Learning Continuity during COVID-19: An Analysis of the Higher Education Sector of Bangladesh

Debarshi Mukherjee

Jamia Millia Islamia University, Department of Commerce and Business Studies, Jamia Nagar, New Delhi-110025, India

E-mail address: debarshimukherjee@tripurauniv.ac.in

ORCID: https://orcid.org/0000-0001-9039-0329

Khandakar Kamrul Hasan

Department of Business Management, Tripura University
(A Central University)
Suryamaninagar, Tripura 799022, India

E-mail address: kkhasan@gmail.com

ORCID: https://orcid.org/0000-0002-2462-1165

Abstract

Aim. This study aims to understand the factors determining university students' behavioural intentions toward online learning in Bangladesh. Specifically, this study investigates the relationship between performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and behavioural intention (BI). Moreover, this study explores the influence of pandemic fear (PF) as a moderator in the relationship between exogenous and endogenous factors.

Methods. The study is cross-sectional and followed a quantitative research approach with purposive sampling. Data were collected at a single point using a sample size of 578 respondents who studied online during the various phases of lockdown at five public and five private universities in Bangladesh. Regarding multivariate analysis, the Partial Least Squares - Structural Equation Modeling (PLS-SEM) is applied in this study to test the causal relationships in the structural model, as it is considered a second-generation technique.

Results. Statistically, a positive significance was found between PE, EE, SI, and BI in online learning participation. Whereas the FC and the BI exhibited a negative relationship, a positive relationship was found between PE, EE, and the SI on BI. In addition, a moderating role for PF was investigated, and EE and FC were found to influence BI significantly.

Conclusion. This study presents an extended UTAUT model by integrating pandemic fear as the moderator to study students' behavioural intention to adopt an online learning system under a disruptive situation. Practitioners, especially academicians and policymakers, will find this model useful while developing andragogic interventions for the higher education sector in Bangladesh.

Keywords: online learning, learning continuity, behavioural intention, higher education, Bangladesh

Introduction

The COVID-19 outbreak forced nearly 1.6 billion learners across 200 countries to discontinue physical classes and move to online courses (Shahzad et al., 2020). Online education incorporates peoples' homes, turning them into classrooms and offices (Hasan et al., 2021; Mukherjee & Hasan, 2020). Now teachers and students have various options like Google Meet, Microsoft Teams, Zoom, Skype, WhatsApp, and others for online education (Sangeeta & Tandon, 2020). To stop the spread of the Coronavirus, the Government of the People's Republic of Bangladesh initially declared all educational institutions to remain closed until March 31, 2020, intermittently extended for another two years (Islam et al., 2020). The temporary closure affected almost a million teachers and 36 million students in Bangladesh (Uddin, 2020).

Technology intervention in the teaching-learning process took a phenomenal surge where the usage of learning technologies was augmented to fulfill the need for emergency remote teaching (Rapanta et al., 2020; Wang et al., 2020). The inclusion of media into instructional activities has become an essential element. All instructional activities are coordinated through a centralised communication platform. Students must make considerable progress in learning activities using online knowledge (Ali, 2021). Low cost and support infrastructure to promote learning benefits are two essential elements to justify the development of online learning (Altameemi & Al-Slehat, 2021).

Background of the Study

In Bangladesh, 90% of students participated physical classes before the COVID-19 era (Rahman et al., 2021). As online teaching platforms are growing in Bangladesh at the institutional level, it is paramount to assess the primary stakeholders' interest level and engagement level, i.e., students enrolled for formal education. Mukherjee and Hasan (2020) identified that students select online courses for convenience, flexibility, and easy access to online classes. Researchers found that 55% of students could not attend classes due to poor internet connections, and 44.7% lacked the necessary equipment to participate in online classes among 2038 students drawn from Bangladesh's private and public universities (Islam et al., 2020).

Interestingly students found the practice of evaluation in the online medium is less practical than the physical ones offering lesser impact (Rouf et al., 2022). In the realm of Education 4.0, where the novel andragogical approaches ensure uninterrupted learning even in the formal setting despite hindrances such as natural calamities perpetuated for a long haul, the students attain higher learning gain, which is the prime objective of the learning continuity approach. Switching to different learning modes as the requirement of the recent moment only augments the impact of learning and ensures the students learn well even under stressful situations like the COVID-19 pandemic (Guppy et al., 2022).

