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Factors Influencing Technology Adoption in Online Learning among Private University Students in Bangladesh Post COVID-19 Pandemic

Md Shuhel Miah [1,*], Jugindar Singh Kartar Singh [2] and Mohammed Abdur Rahman [3]

1 School of Business, Brittany University, 75007 Paris, France
2 School of Business, Asia Pacific University of Technology and Innovation, Kuala Lumpur 5700, Malaysia
3 Faculty of Business and Entrepreneurship, Daffodil International University, Dhaka 1341, Bangladesh
* Correspondence: shuhel@brittanyuniversite.fr

Abstract: Technology acceptance in higher education, especially during and after the crisis of COVID-19, is very important in the current environment, especially in online learning adoption. This study aimed to determine the impact of performance expectancy, effort expectancy, social influence, and facilitating conditions on the adoption of the online line among university students in Dhaka in the post-pandemic period. In addition, the moderating role of voluntariness was also ascertained. In this quantitative study, primary data were collected using a survey method. The target population was students of private universities located in Dhaka, Bangladesh. There was a total of 130 respondents, and non-probability sampling was found to be more appropriate. Data were analyzed using the Smart-PLS system. The results revealed that effort expectancy was the most important predictor of intention to adopt online learning. The next significant predictor was facilitating conditions. However, it was found that performance expectancy and social influence were not significant predictors of intention to adopt online learning. Additionally, it was found that voluntariness was not a mediator. In terms of practical implications, educators and designers should focus on effort expectancy and facilitating conditions to increase online learning adoption.

Keywords: UTAUT; voluntariness; effort expectancy; intention to adopt; effort expectancy; social influence; facilitating conditions

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1. Introduction

The effect of the pandemic has taken the world by storm and affected our way of life, including the educational sector, since 2020. Mankind is possibly passing through the most difficult time since COVID-19 hit [1,2]. The COVID-19 outbreak has been declared a pandemic by the World Health Organization (WHO) [3]. Since this virus' effects are bad, infectious movement was controlled and completely restricted. Hence, COVID-19 affected human life and the education sector. This has become a global crisis and has caused turmoil in the social, political, cultural, and economic aspects of life [3]. Countries were forced to comply with strict measures such as a complete lockdown or partial lockdown. Face-to-face teaching and physical interaction were stopped. New circumstances forced educational institutions to stop face-to-face learning and introduce online or distance learning. The traditional concept of education changed dramatically, and many questions were raised regarding the introduction of the internet and technology [4,5]. While the outbreak of this pandemic has created much interest in e-learning, the selection of the right tool and adoption of technologies face many challenges [6].

Following the global trend and trying to break the COVID-19 chain, the government of Bangladesh took the initiative. Schools, colleges, and universities were declared closed, and introduced online classes, using online platforms such as Zoom, Google Meet or Microsoft Teams, among others [7]. The same trend has been observed worldwide, e.g., United States, Canada, Washington, Australia, Germany, India, China, Japan, and many more [4,8–10]. In addition to flexibility, online education cost is lower compared to that of the traditional mode of education [11]. However, the technological foundation to provide online and digital education for Asian countries, particularly Bangladesh, was much different from that in the Western countries [12,13]. Though Asian countries place importance on online education using Android/iOS phones, these countries have some resource constraints. Amid growing concern and to ensure public health, the ministry of higher education and university grant commission (UGC) allowed public and private education universities to run online classes [2,14]. In addition, technology in higher education would develop a sustainable mechanism [15]. Studies [16,17] also show that online education is an exclusive mode of delivery and without examining the factors influencing the adoption of technology, it is a threat to the sustainable production of higher education in an emerging country such as Bangladesh. The outbreak of COVID-19 caused greater dependence on technological education; therefore, meaningful measures should be implemented to adopt technological education [17]. Where online education has become a necessity rather than a means to continue education [18], finding the factors influencing the adoption of online learning would certainly add sustainability in the post-pandemic era in Bangladesh.

