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Influencing factors of e-learning adoption amongst students in a developing country: the post-pandemic scenario in Bangladesh

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Abstract

E-learning is the consequence of the merging of technology and education, and it is now a highly efficient educational medium. Therefore, this study aims to explore the notion of continuous usage of online learning in education. Here, the study examined the key elements influencing whether Bangladeshi university students will continue usage of online learning following the outbreak. It explores a novel setting, extending the UTAUT model and laying the groundwork for upcoming scholars. The UTAUT3 model served as the theoretical foundation for the analysis of the relationship between the components using structural equation modeling. Additionally, this research was conducted as soon as face-to-face education resumed following each pandemic lockdown. According to the study's findings, among the independent variables-performance expectancy, social influence, and behavioral intention were the most important indicators of students' intention to continue use e-learning systems after the COVID-19 pandemic. Moreover, voluntariness of use on social influence was also found to be significant. This is one of the first studies to investigate a new technical service (e-learning services) in the extended framework of UTAUT3 model and gives us an understanding of reasons as to why students keep using e-learning following the epidemic. Furthermore, the findings of the current study provide an innovative perspective for Bangladeshi university administration and policymakers to assess and apply to ensure the successful application of e-learning technologies.

Keywords E-learning, Developing countries, Structural equation modeling, UTAUT3, Innovation in education, Usage behavior, Higher education

Introduction

The fast advancement of technology has resulted in the development of online learning programs, often known as virtual, distant, or electronic learning. Information and communication technologies (ICTs) offer special education and training opportunities as they foster innovation and creativity in people and organizations alike and contribute to better teaching and learning [63]. The availability of online learning reduces the need for a facilitator to be present in the classroom. The primary solutions of an e-learning system are inexpensive learning, the reduction of geographical gaps, and the availability of course content (using learning management systems). Online conferencing and classroom management tools such as Zoom, Microsoft Teams, Google Meet, and Google Classroom saw substantial use among college students [78]. If implemented properly, online education could help developing nations counteract some of the problems plaguing conventional classrooms. E-learning enhances output quality and institutional performance by making education accessible regardless of time or place and

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permitting better performance monitoring and skill development [13].

As many schools were forced to close to the COVID-19 pandemic emergency, remote teaching was developed [92]. While some schools had prior experience with distance learning, implementing it on a broad scale was challenging, and many children had never been exposed to online education before the pandemic. Since teachers have been pushed into remote online instruction, digital technology has played crucial in enabling them to instruct students remotely using a variety of online platforms and resources. Online education makes use of a variety of media, including video lectures, online courses, e-learning platforms (like Coursera), and electronic textbooks [42].

Bangladesh is among the many countries that have made the transition away from face-to-face classroom instruction and toward more modern forms of distance learning. A large number of prior research looked at the influence of system quality on students' and instructors' e-learning adoption intentions. The application of e-learning as the subject of study has been the focus of a plethora of studies (e.g. [67, 83]). Several research has also addressed e-learning adoption challenges in higher education during the COVID-19 pandemic [16, 54, 86, 87, 100].

This research aimed to determine what factors influence university students' behavioral intentions to adopt e-learning platforms in the post-pandemic normal/era (e.g., effort expectancy, performance expectancy, social influence, facilitating condition, and personal innovativeness in IT). The study looked at the most influential elements in determining whether Bangladeshi university students will use e-learning post-epidemic. The study used Structural Equation Modelling (SEM) to analyze the connection between the components and used the UTAUT3 model as a theoretical framework.

Furthermore, there is a scarcity of research on university students' behavioral intentions to use e-learning post the pandemic using the UTAUT3 model, which includes personal innovativeness in IT as a construct, especially in developing countries like Bangladesh, where e-learning was not widely used in universities before the pandemic. The fact that the research was done immediately after the successive lockdowns, i.e., with the return to face-to-face instruction, is crucial. Moreover, as the study will be more viable on tertiary level, where students are adults and autonomous learners, we have selected university students to be our respondents. Adopting e-learning (platforms) by students is essential for the effectiveness of online learning in this setting. After the pandemic, researchers believe blended and online learning will become the new normal globally [20, 30].

Literature review, hypotheses development and the theoretical framework

UTAUT3 model and e-learning

Farooq et al. [44] proposed the UTAUT-3 framework as an expansion to the UTAUT-2 model, which includes eight determinants of technology acceptance: PE, EE, SI, FC, HB, HM, reward value, and personal innovativeness in IT, which was included as the eighth element. UTAUT-3 was first used in a higher education setting, where it was used to examine an educational technology in an Asian nation, which is comparable to the context of this study. Finally, this study will add to theory in the field of e-learning adoption by testing a unique theoretical model in a new technical and cultural setting. To our knowledge, there is limited study on the influence of past learning achievement on e-learning intention.

The willingness of students to adopt an e-learning system is critical to the effectiveness of its implementation [11]. Additionally, Zalat et al. [106] pointed out that before COVID-19, developing nations undervalued e-learning, and that the present epidemic drove nations all over the world to rely on e-learning for education. Membership, classroom management, announcements, learning materials, Zoom links, learner groups, quizzes, learning records, grades, and grade processing systems are some of the aspects of e-learning [71]. Experts may convey their knowledge and skills to a large number of learners and assess their progress through e-learning, while learners can engage with experts and gain information [4]. Online education management systems (LMSs) are rapidly becoming an essential infrastructure for schools, businesses, and individuals committed to continuous education [57]. Students' success in online education is demonstrated by higher rates of course completion, greater levels of student satisfaction, and a greater desire to pursue further online education, as reported by Bernard et al. [25]. Moreover, several studies have found that online education is more effective than conventional approaches [60, 77].