Problem statement

The Government of Bangladesh suspended all academic activities issuing a notice followed by the COVID-19 outbreak. Initially, learning continuity suffered due to inadequate technological infrastructure, but a few universities in Bangladesh gradually launched online learning platforms, like IBA, the University of Dhaka (Mukherjee & Hasan, 2020). However, many institutions in Bangladesh still need to evolve to online learning due to the need for teaching-learning technologies and a general willingness of students arising out of various issues, including psychological and financial constraints (Hasan et al., 2021).

Objectives of the Study

A limited amount of research has been conducted on online learning deployment in developing countries and specialised fields. The present study aims to explain the BI of university students in Bangladesh toward the OL. The objectives of the study are as follows:

- To identify the present learning continuity situation in Bangladesh during the pandemic.
- To examine the factors determining university students' Behavioural Intentions (BI) by investigating the relationship between Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) to adopt online learning during COVID-19.
- To explore the influence of Pandemic Fear (PF) as a moderator in the relationship between exogenous and endogenous factors.

Identification of Research Variables

The variables used to develop the research model are summarised in Table 1.

Table 1
Hypothesis-based model variables

Constructs		*Meaning*	*Role*	*Sources*
Performance Expectancy	PE	It is the extent to which people believe a particular technology will improve their performance.	Independent	Abbad, 2021
Effort Expectancy	EE	Using a particular technology is easy for people.	Independent	Abbad, 2021
Social Influence	SI	the amount of social pressure (from people like friends, family, and coworkers) to use a particular piece of technology.	Independent	Abbad, 2021
Facilitating Conditions	FC	A set of organisational and technical structures that makes it possible to use a particular technology.	Independent	Abbad, 2021
Behavioural Intention	BI	The degree to how committed people are to using a particular technology, the volume of use (frequency), and the quality of use (variety of usage).	Dependent	Abbad, 2021
Pandemic Fear	PF	Individuals' perception of their risk of becoming ill due to an outbreak (e.g., Coronavirus (COVID-19)).	Moderator	Ahorsu et al., 2020

Source. Own research.

Gap Analysis

A review of the existing literature was conducted to identify the gaps in the research domain. Table 2 below represents a focal analysis of the research gaps drawn from eight key research papers.

Table 2
Study Gap

Title and Year of Publishing	*Name of Journal*	*Name of Author/s*	*Major Findings*	*Future scope*
Using the UTAUT model to understand students' usage of e-learning systems in developing countries. (2021).	*Education and Information Technologies*, 1-20. (Scopus, UGC-CARE)	Abbad, M. M.	Educational institutions must embrace online learning platforms (OLPs) and rethink their concentional teaching methods.	BI's can predict whether or not students would accept and use online learning platforms (OLPs).
The Development and Adoption of Online Learning in Pre-and Post-COVID-19: Combination of Technological System Evolution Theory and Unified Theory of Acceptance and Use of Technology. (2021).	*Journal of Risk and Financial Management*, *14*(4), 162. (Scopus, WoS, ESCI)	Qiao, P., Zhu, X., Guo, Y., Sun, Y., & Qin, C.	It is required to investigate the affiliation between technological advancement and adoption in the several UTAUT emphasis areas for online learning technologies.	The future scope is to track changes in behaviour intention due to the fear of COVID-19 as a moderator for higher education students adopting Online Learning Platforms (OLPs).
Depression and anxiety among university students during the COVID-19 pandemic in Bangladesh: A web-based cross-sectional survey. (2020).	PLOS ONE (Scopus, WoS, ESCI)	Islam, M. A., Barna, S. D., Raihan, H., Khan, M. N. A., & Hossain, M. T.	There is an unprecedented increase in depression and anxiety among university students in Bangladesh due to COVID-19.	The university should develop online educational programmes in remote areas.
Students' Perceptions of the Adoption and Use of Social Media in Academic Libraries: A UTAUT Study. (2021).	*Communication*, *47*(1), 76-94. (Scopus)	Williams, M. L., Saunderson, I. P., & Dhoest, A.	Need for qualitative exploration to ascertain students' perspectives of social media use in an academic library context.	To ascertain how various factors affecting their acceptance and use of social media in a library setting affect their perceptions.