2. Literature Review

Studies [7,19] have reported that 40% of students are attending online classes, while almost 50% of students cannot attend online classes due to a lack of device availability. While at a global scale, online learning allows students and academic institutions to enhance accessibility, interoperability, and flexibility of learning behaviors suitable to time and place [5,20,21], students in Bangladesh are way behind and gaps in economic conditions are wider [22]. The rapid advancement in information technology in education has increased the flexibility and functionality of higher learning [23,24]. However, under the post-pandemic situation, students, particularly private university students, were facing difficulties in adopting technology to receive an education. Most failed to embrace technology in education, while only a few provided online learning management systems. Scarcity of the resources of the teachers and students also affects the adoption of online education [25,26].

Online learning enriches the classroom experience [27–29] by identifying the factors influencing students in their online learning, which certainly add new experiences. Studies [29–32] show that unified theory of acceptance and use technology (UTAUT) is an effective tool to determine the factors influencing to adopt the technology. This valuable tool provides the university decision-makers with a better understanding, and the faculty members system designers with an understanding of the factors influencing the adoption of technology in higher education by the students [28,33].

There are 161 universities in Bangladesh, 108 universities of which are private, 50 are public universities, and 3 are international universities [34]. Private universities in Bangladesh play a pivotal role in the catering needs of higher education in Bangladesh. Studies report that some of the private universities in Bangladesh provide a good standard of quality education and an excellent teaching atmosphere [35]. Moreover, out of 108 private universities, more than 50 are located in Dhaka. Just as public universities did, private universities started to provide online education during the pandemic. Undoubtedly, online education is the most globally beneficial step during this pandemic. Online education allows students to participate outside the physical classrooms without any restrictions [36–38]. Unfortunately, students experienced many obstacles when they started online learning. Some of them have limited access to the resources, while others were not familiarized with online platforms. Several studies [18,36,39] indicated that students' intention to use online education is influenced by factors such as performance expectancy, effort expectancy, social influence, facilitating conditions and voluntariness.

This study aims to investigate the factors influencing technology adoption among private university students in Bangladesh using the theory of acceptance and use of technology (UTAUT) [40,41]. To study the student's intention to adopt technology, UTAUT emerges as one of the most widely accepted and applied models [42]. This particularly focuses on constructs such as as performance expectancy, effort expectancy, social influence, and facilitating conditions, which explains the intention to use information technology. All research hypotheses are indicated in Figure 1.