The field of e-learning has piqued the interest of academics [58, 98, 93]. This is because of its potential to alter learning and expand its reach to include more individuals. It can improve living conditions by providing education to a larger population. Many researchers regard e-learning as a digital revolution and a significant educational accomplishment [66, 73] . It improves the learning process by delivering a cutting-edge virtual environment and student happiness [99]. It also allows for connectivity between different regions of the world and between instructors and students, giving an atmosphere and tools that encourage creativity and innovation [99]. The versatility of eLearning is one of its main characteristics [43]. It can provide both instructor-led and student-led courses, in which students select their learning schedules and tactics rather than adhering to a pre-determined course framework [12]. Additionally, because eLearning enables interaction between students, resulting in a process known as peer-learning [70, 74], the learning experience may be comparable to that of a social network [35].

Performance expectancy (PE)

PE was proposed as a direct determinant of BI in the UTAUT. PE was found to have a much stronger connection with BI than Effort Expectancy (EE) when compared to the other behavioral belief construct, Effort Expectancy (EE) [95], and the same finding has been reported in e-learning research [21, 34, 88]. Many studies have shown that PE significantly impacts BI's ability to use web-based learning resources [8, 34, 64]. Moreover, according to online learning studies, PE has a significant effect on learners' continuous usage of online learning platforms [7, 31, 61]. As a result, the following hypotheses proposed:

H1a Students' performance expectancy positively influences behavioral intention to use e-learning systems.

H1b There is a positive association between students' performance expectancy and continued usage behavior of e-learning.

Effort expectancy (EE)

Effort expectation is one of the critical components in studies on technology acceptance [14, 97]. It indicates how easy it is to use technology. Users' satisfaction is directly connected to effort expectation [15, 19], and it impacts satisfaction in online learning [15, 55]. According to a review of the literature, the bulk of the subsequent studies on student perceptions of technology use indicates the importance of EE in predicting the BI [2, 8]. Chen et al. [31] discovered that EE had a significant influence on learner continued Usage of LMSs. As a result, this factor is regarded as one of the most important in affecting Continued Usage of an e-learning platform for learning [7, 102]. It is expected that if students find the system simple to use, they will be more inclined to accept and use it. As a result, we provide the following hypotheses:

H2a Students' effort expectancy positively influences behavioral intention to use e-learning systems.

H2b There is a positive association between students' effort expectancy and continued usage behavior of e-learning.

Facilitating condition (FC)

In this investigation, the facilitating condition will be evaluated based on students' reports of their experiences with gaining access to relevant content and receiving adequate assistance while making use of the analyzed e-learning services. The external influence of facilitating conditions on decision-making is an essential antecedent of human behavioral roles within information systems studies [17, 24, 40, 101] and the e-learning environment. One of the most important factors in shaping people's propensities to act in particular ways is the impact of exogenous factors on their decision-making [34, 64, 91]. According to Ambarwati et al. [18], facilitating conditions do not impact behavioral intentions but do affect usage behavior. Furthermore, experts in e-learning and web-based learning research (e.g., [7, 61]) have discovered a favorable influence of facilitating conditions on learners' continued usage behavior. As a result, the researcher comes up with the following hypotheses:

H3a Students' facilitating condition positively influences behavioral intention to use e-learning systems.

H3b There is a positive association between students' facilitating condition and continued usage behavior of e-learning.

Personal innovativeness in IT

Individual inventiveness is often seen as an essential factor in building good attitudes regarding using new technologies [23]. In this scenario, new technology may imply e-learning. Because they are more or less open to change and prepared to take more or less risk, these individuals adopt innovations earlier than others [3, 37, 48, 65, 75, 105]. According to Martins [65], individual innovativeness theory has been shown to be a beneficial tool in designing short- and long-term strategic plans to boost technology integration in schools, especially in higher education institutions. Both user intention and technology usage behavior are influenced by PI [47]. Furthermore, several scientists have proven that personality traits such as PI impact technology adoption, particularly in the domain of IT [39, 44]. As a result, the following hypotheses has been proposed:

H4a Students' personal innovativeness in IT positively influences behavioral intention to use e-learning systems.

H4b There is a positive association between students' personal innovativeness in IT and the continued usage behavior of e-learning.

Social influence (SI)

People might be affected by others' opinions and hence participate in certain behaviors even if they don't want to justify SI's direct effect on BI. According to Venkatesh and Davis [94], the impact of SI occurs exclusively in forced situations and has no impact in voluntary ones. Students' decisions to use and accept e-learning systems are frequently impacted by demands from other colleagues/students and superiors/lecturers [34, 64, 81, 91]. The previous studies indicated that social influence has a substantial effect on actual usage and continued usage of online learning platforms [7, 31, 104]. As a result, the following hypotheses proposed in this study:

H5a Social influence positively influences behavioral intention to use e-learning systems.

H5b There is a positive association between students' social influence and continued usage behavior of e-learning.

Voluntariness of use

The degree to which use of the invention is viewed as voluntary or of free will is described as voluntariness of usage [72]. Buche et al. [29] discovered that those with a lower degree of past educational performance are more likely to do poorly if they also have a lower willingness to accept technology than their peers who have a greater willingness to accept technology. Sufficient resources make it easier to implement new technological systems [27, 28]. This has repercussions on how potential users, as well as experienced users, interact with technology systems. Attuquayefio and Addo [22], and 29, 30 found a positive and significant relationship between the two variables in their studies, explaining that the environment created within an organizational framework for technology uptake serves as a proxy that has direct control over user behavior. Bervell and Arkorful [26] stated that voluntariness of the usage condition of technology has an influence on user behavior patterns and have empirically validated this association in LMS study. Furthermore, Shin and Dai [84] found that when people see how easy it is for others to utilize technology, they are more likely to use it themselves. Thus, hypotheses proposed as following:

H6a Students' voluntariness of use positively influences behavioral intention to use e-learning systems.