Title and Year of Publishing	*Name of Journal*	*Name of Author/s*	*Major Findings*	*Future scope*
Fear from COVID-19 and technology adoption: the impact of Google Meet during Coronavirus pandemic. (2020)	*Interactive Learning Environments*, 1-16. (Scopus)	Al-Maroof et al.	Parents, teachers, and educators are most concerned about lockdowns, academic failure, and social isolation during the pandemic.	Develop strategies for implementing new technology during the Coronavirus outbreak.
Social Media Use, Self-Efficacy, Perceived Threat, and Preventive Behaviour in Times of COVID-19: Results of a Cross-Sectional Study in Pakistan (2021).	*Frontiers in Psychology.* (Scopus)	Mahmood, Q. K., Jafree, S. R., Mukhtar, S., & Fischer, F.	Despite the high perception of COVID-19 as a threat, most people took self-preventive measures and believed they were beneficial.	The future scope is to examine other factors related to social media use, such as psychological stress and family influences.
Online learning: A panacea in the time of COVID-19 crisis. (2020).	*Journal of Educational Technology Systems*, *49*(1), 5-22. (Scopus)	Dhawan, S.	Online learning is beneficial to COVID-19 research.	Develop skills through lifelong learning at any time and any location.
Social Isolation and Acceptance of the Learning Management System (LMS) in the time of the COVID-19 Pandemic: An Expansion of the UTAUT Model (2020).	*Journal of Educational Computing Research.* (Scopus)	Raza, S. A., Qazi, W., Khan, K. A., & Salam, J.	Need to improve the LMS experience to increase behavioural intentions among students.	Future intend to investigate the extended UTAUT model during the pandemic in developing countries to adopt online learning systems.

Source. Own research.

Literature Review

Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT model was developed by Viswanath Venkatesh et al. in 2003. The following theories collectively comprise the UTAUT: The theory of Reasoned Action (Fishbein & Ajzen, 1977), the Theory of Planned Behaviour (Ajzen, 1985), the Social Cognitive Theory (Bandura, 1986), the Technology Acceptance Model (Venkatesh & Davis, 1996), Diffusion of Innovation Theory (Rogers, 1983), Model of PC Utilisation (Thompson et al., 1991), Motivational Model (Davis et al., 1992), Combined TAM and TPB (Taylor & Todd, 1995). Venkatesh et al. (2003) combined eight conflicting hypotheses into a complete model that explained almost 70% of the variances in behavioural intention to accept and employ specific technologies (Azam et al., 2021). Compared to all other models for predicting technological acceptance and use, the UTAUT model performed the best in this study.

Relationship between PE and BI

Due to online learning-based platforms, PE is the degree to which students and teachers anticipate their performance in teaching, learning, and assessing will improve. PE is an influential factor when evaluating the effectiveness of online learning systems (Abbad, 2021). Therefore, PE is one of the significant factors influencing students' intention to engage in online learning, according to Balakrishnan et al. (2022). Further, Teo et al. (2019) found that perceived usefulness is a significant predictor of online learning intentions among university students. Based on prior research, it is possible to hypothesise that PE relates to BI regarding online learning acceptance. It is therefore posited that, *H1*: PE significantly and positively impacts the students' BI to adopt OL.

Relationship between EE and BI

UTAUT's model integrates EE as an integral component, according to Chen and Hwang (2019) and Raza et al. (2021). EE significantly and positively influences online learning (Gunasinghe et al., 2019). Moreover, the effort expectancy factor is intrinsic since it takes human effort to take advantage of the technology's user-friendly features (Persada et al., 2019; Raza et al., 2021). Venkatesh et al. (2003) demonstrate the direct impact of EE on BI in technology acceptance systems. Venkatesh et al. (2003) found that EE is consistently and convincingly associated with BI. It is therefore posited that, *H2*: EE significantly and positively impacts the students' BI to adopt OL.

Relationship between SI and BI

SI is defined as a person's belief that the people close to them significantly impact whether or not they can effectively utilise new technologies (Venkatesh et al., 2003). In previous studies, essential persons such as friends, family, colleagues, teachers, and teaching assistants have recommended using online learning platforms (Lolic et al., 2020). This study will explore how much respondents are influenced to use online learning by their family, friends, and teachers. Dhawan (2020) has found that SI is associated with a high intention to use the Internet for health promotion purposes. The perceptions of others regarding online learning during the pandemic are influenced by socially significant individuals (Mahmood et al., 2021). It is therefore posited that, *H3*: SI significantly and positively impacts the students' BI to adopt OL.