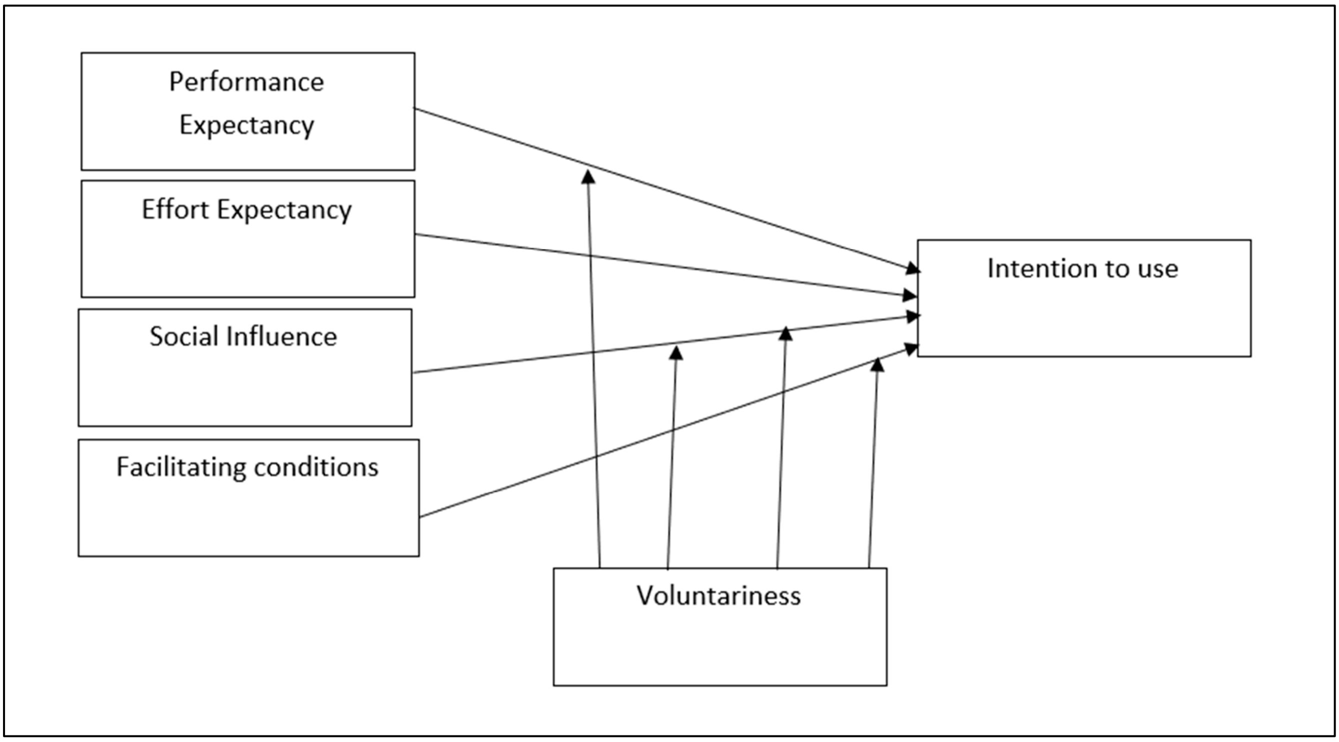

Figure 1. The research framework.

Performance expectancy is an important variable in determining learners' acceptance of online learning. Venkatesh et al. and Alrajawy et al. [41,43] defined performance expectancy as the extent to which a person believes that using an information system would help him or her benefit in terms of job performance. In the context of online learning, performance expectancy suggests that students will find online learning useful due to the opportunity that the online environment presents for easily gaining access to information and as a flexible mode of education [44]. Students can attend classes from anywhere at any time to substantiate their studies. Some studies reflect that performance expectancy strongly influences students to use online learning.

H1: There is a positive and significant relationship between performance expectancy and students' intention to adopt online learning.

Effort expectancy is similar to the construct of perceived ease of use appearing in the technology acceptance model (TAM). The author of [41] defined effort expectancy as the degree of ease that individuals think they will have when using an information system. Effort expectancy also refers to another variable from TAM, i.e., perceived ease of use, perceived complexity, and ease of use. In the context of online learning, effort expectancy will strongly affect the students' behavioral intention. Past studies [45,46] also validated that effort expectancy significantly and positively impacts an individual's intention to use technology. Refs. [44,47] posit that effort expectancy will positively affect the intention to use online education.

H2: There is a positive and significant relationship between effort expectancy and students' intention to adopt online learning.

Social influence (SI) is the extent to which users perceive that others important to them believe they should use a new information system. Social influence was divided into two dimensions: superior and peer influence [39]. In this study, superior influence refers to the student's influence, defined as the extent to which immediate faculty members, lecturers, or even fellow students directly encourage or motivate their students/friends to pursue online learning. Studies also reveal that SI significantly influences behavioral intention to adopt a system [44,45].

H3 : There is a significant positive relationship between social influence and intention to adopt online learning.

Facilitating conditions (FC) are defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system [41]. Facilitating services being provided to users can affect the level of acceptance of new technology [39,48]. Facilitating conditions significantly affect the behavioral intention and use of online learning systems [44,49].

H4: There is a significant positive relationship between performance expectancy and acceptance of mobile learning.

Voluntariness to use refers to the use of technology or online platforms being perceived as free will [50]. Voluntariness is a dominant influence on user behavior [42,47,51]. Voluntariness is the extent to which potential adopters perceive the adoption as not mandatory. Voluntariness determines other factors that influence the user's behavior. Voluntariness is the context where the user will accept technology without any influence. This was used by the authors of [41] as a moderator, and the study revealed that technology adoption was significantly increased from 35% without a moderator to 55% with a moderator. In this study, this construct was used as moderating variable to see the influence of voluntariness in the online system on performance expectancy, effort expectancy, social influence, and facilitating conditions.

H5: Voluntariness to use moderates the relationship between performance expectancy and intention to adopt technology in online education.

