al Rababaa, 2013). Intention acts as a mediating variable to carry out the action in support of the activity to which one's aim to use AI is indicated (Nasrallah, 2014). The most important predictor of people's behavior, according to a variety of research, is behavioral intention. In their most recent study, Alam and Uddin (2019) discovered a positive influence of ERP intention on the actual implementation of ERP. According to their consequences (Chatterjee & Bhattacharjee, 2020), there is a suitable and massive relationship between intent to act and actual application when it comes to the adoption of artificial intelligence in higher education. We can construct the following assumptions based on the information presented above:

H5: Intention to use positively influences the actual usage.

1.4 The theoretical framework of the study

Artificial Intelligence

Artificial intelligence is not a new concept. McCarthy (Cristianini, 2016), who continued Turing's (Turing, 1937, 2009) work, created the phrase in 1956. Turing explained how intelligent computers are capable of intelligent reasoning and thought. Since 1956, the concept of AI has expanded and altered as a result of major improvements in its capabilities. Due to its multidisciplinary character and developing capabilities, the phrase is challenging to define even for professionals. AI is now defined as "computing systems that can engage in human-like processes such as learning, adapting, synthesizing, self-correction, and the use of data for complex processing tasks" (Popenici et al., 2017). The

term "artificial intelligence" (AI) can also refer to a computer system that can perform a certain task using features (such as voice or vision) and intelligent behavior that were previously thought to be exclusive to humans (Russell, 2010). In plainer language, the word "AI" refers to intelligent machines that can carry out jobs that have historically been done by people. Indeed, people read about AI in the context of the ongoing digital era, in which our way of life is changing due to growing digital transformation (Chaudhry & Kazim, 2022). As a result of such transformation, people's abilities and knowledge must adapt to the new situation. In this regard, the World Economic Forum recognized sixteen skills as being essential for the future workforce in the twenty-first century (World Economic Forum and The Boston Consulting Group, 2015). Technology literacy, communication, leadership, curiosity, flexibility, and other traits are included in this. When defining AI, may be difficult because of the multidisciplinary interest of researchers in linguistics, psychology, education, and neuroscience who tie AI to terminology, perceptions, and knowledge in their respective fields. As a result, it has become necessary to categorize AI inside particular disciplinary domains (Crompton & Burke, 2023). But artificial intelligence (AI) is playing a growing role in education. One significant example is individualized teaching methods, which are well-proven to be beneficial in enhancing learning (Khosravi et al., 2022; Kulik & Fletcher, 2016; du Boulay, 2016). Systems utilizing AI in Education (AIED) may also employ a variety of advanced AI techniques to develop the crucial interface for the learning process.

The UTAUT Model

To figure out how well any new technology is received, models from the literature on technology adoption are frequently utilized. Sun & Zhang (2006) and Venkatesh, Chan & Thong (2012) assert that these models frequently explain the factors that affect acceptance. The Theory of Reasoned Action (TRA), often known as the adaptation of psychological theory, is one of the most significant models in the research on technology adoption (Park, 2009). Despite being widely used, according to Venkatesh and Davis (2000), TAM only accurately estimated fewer than 50% of cases regarding technology use. After thoughtfully reviewing studies on the adoption of technology, Venkatesh et al. (2003) constructed the UTAUT model, which inevitably aids in solving and addressing the TAM dilemma. They designed a model known as the unified theory of acceptance and use of technology (UTAUT) to amalgamate the key components from eight well-known theories and models to predict and explain the adoption and usage of new technologies. It is important to note that the UTAUT model also includes the theory of reasoned action (TRA), information diffusion theory (IDT), theory of planned behavior (TPB), theory of technology acceptance (TAM), combined model of TAM and TPB (C-TAM-TPB), motivational model (MM), model of personal computer usage (MPCU), and social cognitive theory (SCT). Al-Qaysi et al. (2023) assert that the Unified theory on the adoption and usage of technology is an appropriate framework for examining how people accept new technologies. This theory expands on Brown et al.'s (2010) cooperation theory by analyzing the impact of technology throughout both the initial and

post-adoptive eras (Venkatesh et al., 2011). The concept, according to Venkatesh et al. (2003), aims to explain how people utilize technology and behave while doing so willingly. Performance expectations, effort expectations, social influence, and enabling environments are the four elements that affect how individuals utilize technology. The UTAUT model is capable of reliably describing a sizable portion (70%) of the heterogeneity in users' motivation to use technology, according to past studies. However, it has been found that the conventional UTAUT model is inadequate for investigating AI since it only focuses on the employment of functional techniques and is unable to adequately capture the complex procedures involved in the adoption of AI (Gursoy et al., 2019). Montesdioca and Maçada (2015) claim that some research that made use of the UTAUT standards condensed their subject matter by evaluating the efficacy of technology in terms of performance and user satisfaction. Through UTAUT, students will obtain a thorough understanding of their efficacy while applying AI (Rishi Agarwal, 2017). Efficiency, knowledge, and skills among students may all be improved with the usage of AI (Jacques Bughin, 2018). Preparing them for the current, competitive business climate, helps students make smart judgments.