H6b There is a positive association between students' voluntariness of use and continued usage behavior of e-learning.

H6c Students' voluntariness of use significantly impacts the e-learning system's social influence.

Behavioral intention

Behavioral intention (BI) refers to a person's intention to embrace the usage of a given technology for various tasks [5]. In a paper, Nicholas-Omoregbe et al. [69] found that students' BI on adopting an e-learning system has a positive relationship with their usage behavior, which leads to improved marks. Many researchers [38, 85] have looked at students' intentions in the online learning environment and found it to be a significant effect. The degree to which users perceive their propensity to engage in continuous usage behaviors is referred to as continued usage intentions [107]. With an increase in behavioral intention, students will attempt harder to engage usage behaviors. There are substantial connections between usage intentions and behaviors, and individuals' choices in the IT field have been shown to significantly impact continued usage behavior [80]. It is proposed as follows:

H7 Students' behavioral intention to choose e-learning positively correlates with a continued usage behavior.

UTAUT3 model justification

The developers of the UTAUT-3 model claim that it has a 66% explanatory power in forecasting technology uptake [47]. The teaching sector has mostly neglected technology adoption, but the UTAUT 3 theory has highlighted technology adoption with reference to e-learning in the context of the teaching sector [6, 47]. This study underlined the significance of e-learning by combining UTAUT and UTAUT 3 theoretical principles. As a result, this approach explored the impact of effort expectation, performance expectancy, social influence, personal innovativeness in IT and facilitating conditions on behavioral intention to utilize e-learning by removing certain insignificant variables from UTAUT 3 theory. Furthermore, the association between behavioral intentions to utilize e-learning and e-learning continued usage behavior was also underlined.

Venkatesh et al. [95] examined the moderator factors of gender, age, experience, and voluntariness of usage in the original UTAUT model. University students in our study are the same age group (20–24 years old) and have similar experiences with the e-learning system. As a result, we did not take into account the moderator factors of age, gender and experience and have only investigated the impact of voluntariness of use on social influence, behavioral intention and continued usage behavior (Fig. 1).

Research methodology

Target population

The target population for this analysis is Bangladesh students of e-learning services. These student groups represent a considerable proportion of the total number of education services consumers. In Bangladesh, the number of people using e-learning services is also increasing due to the increasing number of internet users. Our research aimed to identify the students' influencing factors towards adoption behavior on the tertiary level. Students from various Bangladeshi private and public universities provided data for this study.

Measures

Appendix Table 8 shows the details of measurement scales and the statements overview. The study employed quantitative survey methods to test hypotheses and generate responses to the research questions. A self-administered questionnaire was circulated using Google forms to obtain empirical data. The items selected for the constructs in our research were mainly adapted from previous studies and modified to fit e-learning adoption in the context of Bangladesh. The questionnaire was divided into three components; the first was responsible for capturing user data and experiences. The second set included 20 items that rated UTAUT3 assertions on a five-point scale with "strongly disagree" and "strongly agree" as endpoints. Finally, the final component had ten things that ordered UTAUT3 statements on a five-point scale with "strongly disagree" and "strongly agree" as endpoints. The respondents took an average of 20 min to complete the questionnaire. The eight constructs that were selected, namely, Performance expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Personal Innovativeness, Voluntariness of Use, Behavioral Intention, and Continued Usage Behavior. The questionnaire includes both favorably and negatively phrased items to reduce acquiescent bias.

Pretesting

A pretest was undertaken to improve the questionnaire's content validity. The questionnaire was tested with thirty respondents selected for the pilot test before starting. The findings obtained from the questionnaire were changed due to specific problems found during the pre-pilot test; thus, adjustments were made accordingly. Based on the pretest tests, the products that matched the definitions of interest and purpose to follow were kept.

Questionnaire design and data collection

The respondents for the research were screened for whether they had previously used e-learning services—only those who had previously experienced e-learning services were given the questionnaire. The first part of the questionnaire consisted of questions based on the respondents' demographic profiles, and the second part included questions about each variable in the research model. Due to the absence of a reliable list of e-learning services users and their addresses, a convenience sampling method was used as the survey instrument. The convenience sampling method is cost-effective and has been widely accepted in Information System Research [76]. All respondents were given consent forms and