H6: Voluntariness to use moderates the relationship between effort expectancy and intention to adopt technology in online education.

H7: Voluntariness to use moderates the relationship between social influence and intention to adopt technology in online education.

H8: Voluntariness to use moderates the relationship between facilitating conditions and intention to adopt online education.

3. Methodology

3.1. Research Design

The explanatory study and quantitative study sought to assess the influence of performance expectancy, social influence, effort expectancy, and facilitating conditions on intention to adopt online learning. In this study, voluntariness use was the moderator in all the direct relationships between the independent variables and dependent variables. Since measurements for the constructs were available to assess the hypothesized predictions of cause and effect, positivism was a more appropriate philosophy for this study [52]. It was important to use a deductive approach as the study started with theory, and hypotheses for testing were developed. In this study, self-administered questionnaires were employed to collect numerical data. The strategy used was a survey method, and the time horizon was cross-sectional as a snapshot of the data were collected. In order to analyze data, the SPSS tool and Smart-PLS software were used.

3.2. Target Population, Sampling, and Sample Size

The intended target population in this study consisted of post-graduate students from Bangladeshi universities in Dhaka. The target population was described as the people that qualified to participate in this survey [53]. A representative sample of the target population was recruited for this extensive study in order to provide the necessary data [52]. Nonprobability sampling was used as a sampling frame that could not be developed or obtained [52]. Convenience sampling was utilized as a list of prospective responders was not easily accessible. The formula proposed by [37] was used to determine the sample size. The minimum number of samples needed, 82, was determined using the formula "50 + 8 m," where "m" stands for the number of variables. For structural equation modeling, the authors of [54] recommended sample size of two hundred.

3.3. Instrumentation

Two sections make up this questionnaire. Questions on the respondents' background, including gender, marital status, and employment history, make up the first section of the survey. The respondent was questioned on whether they were post-graduate students in private universities in Dhaka, which was a filter question that was inserted. The constructs used in this study were intended to be measured via section B of the questionnaire. The questions were adapted from past studies [45,55]. Because it is simple to administer and simple for respondents to comprehend and reply to the questions, the interval scale (Likert type) was employed to measure the respondents' responses.

3.4. Data Collection

This study used a survey method, and self-completed questionnaires were utilized to collect primary data [52]. Self-administered questionnaires were employed for this study because they enable faster data collection from a greater sample size. In addition, this method reached a wider geographical range [52]. Questionnaires were distributed manually and electronically to the qualified respondents in order to increase the response rate. Follow-up was performed. After a lapse of three months, 137 responses were received. Seven responses were removed due to missing data. There were 13 good questionnaires for data analysis. The questionnaires were distributed both manually and online in an effort to increase response.

3.5. Data Analyses

After the completion of data collection, the survey's data were edited and cleaned up. The next step was to create an Excel file. The data were uploaded to SPSS and Pls statistical software for further analysis. The descriptive analysis was carried out with the aid of IBM SPSS software. The testing for reliability validity was carried out using the Smart-PLS tool. Next, the inferential statistics were produced using the Smart-PLS software package to test the hypothesis, including the mediation effect.

The consistency or reliability of data were evaluated using the Cronbach alpha value and the composite reliability index [56]. As a general rule, the reliability value of each construct must be at least 0.70 or higher [56]. The convergent and discriminant reliability was evaluated using the Smart-PLS approach. Ref. [57] asserts that if all the measurement model's components are statistically significant, convergent validity is not compromised. The average variance extracted (AVE) for each construct served as the foundation for the convergent validity, and the value of AVE must be 0.5 or greater. Factor loadings were checked, and items with low factor loading were removed [56]. Discriminant validity evaluation was based on the multitrait–multimethod matrix: the heterotrait–monotrait ratio of correlations (HTMT). The authors of [58] stated that the HTMT approach is better than the traditional Fornell–Larcker criterion. The Smart-PLS software was used for hypothesis testing. The structural model provided the correlation coefficients and the significance level of the hypothesized relationships among the variables.

4. Results

4.1. Respondents Demographics

There were 130 respondents in this study. All the respondents were undergraduate and post-graduate students at private universities in Dhaka, Bangladesh. There were 85 male and 45 female respondents in this study.