Relationship between FC and BI

Facilitating conditions can be considered into four categories: procedural support, human support, technical support, and organisational support. An online learning system must have a technical support system to be accepted and used (Lai, 2020; Raza et al., 2021). Technological assistance, training, and necessary infrastructure are all a part of online learning, as stated by Venkatesh et al. (2003). FC's involvement is minimal in the original UTAUT model due to the use of multiple technologies. Qiao et al. (2021) indicate that university students are reluctant to accept online learning because of poor system support, inadequate technical support, and a lack of information. The FC is enhanced by teachers' support, technical efficiency, and knowledge; thus, FC influences students' BI (Almisad & Alsalim, 2020; Raza et al., 2021). It is therefore posited that, *H4*: SI significantly and positively impacts the students' BI to adopt OL.

Moderating Effect of PF

COVID-19 presents many dangers for which PF is an appropriate response (Mertens et al., 2020). In higher education, the moderating role of PF can be seen in Figure 1, affecting four other components in the UTAUT model and behavioural intention (Raza et al., 2021). Thus, the existence of COVID-19 dread contributes to strengthening the relationship between PE, EE, SI, and FC. However, users are less likely to accept online learning because of the performance standards. However, they are more determined to do so after hearing from their colleagues, friends, instructors, and other students. COVID-19 concerns student experience (Raza et al., 2021).

PF Moderates the Relationship between PE and BI

As a result of the Pandemic Fear of COVID-19, discrimination and loss have increased, creating a much more difficult situation for those who are sick (Ahorsu et al., 2020; Lin et al., 2021). There has been a profound impact on online learning caused by fear of infiltrating educational institutions and obstructing the teaching and learning process. Anxiety or fear can take several forms, including fear of security, missing out, failure, and taking risks (Al-Maroof et al., 2020; Gasparro et al., 2020). In general, universities and colleges have reported problems with their faculty members' knowledge and ability to apply this knowledge through technology, their students' comprehension and proficiency, and their inability to transfer classroom instruction to virtual classes (Lolic et al., 2020). Online learning can be moderated by PF based on PE and BI, even if technology adoption has been the subject of numerous earlier studies (Koçak et al., 2021; Raza et al., 2021). Consequently, based on the literature, we posited that, *H5:* PF moderates the relationship between PE & BI of the students to adopt OL.

PF Moderates the Relationship between EE and BI

Another essential factor influencing technology usage and acceptance is the fear associated with its use, which is influenced by anxiety and illiteracy. This physiological aspect must therefore be paid particular attention by teachers and students so that students can freely adopt the technology by developing the necessary skills and information. Another underlying issue impeding the adoption of new technology is a lack of technical expertise and preparedness in the educational sector (Ali, 2020; Al-Hamad et al., 2021). There is a reluctance to adopt new technologies in domains other than education. Recent research has looked into the issues of fear and technical acceptability. The TAM and other models are used in this new study (Bailey et al., 2020; Kamal et al., 2020). PF can moderate online learning based on EE and BI (Koçak et al., 2021; Raza et al., 2021). Consequently, based on the literature, we posited that, *H6*: PF moderates the relationship between EE & BI of the students to adopt OL.

PF Moderates the relationships Between SI and BI

PF reacts to the COVID-19 threat (Mertens et al., 2020). All educational institutions in most nations have decided to transition to online instruction due to PF caused by COVID-19. Even though government rules on SI differ from country to country, they face new challenges. SI and BI (Koçak et al., 2021; Raza et al., 2021) can be moderated by PF to adopt online learning. Consequently, based on the literature, we posited that, *H7*: PF moderates the relationship between the SI & BI of the students to adopt OL.

PF Moderates the Relationships between FC and BI

Regarding online learning, FC refers to the availability of technical and organisational resources. A comprehensive infrastructure is required, including instruction, technical assistance, and essential infrastructure (Miranda et al., 2021). Based on the original UTAUT models, FC has a direct but small impact on individuals' ability to utilise a given technology (Venkatesh et al., 2003). Md Yunus et al. (2021) found that FC and BI were the least significantly associated among the four components of the UTAUT model. Due to a lack of resources and knowledge, students will be hesitant to use web-based technology (Rahman et al., 2021). According to the literature, FC influences online learning adoption (Sangeeta & Tandon, 2020). Students' perceptions of FC are a valid predictor of their BI toward online learning, although PF may moderate this relationship. Consequently, based on the literature, we posited that, *H8*: PF moderates the relationship between FC & BI of the students to adopt OL.