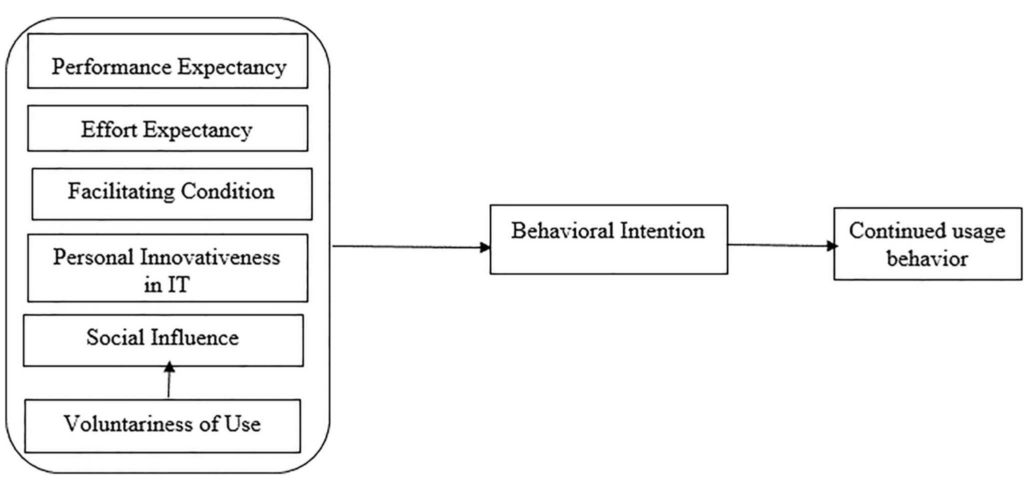

Fig. 1 A proposed research model. *Source*: Proposed by researchers

information sheets explaining the study's purpose. There were 34 questions in the questionnaire, and the respondents were given enough time to fill up the state at their convenience. Approximately 300 questionnaires were returned, and 15 incomplete questionnaires were excluded from the analysis. After removing the incomplete cases and outliers, 285 valid responses were obtained and were subjected to further analysis.

Statistical tool

The present study used partial least square grounded structural equation modeling (SEM-PLS3.3.9), which focuses on the principle component concept [62]. In a study, the researchers [50] mentioned SEM-PLS as a nonparametric approach appropriate to examine the cause-effect relationship. Besides, covariance-based structural equation modeling (CB-SEM) is used, which indicates the factor analysis that uses maximum likelihood estimation [62].

Data analysis and results

Demographic characteristics

Table 1 shows the details of the demographic profile of the respondents. A well-structured self-administered survey questionnaire's cross-sectional data set has been used to investigate the students' factors towards the e-learning system—structural Equation Model (SEM) by running the SmartPLS3.3.9 version. The 285 respondents surveyed, 50.88% were male, and 49.12% were female. The majority of respondents, 83.12%, age group between 21 and 25 years. Regarding the level of education, 55.44% of respondents belonged to the undergraduate level. In comparison, most respondents considered e-learning facilitating better conditions and convenience, whereas the proportion covered 41% (see Table 1).

The measurement model assessment

Table 2 shows composite reliability, factor loading, average variance extracted, and Cronbach's alpha were used to examine the characteristics of reliability, convergent validity, and discriminant validity on SmartPLS3.3.9. The average variance extracted (AVE) for each measure, the composite reliability index, and the internal consistency reliability have all been used to assess convergent validity [51]. In this investigation, a relative measurement model was applied to each set of multiple-item scales, resulting in a total of eight latent variables.

Both the construct reliability and outer model values, shown in Table 2, were greater than 0.7, showing convergent validity. It was determined by Vinzi et al. [41] that an outside values of 0.5 or higher is acceptable, hence this number is now commonly used as a rule of thumb. Cronbach's alpha was used to calculate composite reliability scores for the measuring scales in this study, and the validity of convergent and internal accuracy was calculated using the AVE. The results demonstrated that Cronbach's alpha was above 0.6, indicating that the scales' internal consistency was adequate [51]. Additionally, the average variance estimates (AVEs) were utilized to characterize the range of measurement for each construct of interest, and those with AVEs greater than 0.5 were considered to be reliable [33]. An estimated coefficient of 0.564 to 0.842 was found in the data analysis. Cohen [36] measured their different implications of adjusting

Table 1 Demographic profile of the respondents. *Source*: Researchers' computation

Demographic attributes	Category	Frequency	Percentage (%)
Gender	Male	145	50.88
	Female	140	49.12
Age	15–20	15	5
	21–25	237	83.12
	26–30	30	10.53
	Above 30	03	1.05
Level of education	Higher Secondary	06	2
	Undergraduate	158	55.44
	Graduate	51	17
	Post-graduate	69	23
Reasons for using e-learning (Multiple options)	Facilitates better learning	123	41
	Saves resources	51	17
	Convenient	123	41
	Better time management	84	28
	Self-paced learning	104	34.7
	Added flexibility	97	32.3

Table 2 Construct reliability and the results of the outer model. *Source*: SmartPLS 3.3.9 analysis

Constructs	Measurement items	Loadings	Cronbach's alpha (*α*)	Composite reliability (CR)	Average variance extracted (AVE)	*R*-square (R^2)
Performance expectancy	PE1	0.879	0.854	0.900	0.694	
	PE2	0.876				
	PE3	0.769				
	PE4	0.802				
Effort expectancy	EE1	0.794	0.862	0.906	0.706	
	EE2	0.846				
	EE3	0.842				
	EE4	0.877				
Facilitating condition	FC1	0.821	0.842	0.905	0.761	
	FC2	0.866				
	FC3	0.926				
Personal innovativeness in IT	PPIT1	0.892	0.802	0.880	0.712	
	PPIT2	0.734				
	PPIT3	0.896				
Social influence	SI1	0.904	0.906	0.941	0.842	
	SI2	0.929				
	SI3	0.919				
Voluntariness of use	VoU2	0.708	0.615	0.795	0.564	0.005
	VoU3	0.758				
	VoU4	0.785				
Behavioral intention	BI1	0.872	0.864	0.917	0.787	0.291
	BI2	0.871				
	BI3	0.918				
Continued usage behavior	CUB1	0.914	0.752	0.889	0.800	0.570
	CUB2	0.874				

for changes in the endogenous variable(s): a modest impact ($R^2=2\%$), a medium impact ($R^2=13\%$), and a significant impact ($R^2=26\%$). According to the results, the behavioral intention significantly affects the exogenous variables effect size 0.291 or 29.1%. Currently, sustained usage behavior influences 0.570, or 57%, of the exogenous factors. Additionally, the exogenous variables are hardly affected by the voluntariness of usage 0.050 or 5%.