1.5 Statement of the Problem

Artificial intelligence has already had a direct and indirect impact on our way of life and will continue to do so in the future. Many scholars have presented an intriguing question: how much will technology transform education? As a result, this study will examine the future of higher education if artificial intelligence is adopted, as well as the intention of Bangladeshi university students to employ AI in their educational institutions.

1.6 Research questions

However, this study will find out the answer to the following question:

1. How do students perceive AI?
2. Which of the driving factors are pushing students to adopt AI?

1.7 Objectives of the Study

The primary objective of the study is to investigate the intention of students in using AI for their classroom management.

The specific objectives will be as follows:

1. To evaluate the perceptions of students towards AI.
2. To examine the factors pursuing students to adopt AI.
3. To inspect the problems of using AI according to the perspective of Bangladesh.

2.0 Materials and Methods

2.1 Research design

This study uses a quantitative methodology that enables the researchers to validate their hypotheses and find solutions. The initial stage is to base the survey's questions on the study undertaken by Alam et al. (2020), who used the UTAUT model to look at people's attitudes toward technology. It took around 10 minutes to complete the study's questionnaire, which had two parts for evaluating our theoretical model. In the first portion, demographic questions about the respondent are asked, and in the second, questions assessing the components of the study model are asked. The research model comprises 22 elements in six constructs. The questions were composed to ensure they were uncomplicated for the respondents to grasp. The purpose of the inspections was to discover more about the mindset and attitudes of the students from multiple universities who have experience with and knowledge of AI technology. The survey questionnaire questions for each concept were graded on a 5-point Likert scale, with 1 denoting "strongly disagree" and 5 denoting "strongly agree".

2.2 Sampling and data collection

Both the face-to-face survey and the online survey methods were used for collecting data for this study. A simple random sampling technique was applied for collecting the data. The researcher visited different universities in Bangladesh to collect data through the survey method and the respondents were chosen from an array of Bangladeshi public and private universities. The students from these universities who have employed AI technology and gained experience were chosen at random. Besides, the researchers contacted students who were interested in completing the survey via phone and email. From January 6 through March 30, 2022, data were collected. A total of 635 students from 15 universities participated in the survey. When the questionnaire was given to the possible respondents, an immediate answer was sought. The survey protects the privacy and identity of the respondents. At the end of the specified time frame, 372 replies had been received, with a response rate of 58.6%. 68 submissions were missing information after being reviewed after 372 were made. 68 replies were found to be lacking information after a careful examination, either as a consequence of respondents checking several options or by leaving the response page completely blank. The online survey was conducted through an online questionnaire survey (Google Form) via Facebook Messenger, email, and WhatsApp. A final dataset of 304 responses from respondents was the outcome of this.

3.0 Data Analysis

Statistical software tools like the Statistical Package for Social Sciences (SPSS) version 24.0 and Smart PLS 3 were used to statistically evaluate the quantitative data. The nature of relationships and the effects of mediation between the variables were examined using Smart PLS. Due to its dependability in psychometric model analysis, PLS-SEM has gained popularity among business and social science academics (Wold, 1985). PLS-SEM

is an alternative to covariance-based SEM (CB-SEM) because of this useful property, particularly when there are several indications, routes, and interactions between important variables in a research model or exploratory study (Hair & Hult, 2016). The hypotheses were tested using the bootstrapping approach. Through the use of the path coefficient () and t-statistics, the study examined the link between independent and dependent variables. The study's use of pre-justified notions and item scales led to the confirmation factor analysis (CFA). The study employed Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), convergent, and discriminant validity statistics as its reliability and validity indicators.

Results

A two-step procedure was used to evaluate the collected data (Anderson & Gerbing, 1988). We started by examining the measurement model's accuracy, convergent validity, and discriminant validity. The structural model was then examined to ascertain the direction and strength of the connections among the theoretical components.

Data Analysis and Reporting

Pretest

The pretest questionnaire was created and delivered to ten students from various departments at Jatiay Kabi Kazi Nazrul Islam University (JKKNIU) who had prior experience using AI technology. They discovered that some of the assertions in the surveys, which were based on the previous literature, were confusing to them. One of the responders, for instance, advised defining the area of effort efficiency. Another user proposed that the term 'facilitating conditions' should be defined more clearly. Various adjustments to each section of the questionnaire were made in response to participants' feedback. The final version of the questionnaire for the pilot study was developed with minor changes and modifications.

Pilot study

The pilot research was conducted to examine the internal consistency and reliability of the measurement scales. The survey utilized in the pilot research was a 5-point Likert-type scale with the following responses: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. Six constructs and 22 associated items made up the questionnaire. A total of 372 replies from students at different public and private universities in Bangladesh were gathered during the one-month pilot project, which began in the middle of November 2021.

3.1 Sample characteristics

The respondents were found to be from 15 different public and private universities in Bangladesh. The following Table 1 provides a brief overview of the respondents' profiles:

Table 1: Profile of the respondents

Particulars	Percentage
Gender	
Male	68.4
Female	31.6
Total	100.0
University	
Public	76.3
Private	23.7
Total	100.0
Degree	
Honors	72.2
Masters	27.8
Total	100.0
Discipline	
Science	46.4
Arts	43.2
Business	10.4
Total	100.0
CGPA	
Above 3.50	28.7
Below 3.50	46.8
Below 3.00	24.5
Total	100.0
N = 304	

3.2 The Measurement Model

We evaluated the validity and reliability of the underlying constructs of the study to evaluate the measuring approach. As a result, composite reliability and Cronbach's alpha are used to evaluate dependability. But our measurement model is described in the following sections.