Study of Research Model
UTAUT is a research framework that integrates determinants from various technology acceptance theories. Figure 1.1 shows four antecedents of BI, and the PF moderates the relationships between all antecedents and outcomes (intention).

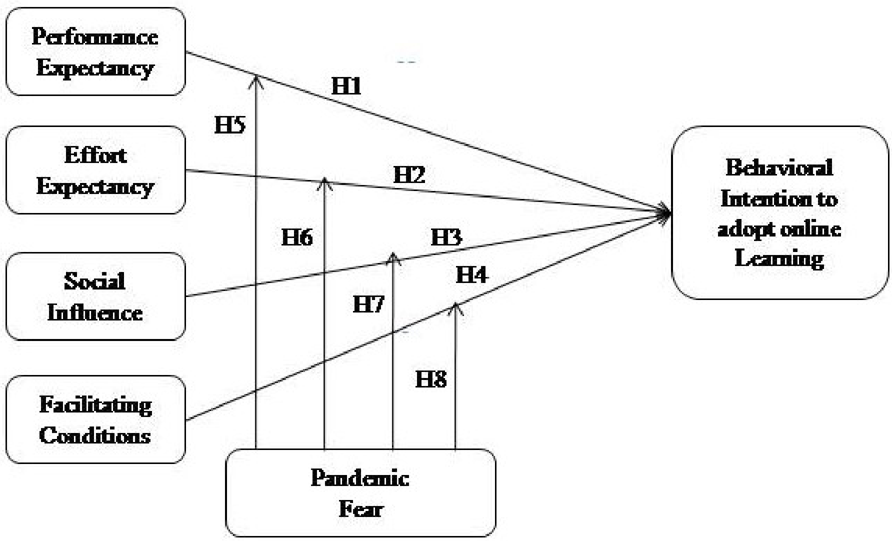

Figure 1
The proposed research model
Source. Own research.

Research Method

Study Area
A sampling frame of 10 Bangladeshi (five public and five private) universities approved by the UGC of Bangladesh was considered for the target population. This research involves the collection of 578 samples, which is more than the recommended number per numerous criteria in the literature, out of which 78 responses of spurious nature were discarded. For the analysis, 500 responses were considered.

Statistical Analysis
SmartPLS (version 3.0) statistical approaches were adopted for data analysis and hypothesis testing via PLS-SEM (Partial Least Squares - Structural

Equation Modelling). Cross-sectional data gathered to perform the study, obtained respondents' opinions at a particular time (Mahmood et al., 2021). Data for this study was collected through online surveys. The survey was concluded by the end of April 2022. The current study used a purposive sampling technique. Data from a particular group chosen for the current investigation were collected using this sampling technique.

Results and Observation

Common Method Bias/ Variance

The "Harman single-factor test" was employed to address this potential concern. Five factors with eigenvalues greater than one were identified through a factor analysis of all measuring items. The following table shows that the first component explains only 34% variance, which is below the recommended threshold of 50%. Therefore, Common Method Variance (CMV) was shown to be of minor importance in this investigation since no one component appeared and did not account for a significant portion of the variation.

Table 3

Total Variance Explained

Component	*Initial Eigenvalues*			*Extraction Sums of Squared Loadings*		
	Total	*% of variance*	*Cumulative %*	*Total*	*% of variance*	*Cumulative %*
1	9.196	34.060	34.060	9.196	34.060	34.060
2	3.474	12.866	46.926	3.474	12.866	46.926
3	1.885	6.981	53.907	1.885	6.981	53.907
4	1.416	5.246	59.153	1.416	5.246	59.153
5	1.210	4.482	63.635	1.210	4.482	63.635
6	.959	3.551	67.186			
7	.789	2.921	70.108			
8	.751	2.780	72.888			
9	.658	2.436	75.324			
10	.628	2.327	77.651			
11	.588	2.177	79.828			
12	.555	2.057	81.885			
13	.517	1.914	83.799			
14	.478	1.772	85.571			
15	.429	1.591	87.161			
16	.408	1.513	88.674			
17	.404	1.498	90.172			
18	.377	1.397	91.569			
19	.340	1.260	92.829			

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
20	.309	1.145	93.975			
21	.301	1.115	95.090			
22	.268	.991	96.081			
23	.247	.915	96.997			
24	.230	.852	97.849			
25	.220	.813	98.662			
26	.200	.741	99.404			
27	.161	.596	100.000			

Source. Own research, Extraction Method: Principal Component Analysis (PCA).