Indicators from Stone Geisser indictor's (Q^2) and Cohen's indicator (f^2) are displayed in Table 3. In the context of structural equation models, Chin [32] noted that Q^2 value above zero indicates predictive relevance,

Table 3 Values of Stone Geisser indicator (*Q* square) and Cohen's indicator (*f*-square) of the model

Variables	Q^2	Behavioral intention (f^2)	Continued usage behavior (f^2)	Social influence (f^2)
Performance expectancy	0.487	0.080	1.327	
Effort expectancy	0.500	0.002		
Facilitating condition	0.503	0.004		
Personal innovativeness in IT	0.427	0.000		
Social influence	0.640	0.021		
Behavioral Intention	0.544			
Continued usage behavior	0.360			
Voluntariness of use				0.053

Large effect > 0.34; medium effect > 0.14; small effect > 0.01 [36] whereas a value below zero indicates a lack of predictive relevance. Cohen [36] states that values 0.02, 0.15, and 0.35 for the relative predictive relevance predictor suggest that the construct has minor, medium, or high predictive relevance to the predicted model. In this experiment, the predictive relevance of the model was assessed in a blindfolding using the cross-validated communality method. According to Table 3, there is also little correlation between performance expectancy, effort expectancy, facilitating condition, personal innovativeness in IT, and social influence on behavioral intention. Thereafter, the behavioral intention has a substantial effect on the continued usage behavior. There is also just a minimal effect on social influence from the fact that voluntariness of use.

Discriminant validity: Fornell–Larcker criterion

Henseler et al. [53] mentioned two ways to discriminant validity measures, one is the Fornell–Larcker criterion, and another is cross-loadings. The cross-loadings values were acceptable according to the recommended value of the previous literature. Fornell–Larcker was used to measure the discriminant validity between variables. Furthermore, Fornell–Larcker's discriminant validity was assessed by comparing the square root of the AVE, which will be greater than the correlations between the constructs [45]. In Table 4 shows the matrix of the Fornell–Larcker criterion model.

Moreover, in Table 5, the researchers showed the Heterotrait–Monotrait Ratio (HTMT) analysis matrix. The suggested value of HTMT is below 0.9, and the analyzed result passed the rule of thumbs lower than the recommended value presented by Gold et al. [46]. Then, it concluded that the analyzed result has no issue with the discriminant validity.

The structural model assessment

Structural model test

To assess the structural model test, firstly, the SmartPLS algorithm is run, and the results of VIF are presented in Table 6 (see Table 6). In a study, Hair et al. [52] mentioned that collinearity is the measure of variance inflation factor. Besides, Hair et al. [49] recommended that a potential collinearity problem exists if the VIF value is 5.0 or higher. According to the existing literature's recommended VIF value, the output passed the cut-off value, and the analyzed result ensured that collinearity is not an issue in this structural model.

Table 4 Fornell and Larcker criterion model

Constructs	BI	CUB	EE	FC	PE	PITT	SI	VoU
BI	*0.887*							
CUB	0.755	*0.894*						
EE	0.428	0.365	*0.840*					
FC	0.357	0.245	0.709	*0.872*				
PE	0.510	0.474	0.681	0.513	*0.833*			
PIIT	0.270	0.279	0.482	0.551	0.452	*0.844*		
SI	0.399	0.366	0.488	0.398	0.547	0.367	*0.917*	
VoU	0.161	0.197	0.098	0.220	0.101	0.270	0.224	*0.751*

Italic values represent the square root of AVE

Table 5 Heterotrait–monotrait ratio (HTMT)

Constructs	BI	CUB	EE	FC	PE	PITT	SI	VoU
BI								
CUB	0.899							
EE	0.485	0.437						
FC	0.416	0.305	0.837					
PE	0.579	0.578	0.784	0.596				
PIIT	0.311	0.358	0.569	0.651	0.549			
SI	0.451	0.442	0.547	0.459	0.627	0.447		
VoU	0.218	0.294	0.169	0.307	0.151	0.404	0.296	

Table 6 Collinearity statistics (VIF)

Items	VIF	Items	VIF	Items	VIF	Items	VIF
BI1	2.082	PIIT1	2.002	EE4	2.332	PE3	1.757
BI2	2.188	PIIT2	1.492	FC1	1.771	PE4	1.980
BI3	2.786	PIIT3	1.946	FC2	2.209	EE2	2.078
CUB1	1.569	SI1	2.778	FC3	2.831	EE3	2.309
CUB2	1.569	SI2	3.154	VoU2	1.157		
PE1	2.308	SI3	2.948	VoU3	1.305		
PE2	2.392	EE1	1.804	VoU4	1.254		