4.2. Reliability

The degree to which a construct in this research was consistent with what it was meant to measure was considered to be its reliability [59]. Based on defined and validated metrics, the reliability score must be at least 0.70. Refs. [60,61] recommend a value of at least 0.6 as the minimum for internal consistency reliability. All of the constructs in this analysis, as shown in Table 1, had rho values better than 0.8. The composite with Cronbach's alpha was higher than 0.7. Therefore, reliability was established in this study.

Table 1. Construct validity and reliability SmartPls version 3. Extracted by researcher.

	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
EF1	0.810	0.810	0.888	0.727
FC	0.791	0.819	0.878	0.707
Intention	0.837	0.848	0.902	0.754
PE	0.869	0.870	0.920	0.792
Social Influence	0.852	0.853	0.900	0.693
Voluntariness	0.796	0.816	0.878	0.706

4.3. Convergent Validity

Based on data obtained from the Smart-PLS system, convergent validity was confirmed in this study. Convergent validity in this study refers to how well the construct converges to account for the variation of its elements [56]. In this study, the convergent validity of the concept was examined using the average variance extracted, frequently abbreviated as "AVE". The mean value in this study was calculated using the square loadings of each indicator on a construct. The Smart-PLS system results revealed that the AVE value was 0.5 and above, which is higher than 0.5. [56] set the minimum threshold value (0.5 and above. Items with factor loadings of below 0.5 were removed.

4.4. Discriminant Validity

To measure discriminant validity, the Fornell–Larcker criterion was used. According to the Fornell–Larcker criterion, the diagonal value must be greater than all the other values in the same row and column [56]. The constructs in Table 2 are distinct from each other. Therefore, the discriminant validity of the data in this study was clearly established.

Table 2. Fornell–Larcker criterion SmartPls version 3. Extracted by researcher.

	Effort	FC	Intention	Performance	Social	Voluntariness
Effort	0.853					
Facilitating C	0.639	0.841				
Intention	0.823	0.727	0.868			
Performance Ex.	0.804	0.539	0.649	0.890		
Social Influence	0.8935	0.789	0.852	0.725	0.832	
Voluntariness	0.662	0.502	0.707	0.554	0.677	0.840

4.5. Multicollinearity

According to ref. [59], multicollinearity describes how much the other factors in the analysis are correlated or can be used to explain a particular variable. The presence of high multicollinearity can affect the overall results. The presence of multicollinearity in this study was checked using the value of the variance inflation factor (VIF). According to the authors of [56], VIF values of five or more signify the presence of the multicollinearity problem. In this study, there is no problem with multicollinearity as the value of VIF is around three or below in Table 3.

Table 3. Variance inflation factor (VIF) SmartPls version 3. Extracted by researcher.

Item	VIF
EF11	1.406
EF12	2.669
EF13	2.502
EF14	1.150
FC11	2.241
FC22	1.762
FC23	1.554
IOU111	2.398
IOU222	2.116
IOU333	3.170
IOU444	3.168
PE1	2.512
PE2	2.712
PE3	1.966
SI111	1.951
SI222	2.399
SI333	2.145
SI444	1.269
SI555	2.076
VTU111	1.952
VTU222	1.771
VTU333	1.528

4.6. Coefficient of Determination (R Square)

Based on the measurements, the model used in this study is good as shown in Table 4, the value of R square is high. Collinearity was not a problem either. Based on the coefficient of determination value (R-square), the endogenous construct, intention to use, had an R square value of 0.74. This means that the predictors account for 81.8% of the variance in the intention to use.

Table 4. Coefficient of determination.