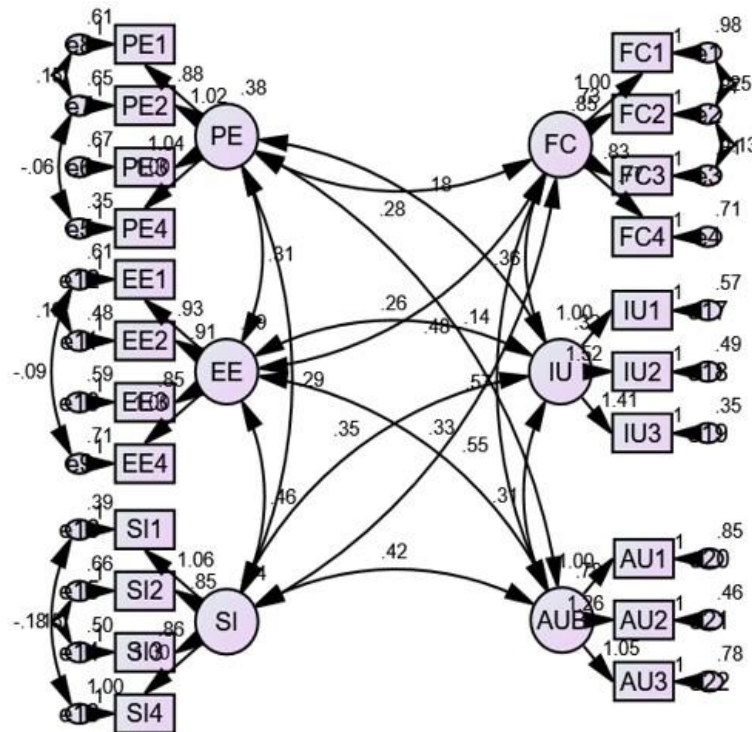


Figure: Measurement model of the study.

Reliability and validity of data

The reliability was evaluated using the composite reliability (CR) and Cronbach's alpha (rho_A) indices. According to theory, dependability is seen to be enough when the composite reliability, rho_A, and Cronbach's alpha all exceed 0.70 (Hair, 2006). According to Table-4.3 below, all of the constructions have composite reliability (CR) and rho_a values that are greater than the suggested value, or 0.7 and are thus considered to have appropriate reliability.

Both convergent and discriminant validity were evaluated in the study. When measuring constructs have an average variance extracted (AVE) of at least 0.50 and items/factors loading are significantly higher than 0.70, convergent validity is said to be good (Hair et al., 2021). The item loadings are shown in the table above. The item loadings, which range from 0.712 to .889, and the AVE (in Table 3), which ranges from 0.553 to .712, are

both higher than the suggested value. As a result, the prerequisites for convergent validity have been met.

Table 2: Construct's reliability and validity

Particulars	Measur- ement Items	Factor Loadings	VIF	Reliability			Validity
				Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	The average variance extracted (AVE)
Actual Use Behavior	AU1	0.813	2.03	0.798	0.808	0.881	0.712
	AU2	0.889	1.16				
	AU3	0.828	1.42				
Effort Expectancy	EE1	0.813	2.07	0.783	0.783	0.861	0.608
	EE2	0.826	1.11				
	EE3	0.759	2.03				
	EE4	0.717	1.37				
Facilitating Conditions	FC1	0.787	1.83	0.727	0.706	0.831	0.621
	FC2	0.749	1.64				
	FC3	0.754	2.24				
	FC4	0.766	2.37				
Intention to Use	IU1	0.738	1.19	0.763	0.778	0.864	0.682
	IU2	0.859	1.51				
	IU3	0.878	1.67				
Performance Expectancy	PE1	0.712	1.27	0.733	0.741	0.832	0.553
	PE2	0.729	2.52				
	PE3	0.748	2.04				
	PE4	0.783	1.94				
Social Influence	SI1	0.832	1.01	0.799	0.811	0.881	0.711
	SI2	0.796	1.58				
	SI3	0.835	1.79				
	SI4	0.746	2.23				

The square root of the AVE (FL test) and the HTMT tests were taken into account to evaluate the discriminant validity (Table 4). A construct's correlation with other constructs must be bigger than its square root for discriminant validity to be adequate (Henseler et al., 2009). In the accompanying table 4.4, each latent construct's square root of the AVE (bolded in the diagonal) is larger than its associated correlation, indicating that the data utilized in this study have strong discriminant validity. And according to Bagozzi et al. (1991), all other inter-item correlations are below the .80 cutoffs, demonstrating the distinctness of each concept.

When using the HTMT test, discriminant validity between two reflective conceptions has been shown in the HTMT value is less than .90 (Henseler, Ringle, and Sarstedt, 2015). We can observe that all of the HTMT values in Table 4 below are less than .90. The prerequisites for the discriminant validity are therefore properly satisfied. Table 6 below displays the outcome of the findings.

Table 3. Inter-construct correlations and discriminant validity (Fornell–Larcker Criterion).