Test of hypotheses

Table 7 displays the direct and indirect effect path coefficients of the hypotheses. Bootstrapping of the PLS was used to examine t-values in statistics. In this case, the p value for SmartPLS3.3.9 was computed using a 95% confidence interval. The purpose of the bootstrapping is to calculate the standard error of the estimations of the coefficients in order to test the statistical significance of the coefficients [41]. The researchers came up with 14 hypotheses that shed light on the connections. According to the data shown in Table 7, there is a positive and substantial relationship between performance expectancy and behavioral intention ($\beta=0.347$, $t=4.137$, $p=0.000$). Performance expectancy positively correlates with continued usage behavior ($\beta=0.262$, $t=3.957$, $p=0.000$), confirming H1a and H1b. So, the analyzed hypotheses H1a and H1b are sustained. Effort expectancy has found insignificant influence on behavioral intention to use e-learning system ($\beta=0.076$, $t=0.811$, $p=0.418$) and continued usage behavior ($\beta=0.057$, $t=0.810$, $p=0.418$). Hypotheses H2a and H2b did not support the proposed hypotheses. Besides, facilitating condition has found insignificant influence on behavior intention to use e-learning system ($\beta=0.074$, $t=1.102$, $p=0.271$) and continued usage behavior ($\beta=0.055$, $t=1.106$, $p=0.276$). Here, hypotheses H3a and H3b did not support the proposed hypotheses. Furthermore, personal innovativeness in IT has been found to have a negative and insignificant influence on behavioral intention ($\beta=-0.015$, $t=0.302$, $p=0.763$) and continued usage behavior ($\beta=-0.012$, $t=0.300$, $p=0.765$), which did not support the proposed hypotheses H4a and H4b. Conversely, social influence significantly positively impacts behavioral intention ($\beta=0.149$, $t=2.181$, $p=0.030$) and continued usage behavior ($\beta=0.113$, $t=2.156$, $p=0.032$), which confirmed the proposed hypotheses H5a and H5b. Moreover, the voluntariness of use has been found to have an insignificant influence on behavioral intention ($\beta=0.035$, $t=1.823$, $p=0.069$) and continued usage behavior ($\beta=0.026$, $t=1.837$, $p=0.067$), which rejected the proposed hypotheses H6a and H6b. Finally, the voluntariness of use has been found to have a significantly

Table 7 Result of path coefficients for direct and indirect hypotheses effects

No.	Hypotheses	Path Coefficient (β)	Standard error	t-value	p value	Decision
H1a	PE->BI	0.347	0.084	4.137	0.000	Supported
H1b	PE->CUB	0.262	0.067	3.957	0.000	Supported
H2a	EE->BI	0.076	0.087	0.811	0.418	Not supported
H2b	EE->CUB	0.057	0.065	0.810	0.418	Not supported
H3a	FC->BI	0.074	0.073	1.102	0.271	Not supported
H3b	FC->CUB	0.055	0.055	1.106	0.276	Not supported
H4a	PIIT->BI	− 0.015	0.069	0.302	0.763	Not supported
H4b	PIIT->CUB	− 0.012	0.052	0.300	0.765	Not supported
H5a	SI->BI	0.149	0.068	2.181	0.030	Supported
H5b	SI->CUB	0.113	0.052	2.156	0.032	Supported
H6a	VoU->BI	0.035	0.018	1.823	0.069	Not supported
H6b	VoU->CUB	0.026	0.014	1.837	0.067	Not supported
H6c	VoU->SI	0.238	0.061	3.653	0.000	Supported
H7a	BI->CUB	0.755	0.034	22.167	0.000	Supported

positive impact on social influence ($\beta=0.238$, $t=3.653$, $p=0.000$), which confirmed the proposed hypothesis H6c. In addition, the behavioral intention significantly positively influences continued usage behavior ($\beta=0.755$, $t=22.167$, $p=0.000$) and confirmed the proposed hypothesis H7 (Fig. 2).

Discussion

COVID-19 has significantly impacted the global education system in these current circumstances. Education institutions shifted physical activities to the online learning system. Students no longer rely on physical classrooms for their education purposes except in the context of the global pandemic, especially the youth of today's generation. The study seeks to explore from students' perspective the process by which students intend to adopt an e-learning system during the COVID-19 pandemic, particularly in online learning facilities. This study represents one of the initial researches in a developing country context, especially in Bangladesh, to analyze students' adoption of online teaching during the COVID-19 pandemic. The study confirmed the role of performance expectancy, effort expectancy, facilitating condition, personal innovativeness in IT, and social influence on e-learners' technological adoption during the crisis. In this study, we formulated 14 hypotheses that accept the proposed hypotheses and somewhere rejected. The researchers presented the research model and empirically tested the model of students' factors towards adopting an e-learning system.

Performance expectancy was one of the significant predictors of students' behavioral intention and continued usage behavior to adopt e-learning facilities. As expected, the main concern for students was enhancing their academic performance using the e-learning system. The study result was consistent with a previously executed study that led to the adoption of new technologies [1, 68, 79, 90]. Besides, effort expectancy was found insignificant in this current study. In India, Mittal et al. [68] found a similar consistent outcome in adopting online teaching in higher education during the COVID-19 pandemic. In this present study, we did not find that facilitating conditions significantly impact e-learning usage behavior, which justified the similar finding of the previous study [108]. In India, a study by Mittal et al. [68] focused on adopting online teaching in higher education during the COVID-19 pandemic. They also found the insignificant association of facilitating conditions with students' behavioral intention and continued usage behavior to adopt an e-learning system. Besides, Samsudeen and