A summary of the study variables and the mean and standard deviation can be found in Table 4. All items were evaluated using a Likert scale of seven points. All variables had an average greater than 4.0. SI had the highest mean value of 4.809 and the lowest standard deviation score of 1.625 of the seven scale values. BI has a mean of 3.886 and a standard deviation of 1.945.

Table 4
The Latent Constructs' descriptive statistics

Constructs	Mean	Std. Deviation
PE	4.046	1.805
EE	4.009	1.795
SI	4.809	1.625
FC	4.628	1.757
BI	3.886	1.945
PF	3.655	1.895

Source. Own research.

Goodness of Measurement Model
The measurement model was tested for individual loading, consistency, composite reliability, and discriminant validity (Hair et al., 2021).

Convergent Validity
Analysing item loadings and calculating average variance extracted (AVE) was used to determine convergent validity. The AVE value should be greater than 0.5. All variables have an AVE of at least 0.5. It is shown in Table 4 that the AVE for each construct was achieved in this investigation.
The researchers recommended composite reliability (CR) cutoff value of 0.70 (Hair et al., 2017). CR values range from 0.945 to 0.815, as shown in Table 5. Cronbach's alpha (CA) measures the internal consistency of a

study. All CA values were greater than or equal to 0.827 when compared to the criterion of 0.70, indicating high reliability. Dijkstra–Henseler indicator (rho A) also surpassed the 0.7 cutoff value. As a result, both the component and construct dependability requirements were met (Hair et al., 2019).

Table 5

Summary of Latent Construct Validity and Reliability for the Measurement Model

Constructs	*Items*	*Loadings*	*Cronbach's Alpha*	*rho_A*	*CR*	*AVE*
BI	BI1	0.882	0.923	0.923	0.945	0.812
	BI2	0.912				
	BI3	0.909				
	BI4	0.901				
EE	EE1	0.818	0.828	0.841	0.886	0.661
	EE2	0.726				
	EE3	0.880				
	EE4	0.820				
FC	FC1	0.713	0.700	0.702	0.815	0.525
	FC2	0.688				
	FC3	0.753				
	FC4	0.742				
PE	PE1	0.871	0.892	0.900	0.916	0.611
	PE2	0.864				
	PE3	0.848				
	PE4	0.656				
PF	PF1	0.728	0.826	0.835	0.886	0.664
	PF2	0.622				
	PF3	0.835				
	PF4	0.824				
	PF5	0.826				
	PF6	0.809				
	PF7	0.803				
SI	SI1	0.688	0.791	0.805	0.865	0.617
	SI2	0.838				
	SI3	0.850				
	SI4	0.756				

Source. Own research.

Discriminant Validity

In a novel method for measuring discriminant validity in SEM, Roemer et al. (2021) suggested the heterotrait-monotrait correlation ratio (HTMT). Naveed et al. (2021) suggest a threshold value of 0.85 for evaluating this using the HTMT, whereas other studies offer a cutoff value of 0.90. In order to meet the requirements of Table 6, the HTMT must be less than or equal to 0.90 (Hair et al., 2019).

Table 6

HTMT-based discriminant validity

Constructs	*BI*	*EE*	*FC*	*PF*	*PE*	*SI*
BI						
EE	0.776					
FC	0.464	0.599				
PF	0.342	0.301	0.283			
PE	0.750	0.900	0.508	0.359		
SI	0.543	0.546	0.610	0.355	0.583	

Source. Own research.

Assessing Structural Model

Direct Effect

Structural model coefficients were estimated using regression equations. Variance inflation factor (VIF) is typically used to determine whether an error was caused by collinearity when examining structural relationships (Hair et al., 2019). Some researchers recommend the VIF threshold to be 5.0 (Hair et al., 2017), while others believe the threshold should be closer to 3, with lower values preferable (Hair et al., 2019). Each construct's VIF value was less than or equal to 3, suggesting no collinearity problems existed. Path coefficients were tested for statistical significance using the bootstrapping approach (minimum resampling = 5,000) (Hair et al., 2017). Correlations were calculated between endogenous and exogenous components based on a 0.05 ($p<0.05$) level of statistical significance.