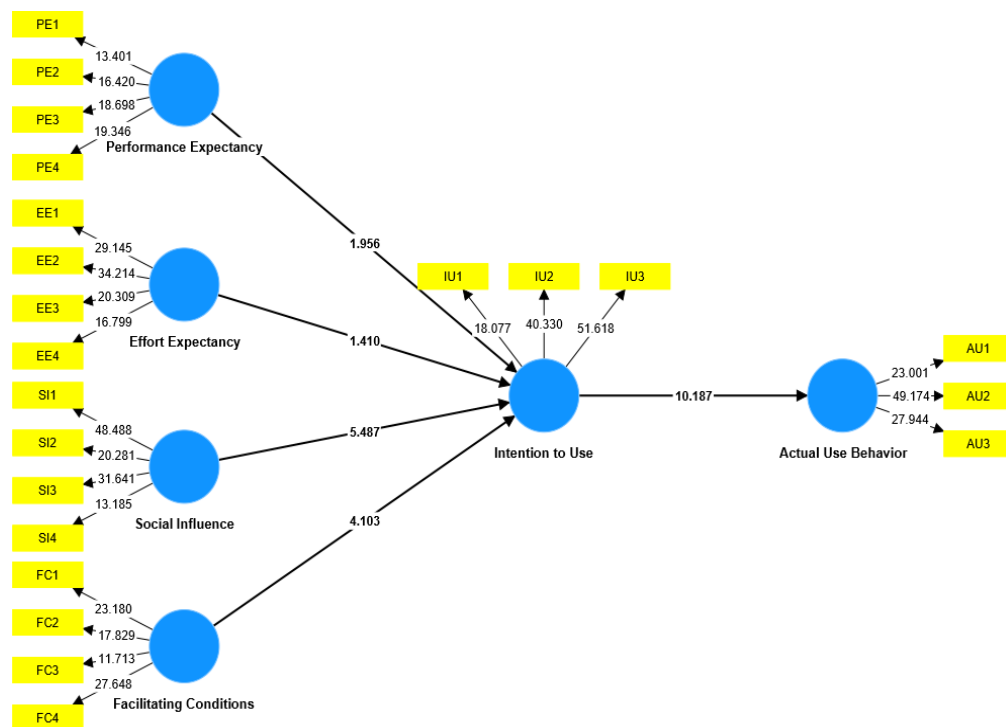
	Actual Use Behavior	Effort Expectancy	Facilitating Conditions	Intention to Use	Performance Expectancy	Social Influence
Actual Use Behavior	0.844					
Effort Expectancy	0.374	0.78				
Facilitating Conditions	0.539	0.494	0.788			
Intention to Use	0.491	0.481	0.572	0.825		
Performance Expectancy	0.169	0.489	0.386	0.413	0.743	
Social Influence	0.436	0.549	0.535	0.601	0.424	0.843

Table 4. Inter-construct correlations and discriminant validity (Heterotrait-Monotrait Ratio [HTMT])

	Actual Use Behavior	Effort Expectancy	Facilitating Conditions	Intention to Use	Performance Expectancy	Social Influence
Actual Use Behavior						
Effort Expectancy	0.468					
Facilitating Conditions	0.723	0.666				
Intention to Use	0.617	0.627	0.76			
Performance Expectancy	0.206	0.643	0.523	0.552		
Social Influence	0.54	0.685	0.709	0.761	0.543	

3.3 Structural Model

This study examined some general hypotheses regarding students' adoption techniques for artificial intelligence (AI) and other associated technologies using the UTAUT theoretical framework. Using the UTAUT framework, we were able to construct and evaluate a structural equation model (SEM), which was trustworthy and highlighted a number of significant discoveries. After that, Figure 4.1 displays the study's structural model. It displays the matching items under each construct (variable) as well as the t-values for each route.



3.4 Hypothesis Testing

Structural Equation Modeling (SEM) (Figure 4.1), which was used to assess the proposed link between the pathways, was based on the measurement model, which was discovered to be a satisfactory fit. The hypothesis was tested using the bootstrap methodology. The research employs beta coefficient (β) t-statistics to examine the link between endogenous and exogenous factors. The outcomes of the research model's hypothesis testing are displayed in Table 5.

Table 5: Results of the hypothesis testing

Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Decision
H1:Performance Expectancy -> Intention to Use	0.108	0.112	0.055	1.976	0.051	Supported
H2:Effort Expectancy -> Intention to Use	0.086	0.09	0.061	1.41	0.159	Not Supported
H3:Social Influence -> Intention to Use	0.351	0.343	0.064	5.487	0.00	Supported
H4:Facilitating Conditions -> Intention to Use	0.269	0.274	0.066	4.103	0.00	Supported
H5:Intention to Use -> Actual Use	0.492	0.495	0.048	10.187	0.00	Supported