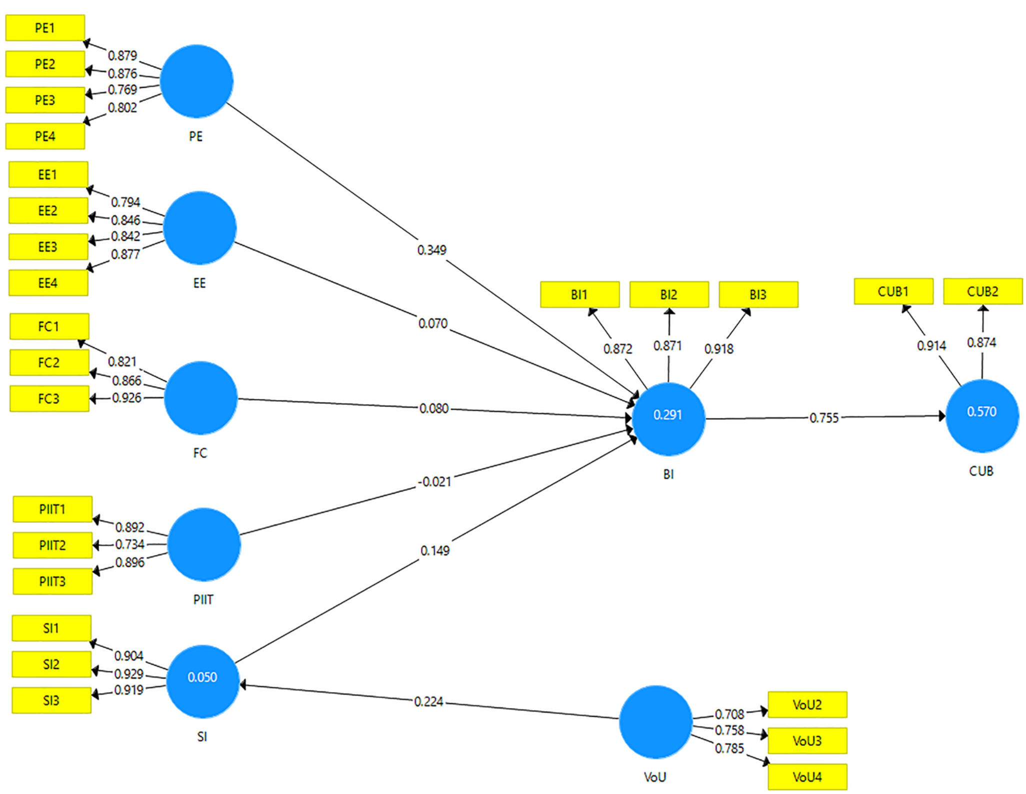

Fig. 2 A structural path model analysis

Mohamed [79] also focused on Sri Lankan university students' perspectives intending the e-learning system, which is also interpreted as insignificant in terms of facilitating conditions and behavior intention. Besides, Ambarwati et al. [18] found that facilitating conditions do not impact behavioral intentions but do affect usage behavior.

The construct, personal innovativeness in IT, found a negative and insignificant relationship between students' behavioral intention and continued usage behavior to adopt e-learning systems. Shetu et al. [82] also found the perceived technological innovativeness insignificant and negative path coefficient to adopt digital wallet in developing country Bangladesh perspective. The present study finding was inconsistent with previous study results that indicated developing country perspectives [90]. These findings justified the not supported construct. Students' social influence plays a significant role in affecting behavioral intentions in the e-learning system. Similar findings interpreted by the researchers justified the context, especially from developing countries' perspectives [79, 90, 108]. The direct and most significant construct behavioral intention has been found to have a significant association in relationship with the continued usage behavior of students in e-learning systems. This study finding revealed that behavioral intention had a strong effect that indicated higher acceptance of e-learning among university-level students. The result also showed consistency in the previous research [1, 79, 90].

Finally, the voluntariness of use in e-learning systems was insignificant between behavioral intention and continued usage behavior. The study finding also supported the existing literature [90]. In addition, Buche et al. [29] discovered that those with a lower degree of past educational performance are more likely to do poorly if they also have a lower willingness to accept technology than their peers who have a greater willingness to accept technology. Besides, the relationship between voluntariness of use and social influence was found significant and sustained that supported the existing literature [26]. In summary, the findings of this study enhanced knowledge of reasons as to why students keep using e-learning following the epidemic.

Contribution to theory

Concerned with a theoretical component, the current study created a conceptual research model to understand better the aspects that influence students' adoption of the e-learning system in Bangladesh. This empirical study contributes to e-learning adoption in developing countries, particularly Bangladesh. This study goes beyond what Venkatesh et al. [95] proposed in UTAUT by including two new constructs (personal innovativeness in IT and continued usage behavior) alongside the UTAUT constructs. These new significant variables of e-learning adoption contribute to the research on information technology adoption behavior in developing nations and account for elements unique to this kind of setting. As a result, this study is one of the first to examine a new technology (a smartphone application), new technical services (e-learning services), and analyze a new environment, expanding the UTAUT model (i.e., Bangladesh). Combining these two extra variables with the UTAUT model is unusual in literature since no other study has done so in a developing country setting.

In terms of methodological aspects, the study has effectively confirmed and validated the research model, causing researchers to pay more attention to quantitative methods. In this study, structural equation modeling (SEM) was used as a statistical analytic tool in education. It's also worth noting that educational research lacks an SEM-based strategy to assess the study situation critically in Bangladesh. As a result, this study provides a foundation for future researchers (particularly in educational research) and thorough statistical analysis.

Implication for practice

The suggested research model was validated with empirical data in this study. The study adds to the body of information in IS adoption theory, particularly in the acceptance of e-Learning by students in underdeveloped nations. The findings can help administrators, instructors, teaching assistants, and policymakers plan and implement their online approach and make informed decisions on how to encourage more students to adopt e-Learning. The findings of this study suggested that behavioral intention significantly impacted the adoption of the e-learning system among university students. If policymakers fail to promote a good view of e-learning among students, the usage of e-learning systems will be worthless.

It is important to emphasize that the spike in this pandemic has quickly stimulated innovation and development in various aspects of everyday life, particularly within the framework of academic innovativeness (including technical growth and development). Thus, the evidence suggests that the country's management and policymakers should reconsider and provide the true necessary logistics and infrastructure for the current e-learning system, while also using this cue as a guideline to improve e-learning system usage among students and instructors. There should be an introduction of policies and guidelines to encourage trial usage and install usage via experience, as well as ongoing awareness development and periodic reviews of the e-learning system to recognize system defects and improve to be more user friendly. Due to these safeguards, a larger student body will be able to make use of e-learning as a means of receiving their education. It is also possible to improve cloud infrastructure in developing countries by replicating the successful implementation of e-learning system in developed nations.