	R Square	R Square Adjusted
Intention to adopt	0.818	0.811

4.7. Significance and Relevance of Path Coefficients

In order to assess the significance of path coefficients and test the moderation effects of the moderator, bootstrapping with a resample of 5000 was performed. The authors of [56] stated that the t-value must be considered in order to determine the significance of the relationship. The standardized beta (β) values and related t-values were checked. Ref. [56] shows a significant link using a t-value greater than 1.96 or a *p*-value less than 0.05. In this study, the first hypothesis, H1, examined the relationship between performance expectancy and the intention to use. The t-value was lower than 1.96, and the *p*-value was greater than 0.05, signifying an insignificant relationship. The second hypothesis, H2, examined the relationship between effort expectancy and the intention to use. The t-value was higher than 1.96, and the *p*-value was lower than 0.05, signifying a positive and significant relationship. The third hypothesis, H3, examined the relationship between social influence and the intention to use. The t-value was lower than 1.96, and the *p*-value was higher than 0.05, signifying an insignificant relationship. The fourth hypothesis, H4, examined the relationship between facilitating conditions and the intention to use. The t-value was higher than 1.96, and the *p*-value was lower than 0.05, signifying a positive and significant relationship. Therefore, only hypotheses H2 and H4 were supported, and H1 and H3 were not supported.

The presence of moderation is shown when the strength direction of a relationship between two constructs depends on a third variable, and in this study, the third variable is voluntariness [62]. The moderating construct affects the strength or the direction of a relationship between exogenous and endogenous variables. Moderation occurs when the significance level of the interaction effect is less than 0.05. This effect will be termed significant; if it is greater than 0.05, then the effect will be insignificant. In this study, the *p*-value for all the moderating effects of the variable voluntariness was not significant. Therefore, hypotheses H5, H6, H7, and H8 were not supported. The summary of all hypotheses are shown in Table 5 and Figure 2.

Table 5. Path coefficients SmartPls version 3. Extracted by researcher.

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	*p* Values
Effort -> Intention to adopt	0.499	0.518	0.172	2.908	0.004
Facilitating -> Intention to Purchase	0.246	0.260	0.109	2.261	0.024
Moderating Effect EE to Intention -> Intention to adopt	−0.047	−0.035	0.208	0.227	0.821
Moderating Effect FC to Intention -> Intention to adopt	0.049	0.055	0.109	0.446	0.656
Moderating Effect PE to Intention -> Intention to adopt	0.130	0.150	0.136	0.952	0.341
Moderating Effect SI to Intention -> Intention to adopt	−0.194	−0.230	0.275	0.703	0.482
Performance -> Intention to adopt	0.112	0.117	0.119	0.942	0.346
Social -> Intention to adopt	−0.025	−0.064	0.231	0.108	0.914
Voluntariness -> Intention to adopt	0.178	0.191	0.078	0.022	0.022

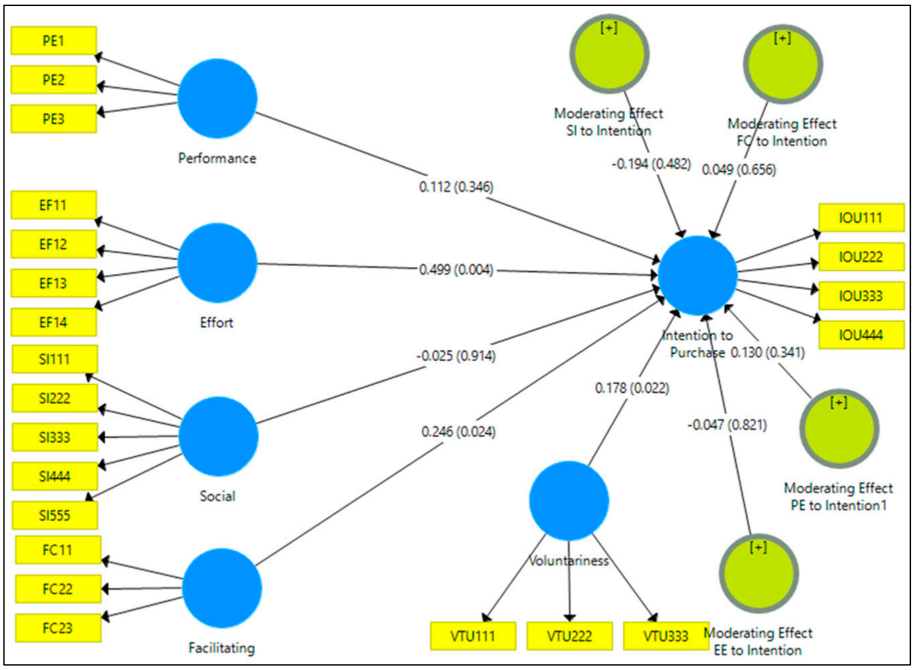

Figure 2. Path co-efficients diagram SmartPls version 3. Extracted by researcher.