The results show that the UTAUT can make certain educated speculations about students' aspirations to use AI and related technologies. First, we discovered that PE significantly influences a person's decision to use these technologies. Thus, H1 gets accepted. The results match those of the studies done by Andrews et al. (2021) and Uddin et al. (2020). This seems to also make logical sense in the context of our investigation. Furthermore, EE failed to demonstrate a substantial influence on the desire to adopt these technologies. H2 is hence rejected. Studies have shown that EE, however, may not be as important in predicting the desire to embrace new technologies (Zhang, 2020; Chang, 2013). Since the results of SI are statistically significant, it follows that it is crucial to ensure that students enjoy utilizing AI technology. H3 has been accepted. The Asia-Pacific Ministerial Forum on ICT in Education 2017 firmly endorses the idea that Member States should create learning environments and communities of practice to help educators and exchange innovations (UNESCO, 2018). The results of the research by Kim et al. (2022) and Rozmi et al. (2019) are likewise in agreement with the findings. Accordingly, the close friends and family members of users in Bangladesh will have a significant impact on whether they choose to employ artificial intelligence or not. Finally, we discovered that Facilitating conditions had a favorable influence on behavioral intention, indicating that organizational infrastructure supports might greatly encourage individuals to utilize artificial intelligence at work. According to earlier research (Alam et al., 2020; Amin et al., 2022; Chatterjee et al., 2021), there is strong evidence that there is a clear link between behavioral intention and actual use behavior. The results are compatible with those of the research projects carried out by Alam et al. in 2020 and Kim et al. in 2022. So, it is likewise agreed upon that hypothesis H4 and H5 are accepted.

3.5 Model Fit Indices

Two fit indices—Standardized Root Mean Square Residual (SRMR), d_ULS (squared Euclidean distance), and d_G (i.e., geodesic distance, Chi-square, Normed Fit Index (NFI), and Root Mean Square Residuals Theta (rms_Theta)—mean the quality of fit of

the model. According to Hu and Bentler (1998), a good match has an SRMR value lower than 0.08. The NFI should be as near to 1 as possible. According to Lohmöller (1989), NFI values greater than 0.9 often indicate a good match. The model's model fit indices are displayed in Table 6 as values. It demonstrates that the estimated model's SRMR value is.073, which is less than the model fit criterion of.08, and that the estimated model's NFI value is.853, which is acceptable (very near to 1).

Table 6: Model fit indices

Fit Indices	Saturated Model	Estimated Model
SRMR	0.063	0.067
d_ULS	8.396	12.319
d_G	3.726	4.218
Chi-Square	3462.674	3539.351
NFI	0.80	0.853
RMS_theta	.0182	.023
df = 1950, Chi-Square/ df = 1.78		

To show that the model has a good fit, the original value of the fit indices SRMR, d_ULS, and d_G should be lower than the upper bound of the confidence interval (Dijkstra and Henseler, 2015). The SRMR value is displayed in Table 7 along with the d_ULS value and the d_G value, both of which have 99% confidence intervals of 12.319 and 13.005. These show that SRMR, d_ULS, and d_G model fit requirements are well satisfied. The rms_Theta value should be close to zero for a successful model fit (Lohmöller, 1989). The rms_Theta value is.023, which denotes a satisfactory model fit, as seen in Table 6 above.

Table 7: The exact fit criteria

SRMR				
Saturated Model	0.063	0.075	0.087	0.094
Estimated Model	0.067	0.089	0.106	0.12
d_ULS				
Saturated Model	8.396	6.146	6.251	8.231
Estimated Model	12.319	7.263	10.195	13.005
d_G				
Saturated Model	3.726	2.667	3.24	4.423
Estimated Model	4.218	3.786	3.982	5.267

4.0 Conclusion

Around the world, education in artificial intelligence (AI) is becoming more and more significant. However, there isn't a test on the market right now to identify the pupils' current point of view. This study set out to develop a tool that would look at student intentions about the employment of AI. This study extends a UTAUT model to explain the objective of students learning about artificial intelligence. Educators can gain from assessing students' intentions to create a curriculum that encourages them to see AI learning favorably. Students' perceptions of AI in education as a novel technology contributed to highlighting the importance of attitude through the UTAUT. This study examines how students utilize and adapt to AI. It was shown that performance effectiveness, social influence, and enabling environments all significantly affect students' intentions to utilize AI. On the other hand, it has also been discovered that effort efficiency has no significant effect on the behavioral intentions of the pupils. This study further demonstrated how adoption influences actual usage. Additionally, it sparked the creation of five hypotheses regarding the goals of students about AI. Four hypotheses predicted a strong relationship between behavioral intention and actual usage behavior. Through an understanding of these concepts, we discovered that there is a connection between students' intentions and their actual usage behavior while applying AI. According to the study, students' intentions to adopt AI or adhere to the AI curriculum may be influenced by their comprehension of how AI might promote social welfare.

4.1 Theoretical implication

Our research generates significant literary contributions. First, the study adds to the growing body of research on AI in organizations. It expands on earlier conceptual studies that showed how useful AI may be for businesses. This model discovers a complete structure to understand how technologies based on AI have been accepted by social development organizations. This empirical study strengthens the case for the use of AI in team management and job execution (Larson and DeChurch, 2020). The results of the study may also aid in the adoption of technology as underdeveloped nations deal with the rise of AI. Considering their low degree of AI knowledge, the findings can be applied to other developing nations. As a result, the discovery may contribute to the establishment of an environment that encourages the use of AI-based technologies in social development organizations in developing nations. Third, the study adds to the body of knowledge about how the employment of AI affects team dynamics in an organizational setting. The majority of previous research on AI adoption in human teams has only been done in laboratory environments (Zhang et al., 2021). Fifth, the study makes a solid case for the UTAUT model's prediction that students would use AI-enabled technologies in social development organizations. Artificial intelligence aversion has been included in the model as an exogenous component that affects usage.