Limitations and future research of the study

As with other studies, the present research has undergone some limitations. The researchers adopted the non-probability convenient sampling procedure to collect the primary data. However, the sampling method did not show the majority representation of the entire student population in Bangladesh, especially in public and private universities. The sampling collection procedure was biased in selecting the expression of both categories' universities. Hence, the findings of this investigation are confirmed in the context of the developing country, Bangladesh; in generalizability, the researchers can take care of citations from developing countries' perspectives.

Furthermore, in the future, the researchers can increase the sample sizes; apply the new sampling procedure predominantly longitudinal data to validate the research outcome more precisely. The researchers can focus on the cross-sectional data set, and the mixed-method research technique could also consider focusing on the researcher's time, effort and resources. Moreover, in future studies, the researchers can expand the research model by incorporating constructs, moderating, and mediating effects to underline the intention to adopt e-learning facilities in the tertiary education system. During the COVID-19 pandemic in Bangladesh, most educational institutions applied an e-learning system to make the education facilities smooth. This study focused on students' factors to understand the e-learning system. Future studies can also investigate the effectiveness of university students where e-learning systems are developed. Besides, knowing about the academicians' perspective and their intention to adopt e-learning systems could be another research dimension to understanding this continuum.

Conclusion

This study contributes to the exploration of enabling factors for the use of e-learning systems post-COVID-19 epidemic, particularly in less digitalized economies and is mainly focused on the tertiary level of education. The proposed theoretical model validated the study context in Bangladesh, especially in higher education, and the measurement model fitted well with the empirical data to proceed with the hypothesis testing. The study findings revealed that performance expectancy, social influence, behavioral intention, and voluntariness of use in between social impact were the most significant predictors of students' behavioral intention towards using e-learning systems post-pandemic. Adopting the UTAUT3 model, the researchers tested the students' factors in incorporating an e-learning system in their educational system. As a result, the current study's findings constitute a new contribution for Bangladeshi university administration and policymakers to analyze and use to ensure the successful use of e-learning systems. Moreover, the researchers suggest that as a remote learning tool e-learning system can make positive changes in academician, professionals, government, and non-government educators to create sustain and likely impact on the e-learning system in these circumstances and beyond the COVID-19 pandemic. Again, the development of components in the conceptual model is a unique and primarily relevant e-learning approach for university administration and education practitioners in underdeveloped nations seeking to secure long-term academic service delivery.

Appendix

See Table 8.

Table 8 Measurement items

Constructs	Code	Statements	Sources
Performance expectancy	PE	PE1: I find the e-learning system useful in my life PE2: Using an e-learning system increases my chances of meeting my needs PE3: Using the e-learning system enables me to accomplish learning activities more quickly PE4: Using the e-learning system increases my learning productivity	[9, 10, 95, 97]
Effort expectancy	EE	EE1: I am skillful at using the e-learning system EE2: Learning to use the e-learning system is easy for me EE3: My interaction with the e-learning system is clear and easy to understand EE4: I find it easy to get the e-learning system to do what I want	[9, 10, 96]
Social influence	SI	SI1: People who are important to me think I should use the e-learning system SI2: People who influence my behavior think that I should use the e-learning system SI3: People whose opinions I value prefer that I use the e-learning system SI4: In general, the university has supported the use of the e-learning system	[9, 10, 96]
Facilitating condition	FC	FC1: I have access to the financial support I need to use the e-learning system FC2: I have the necessary knowledge to use the e-learning system FC3: I have the resources required to use the e-learning system FC4: If I have any doubts about how to use the e-learning system, there will be professionals to help me FC5: The management has provided enough support for using the online learning system and face-to-face interaction	[26, 59]
Personal innovativeness in IT	PITT	PITT1: If I heard about a new thing/technology, I would look for ways to experiment with it PITT2: I am usually the first to try a new thing/technology among my peers PITT3: I like to experience a new thing/technology	[103]
Voluntariness of use	VoU	VoU1: Any online learning system that supports face-to-face distance education delivery should be optional VoU2: Although it might be helpful to use the online learning system to support face-to-face teaching and learning, it is not made compulsory VoU3: I am being forced to use the online learning system in addition to face-to-face instruction VoU4: The institution does not require me to use the online learning system in addition to the existing face-to-face teaching and learning mode	[26]
Behavioral intention	BI	BI1: I intend to continue using e-learning in the future BI2: I will always try to use e-learning in my daily life BI3: I plan to continue to use e-learning services Frequently	[89, 97]
Continued usage behavior	CUB	CUB1: I intend to continue using the e-learning system rather than discontinue its use CUB2: I intend to continue using the e-learning system rather than use any alternative means CUB3: If I could, I would like to discontinue my e-learning system	[56]

Abbreviations

PE	Performance expectancy
EE	Effort expectancy
FC	Facilitating conditions
PIIT	Personal innovativeness in IT
SI	Social influence
BI	Behavioral intention
CUB	Continued usage behavior
VoU	Voluntariness of use

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Author contributions
KM is a principal investigator who led the research and drafted the paper, the research framework, and the data collection procedure. SNS is a co-author who was responsible for the conducted the data analysis, drafting the results, and discussing the manuscript. Furthermore, all authors have read and approved the manuscript.

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Availability of data and materials
The datasets used during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
The researchers provide the consent form to the participants in the data collection procedure. The participants gave their full consent and the researchers collected the primary data.

Consent for publication
Co-authors gave their consent for publication.

Competing interests
The authors declare no competing interests exist in this article.

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