5. Discussion Implications, Limitations, and Recommendations

5.1. Discussion

The aim of this study was to identify the factors influencing technology adoption in higher education in Bangladesh. The UTAUT model was used to determine the factors. The first hypothesis was to investigate the impact of the performance expectancy on the intention to use online learning in the post-pandemic period in Bangladesh. The direct effect of performance expectancy on intention to use was insignificant (p-value = 0.346). The results of this study deviated from past studies [32]. One explanation is that students are technology-savvy, and performance expectancy is no longer a concern. The second hypothesis examined the impact of effort expectancy on intention to use online learning (p-value 0.004). The results showed a significant relationship between effort expectancy and intention to use e-learning. This is consistent with past studies [45,46], which confirmed that effort expectancy significantly and positively impacts an individual's intention to use technology. The third hypothesis (H3) was to examine whether social influence predicts intention to use technology. The relationship between social influence and intention to use online learning was insignificant. The results deviated from past studies [31]. One possible explanation could be that social influence is no longer applicable as all students need to use online learning, particularly after the pandemic. The fourth hypothesis was to examine the impact of facilitating conditions on the intention to use online learning. The results showed that there was a significant relationship between facilitating conditions and intention to use online learning. This is consistent with past studies [44,49] that confirmed that facilitating conditions significantly and positively impact an individual's intention to use technology. The moderating effect of voluntariness was also tested. Voluntariness to use refers to the use of technology or online platform being perceived as free will [50]. Voluntariness was expected to influence the user's behavior [42]. In this study, the moderating role of voluntariness was insignificant. One possible explanation is that voluntariness is the extent to which potential adopters perceive the adoption as not mandatory. For the participants in this study, voluntariness was no longer an option.

5.2. Implications

The results of this study revealed that effort expectancy was the most important predictor of online learning among students in Dhaka, Bangladesh. This was followed by facilitating conditions as the second most important factor that influences online learning among students. Therefore, higher education institutions (HEIs) need to focus on the effort expectancy of students and facilitating conditions. HEIs should strive for learning systems that are easy to use and require low effort from the learners in Bangladesh. The students should be able to access learning systems without difficulty, and assistance or should be readily available. In addition, the system designers and architects should focus on increasing the confidence of students to use online learning. The study calls researchers to test the integrated UTAUT model in other electronic commerce (e-commerce) domains, such as online booking or online shopping websites. This brings us to the second most important predictor of online learning, which is facilitating conditions. The facilitating conditions provided should increase the belief of students in the infrastructure, other support systems should exist to support the use of a system, and shouldbe readily available when they need it.

This study also has some theoretical contributions. The constructs in this study were based on the UTAUT theory, and this study provided some new insights and added to the current body of knowledge. Firstly, this study found that effort expectancy was the most important predictor of online learning among students in Dhaka, Bangladesh. In addition, this study revealed that social influence and performance expectancy are not significant predictors of online learning. It was also found that voluntariness was no longer a choice among students, and the moderation effect of voluntariness was not significant.

6. Limitations

It should also be noted that there were some limitations in this study. Firstly, the participants in this study were the students of private universities in Dhaka. This affects the generalizability of the results. For greater generalizability of results, it is recommended that this study be extended or replicated in other cities. This was a quantitative study that used a self-administered questionnaire. Therefore, the results depend on the honesty and emotions of the respondents. For better results, a mixed method study is recommended. An explanatory sequential study can provide more in-depth information, especially through the qualitative phase of the study. Therefore, an explanatory sequential study is recommended. This study generally looked at online learning. However, there are new technologies such as virtual reality, adaptive learning, and flipped classrooms that can be adapted to enable more interactivity and hybrid models. The new tools are changing teaching, learning, and assessment in several ways. Therefore, it is recommended that future studies include diverse instructional designs and technologies.

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