4.2 Practical implication

AI should be regularly applied to better university work settings to increase students' mental health and wellness. It should be mentioned that new artificial intelligence must be created to enhance student mental wellness and the psychological well-being of the educational system as a whole. New AI should be created and planned with consideration for their psychological requirements to lessen the stress of the studies and contribute to their physical and mental welfare, therefore extending the psychological advantages of AI throughout the entire educational system. The world nowadays is dominated by technology. Without converting them from manual to digital, no organization can last over the long term. Although AI adaption will initially confront enormous difficulties, the beneficial consequence is favorable to organizations' development. This study will help universities, independent organizations, company owners, the government, private firms, and HR consultants focus on policies to deal with issues of AI adaption and to protect best practices. As a result, educators can utilize it to assess pupils' existing conditions or confirm the efficacy of fresh AI teaching strategies. Bangladesh is placing a lot of emphasis on automation, control, and quick technical improvement in several industrial fields. The effective deployment of this system can increase productivity and make this nation more competitive on the world stage, which has just lately attracted the attention of government agencies and IT investors in this country. In addition to fostering industry innovation, the digitization of an economy also creates domestic job prospects, facilitating quicker economic growth. Furthermore, by reading this paper, IT investors, various businesses, and HR experts from various industries can gain more helpful information that they can utilize to create a future environment that is AI enabled across the nation.

4.3 Limitations

We have presented a model with significant explanatory power in this study. However, it is difficult to deny that this research study has certain particular shortcomings. The application of AI in higher education in Bangladesh is still in its infant stages. The responders don't have a lot of experience with AI. As a result, all of the syntheses are prognostic. We received 304 valid replies from the survey work. All of these inputs were from infrequent AI users. So, it is impossible to generalize this result. Adopters should utilize it with the necessary prudence. Results lack a global perspective because they are only dependent on information from institutions in Bangladesh. Even though the study is cross-sectional and only had a small sample size ($N = 304$), the survey was done in a very short amount of time. Since students gain new information via experience, their perceptions of PE, EE, SI, and FC may alter over time. In a survey, there is always a chance that terminology may be misunderstood, and we accept that participants can have varying definitions of some terms. Response bias occurs when respondents don't give their honest thoughts when responding.

4.4 Future directions

The study is carried out among Bangladeshi university students. To have a full picture of it, future research that could be conducted at other South Asian universities must also be examined. As a result, researchers may carry out a longitudinal study with a larger sample size to enable generalization of the findings in the future. Future studies can also make an all-encompassing effort to comprehend how different national cultures affect companies and, ultimately, how those cultures affect those organizations' adoption of AI-CRM. To obtain a clearer picture of the usage of AI in Bangladesh, future researchers are predicted to include more respondents with greater expertise in the field. Future research may be conducted by involving relevant constructs in the model.

References

- Alam, M. Z., Hu, W., & Barua, Z. (2018). Using the UTAUT model to determine factors affecting acceptance and use of mobile health (mHealth) services in Bangladesh. *Journal of Studies in Social Sciences*, 17(2).
- Alam, M. S., & Uddin, M. A. (2019). Adoption and implementation of enterprise resource planning (ERP): An empirical study. *Journal of Management and Research*, 6(1), 1-33.
- Alam, M. S., Dhar, S. S., & Munira, K. S. (2020). HR Professionals' intention to adopt and use of artificial intelligence in recruiting talents. *Business Perspective Review*, 2(2), 15-30.
- Alam, A. (2020). Possibilities and challenges of compounding artificial intelligence in India's educational landscape. Alam, A.(2020). *Possibilities and Challenges of Compounding Artificial Intelligence in India's Educational Landscape. International Journal of Advanced Science and Technology*, 29(5), 5077-5094.
- Aliyyah, R. R., Rachmadtullah, R., Samsudin, A., Syaodih, E., Nurtanto, M., & Tambunan, A. R. S. (2020). The perceptions of primary school teachers of online learning during the COVID-19 pandemic period: A case study in Indonesia. *Journal of Ethnic and Cultural Studies*, 7(2), 90-109.
- Alkhwaldi, A. F., & Abdulmuhsin, A. A. (2022). Crisis-centric distance learning model in Jordanian higher education sector: factors influencing the continuous use of distance learning platforms during COVID-19 pandemic. *Journal of International Education in Business*, 15(2), 250-272.
- Amin, R., Hossain, M. A., Uddin, M. M., Jonv, M. T. I., & Kim, M. (2022, July). Stimuli Influencing Engagement, Satisfaction, and Intention to Use Telemedicine Services: An Integrative Model. In *Healthcare* (Vol. 10, No. 7, p. 1327). MDPI.
- Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological bulletin*, 103(3), 411.

- Andrews, J. E., Ward, H., & Yoon, J. (2021). UTAUT as a model for understanding intention to adopt AI and related technologies among librarians. *The Journal of Academic Librarianship*, 47(6), 102437.
- Barton, D. C. (2020). Impacts of the COVID- 19 pandemic on field instruction and remote teaching alternatives: Results from a survey of instructors. *Ecology and evolution*, 10(22), 12499-12507.
- Bouktif, S., & Manzoor, A. (2021, April). Artificial Intelligence as a Gear to Preserve Effectiveness of Learning and Educational Systems in Pandemic Time. In *2021 IEEE Global Engineering Education Conference (EDUCON)* (pp. 1703-1711). IEEE.
- Brown, S. A., Dennis, A. R., & Venkatesh, V. (2010). Predicting collaboration technology use: Integrating technology adoption and collaboration research. *Journal of management information systems*, 27(2), 9-54.
- Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation*, 106, 102312.
- Chatterjee, S., Nguyen, B., Ghosh, S. K., Bhattacharjee, K. K., & Chaudhuri, S. (2020). Adoption of artificial intelligence integrated CRM system: an empirical study of Indian organizations. *The Bottom Line*. Emerald Publishing Limited, 33(4), 359-37.
- 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, 3443-3463.
- Chatterjee, S., Rana, N. P., Khorana, S., Mikalef, P., & Sharma, A. (2021). Assessing organizational users' intentions and behavior to AI integrated CRM systems: a Meta-UTAUT approach. *Information Systems Frontiers*, 1-15.
- Chaudhry, M. A., & Kazim, E. (2022). Artificial Intelligence in Education (AIED): A high-level academic and industry note 2021. *AI and Ethics*, 1-9.
- Cristianini, N. (2016). Intelligence reinvented. *New Scientist*, 232(3097), 37-41.
- Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: the state of the field. *International Journal of Educational Technology in Higher Education*, 20(1), 1-22.
- du Boulay, B. (2016). Recent meta-reviews and meta-analyses of AIED systems. *International Journal of Artificial Intelligence in Education*, 26(1), 536-537.
- Duan, Y., Cao, G., Xu, M., Ong, V., & Dietzmann, C. (2021, November). Understanding factors affecting the managers' perception of AI applications in information processing. In *Proceedings of the ECIAIR 2021 3rd European Conference on the Impact of Artificial Intelligence and Robotics* (p. 241). Lisbon: Academic Conferences and Publishing Limited.

- Dwivedi, Y. K., Rana, N. P., Jevaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, 21, 719-734.
- Dwivedi, Y. K., Hughes, D. L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J. S., ... & Upadhyay, N. (2020). Impact of COVID-19 pandemic on information management research and practice: Transforming education, work and life. *International Journal of Information Management*, 55, 102211.
- Dwivedi, YK, Ismagilova, E., Hughes, DL, Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., & Krishen, AS (2021) . Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management* , 59 , 102168.
- El Gourari, A., Skouri, M., Raoufi, M., & Ouatik, F. (2020, December). The Future of the Transition to E-learning and Distance Learning Using Artificial Intelligence. In *2020 Sixth International Conference on e-Learning (econf)* (pp. 279-284). IEEE.
- Gursoy D., Chi O., Lu L., Nunkoo R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *Int. J. Inf. Manag.* 49, 157–169.
- Hair, J.F., & Hult, G.T.M. (2016). A primer on partial least squares structural equation modeling (PLS-SEM). US: Sage Publication
- Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.
- Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In *New challenges to international marketing*. Emerald Group Publishing Limited.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, 43, 115-135.
- Hong, W., Chan, F. K., Thong, J. Y., Chasalow, L. C., & Dhillon, G. (2014). A framework and guidelines for context-specific theorizing in information systems research. *Information systems research*, 25(1), 111-136.
- Jacques Bughin, J. S., James Manyika, Michael Chui, and Raoul Joshi. (2018). Notes from the AI frontier: Modeling the impact of AI on the world economy. McKinsey Global Institute.
- Jain, R., Garg, N., & Khera, S. N. (2022). Adoption of AI-Enabled Tools in Social Development Organizations in India: An Extension of UTAUT Model. *Frontiers in Psychology*, 13.
- Jaradat, M. I. R. M., & Al Rababaa, M. S. (2013). Assessing key factor that influence on the acceptance of mobile commerce based on modified UTAUT. *International Journal of Business and Management*, 8(23), 102.

- Kandlhofer, M., Steinbauer, G., Hirschmugl-Gaisch, S., & Huber, P. (2016, October). Artificial intelligence and computer science in education: From kindergarten to university. In *2016 IEEE Frontiers in Education Conference (FIE)* (pp. 1-9). IEEE.
- Kashive, N., Powale, L., & Kashive, K. (2020). Understanding user perception toward artificial intelligence (AI) enabled e-learning. *The International Journal of Information and Learning Technology*. Emerald Publishing Limited, 38(1), 1-19.
- Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y. S., Kay, J., ... & Gašević, D. (2022). Explainable artificial intelligence in education. *Computers and Education: Artificial Intelligence*, 3, 100074.
- Kim, J., & Lee, K. S. S. (2022). Conceptual model to predict Filipino teachers' adoption of ICT-based instruction in class: using the UTAUT model. *Asia Pacific Journal of Education*, 42(4), 699-713.
- Kulik, J. A., & Fletcher, J. D. (2016). Effectiveness of intelligent tutoring systems: a meta-analytic review. *Review of educational research*, 86(1), 42-78.
- Larson, L., & DeChurch, L. A. (2020). Leading teams in the digital age: Four perspectives on technology and what they mean for leading teams. *The leadership quarterly*, 31(1), 101377.
- Li, J., Tan, X., & Hu, Y. (2021). Research on the framework of intelligent classroom based on artificial intelligence. *The International Journal of Electrical Engineering & Education*, 0020720920984000.
- McGovern, S., Pandey, V., Gill, S., Aldrich, T., Myers, C., Desai, C., ... & Balasubramanian, V. (2018). The new age: artificial intelligence for human resource opportunities and functions. *Ey. com*.
- Montesdioca G., Maçada A. (2015). Measuring user satisfaction with information security practices. *Comput. Secur.* 48, 267–280.
- Nasrallah, R. (2014). Learning outcomes' role in higher education teaching. *Education, Business and Society: Contemporary Middle Eastern Issues*, 7(4), 257-276.
- Nayal, K., Raut, R. D., Queiroz, M. M., Yadav, V. S., & Narkhede, B. E. (2021). Are artificial intelligence and machine learning suitable to tackle the COVID-19 impacts? An agriculture supply chain perspective. *The International Journal of Logistics Management*.
- Park, S. Y. (2009). An analysis of the technology acceptance model in understanding university students' behavioral intention to use e-learning. *Journal of Educational Technology & Society*, 12(3), 150-162.
- Popenici, S. A. D., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Res Pract Technol Enhanc Learn* 12 (1): 22. 1-13.

- Pullen, D., Swabey, K., Abadoo, M., & Sing, T. K. R. (2015). Pre-service teachers' acceptance and use of mobile learning in Malaysia. *Australian Educational Computing*, 30(1), 1-14.
- Ransbotham, S., Gerbert, P., Reeves, M., Kiron, D., & Spira, M. (2018). Artificial intelligence in business gets real. *MIT sloan management review*.
- Rishi Agarwal, B. B., Peter Clarke, Murali Gandi, Grant Waterfall. (2017). What's now and what's next in human resources technology. PWC.
- Russell, S. J. (2010). *Artificial intelligence a modern approach*. Pearson Education, Inc.
- Shen, C., & Chuang, H. (2010). Exploring users' attitudes and intentions toward the interactive whiteboard technology environment. *International Review on Computers and Software*, 5(2), 200-208.
- Sun, H., & Zhang, P. (2006). The role of moderating factors in user technology acceptance. *International journal of human-computer studies*, 64(2), 53-78.
- Sun, L., Tang, Y., & Zuo, W. (2020). Coronavirus pushes education online. *Nature Materials*, 19(6), 687-687.
- Turing, A. M. (2009). *Computing machinery and intelligence* (pp. 23-65). Springer Netherlands.
- Turing, A. M. (1936). On computable numbers, with an application to the Entscheidungsproblem. *J. of Math*, 58(345-363), 5.
- UNESCO. (2018). Positioning ICT in education to achieve the education 2030 agenda in Asia and the Pacific: Recommendations for a regional strategy. (<https://unesdoc.unesco.org/ark:/48223/pf0000261661>)
- UNESCO MGIEP. (2018). Artificial Intelligence and the Future of Education: Exploring how Artificial Intelligence can take Learning to a whole new level. Published by United Nations Educational, Scientific and Cultural Organization and Mahatma Gandhi Institute of Education for Peace and Sustainable Development. Available from: <https://unesdoc.unesco.org/ark:/48223/pf0000366389>. [Last accessed on 2020 March 18].
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186-204.
- Venkatesh, V., & Brown, S. A. (2001). A longitudinal investigation of personal computers in homes: Adoption determinants and emerging challenges. *MIS quarterly*, 71-102.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.
- Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178.

- Wahid-Uz-Zaman, M. G. M. (2019). Bracing Artificial Intelligence For Socio-Economic Development: Opportunities, Implications And Challenges For Bangladesh. *NDC E-JOURNAL*, 18(1), 1-22.
- Wang T., Jung C.-H., Kang M.-H., Chung Y.-S. (2014). Exploring determinants of adoption intentions towards Enterprise 2.0 applications: an empirical study. *Behav. Inf. Technol.* 33, 1048–1064
- Wang, Y. (2021). An improved machine learning and artificial intelligence algorithm for classroom management of English distance education. *Journal of Intelligent & Fuzzy Systems*, (Preprint), 1-12.
- World Economic Forum and The Boston Consulting Group. New vision for education unlocking the potential of technology industry agenda prepared in collaboration with the Boston consulting group. http://www3.weforum.org/docs/WEFUSA_NewVisionforEducation_Report2015.pdf (2015).
- Wold, H. (1985). Partial least squares. In S. Kotz & N.L. Johnson (Eds.), *Encyclopedia of statistical sciences* (pp. 581–591). New York, NY: Wiley
- Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—where are the educators?. *International Journal of Educational Technology in Higher Education*, 16(1), 1-27.
- Zhang, W. (2020). A study on the user acceptance model of artificial intelligence music based on UTAUT. *Journal of the Korea Society of Computer and Information*, 25(6), 25-33.
- Zheng, G. (2020, April). The optimization and application of blended teaching based on artificial intelligence. In *2020 3rd International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE)* (pp. 71-74). IEEE.