Table 7

A summary of the direct path (path coefficient and hypothesis testing)

H	*Rlships.*	*Beta*	*Std.*	*T Value*	*P Value*	*2.50%*	*97.50%*	*Decsn.*	*F^2*	*VIF*
H1	PE ->BI	0.258	0.052	4.925	0.000	0.157	0.362	S	0.060	2.457
H2	EE ->BI	0.401	0.050	7.914	0.000	0.297	0.491	S	0.140	2.472
H3	SI ->BI	0.138	0.043	3.406	0.001	0.064	0.232	S	0.031	1.537
H4	FC ->BI	0.015	0.039	0.461	0.645	-0.058	0.092	NS	0.000	1.416

Source. Own research.

The direct effect of the relationships between PE and BI has been supported in H1 (β=0.258, Std.=0.052, T Value=4.925, P Value=0.000, 2.50%=0.157, 97.50%=0.362, F^2=0.060, VIF=2.457). The relationships between EE and BI are supported in H2 (β=0.401, Std.=0.050, T Value=7.914, P Value=0.000, 2.50%=0.297, 97.50%=0.491, F^2=0.140, VIF=2.472). Relations between SI and BI are supported in H3 (β=0.138, Std.=0.043, T Value=3.406, P Value=0.001, 2.50%=0.064, 97.50%=0.232, F^2=0.031, VIF=1.537). A study of the relationships between FC and BI is not supported in H4 (β=0.015, Std.=0.039, T Value=0.461, P Value=0.645, 2.50%=-0.058, 97.50%=0.092, F^2=0.000, VIF=1.416).

Testing the Moderating Effect

An investigation was conducted to determine whether PF moderated the relationships between PE, EE, SI, FC, and BI to adopt online learning.

Table 8

Summary of the indirect path coefficients and hypothesis testing results

H	*Relationships*	*Beta*	*Std.*	*T Value*	*P Value*	*2.50%*	*97.50%*	*Decsn*	*F^2*	*VIF*
H5	PF*PE ->BI	0.073	0.061	1.192	0.233	-0.047	0.192	NS	0.005	2.789
H6	PF*EE ->BI	-0.133	0.049	2.694	0.005	-0.229	-0.038	S	0.015	2.832
H7	PF*SI ->BI	-0.003	0.054	0.046	0.963	-0.104	0.110	NS	0.000	1.599
H8	PF*FC ->BI	0.088	0.041	2.132	0.033	0.009	0.169	S	0.013	1.534

Source. Own research.

PF (H6: β = -0.133, Std. = 0.049,*t* = 2.694, *p = 0.005*, 2.50% = -0.229, 97.5% = -0.038; H8: β = 0.088, Std. = 0.041, *t* = 2.132, *p = 0.033*, 2.50% = 0.009, 97.5% = 0.169) moderated the relationship between EE and BI and FC and BI to adopt online learning. PF (H5, H7) did not moderate the relationship BI between PE and SI. The effect of exogenous factors on endogenous factors, as measured by the explanatory effect value f^2, is known as the effect size. The effect is negligible between f^2 = 0.02 and f^2 = 0.15; The impact is moderate between f^2 values of 0.15 and 0.35; Furthermore, the impact is considerable at f^2>0.35, according to Hair et al. (2019).

The graphical representation of the moderation interaction plot is more important than the calculation, according to Ahmed et al. (2022). The results indicate that students with low PF perceived higher intention than students with high PF when their level of EE increased, and students with high PF perceived higher BI than those with low PF when the level of FC increased.

Predictive Relevance Analysis (R^2 & Q^2)

R^2 measures how well a model's independent variable(s) can forecast the dependent variable (Memon et al., 2021). Hair et al. (2019) classified R^2 cut values of 0.75, 0.50, and 0.25 as considerable, moderate, and weak. This study shows a 0.550 explainability of the endogenous construct (BI), indicating that all exogenous variables (PE, EE, SI, and FC) explain approximately 55% of the variance. This research model is suitable based on the R-square criteria.

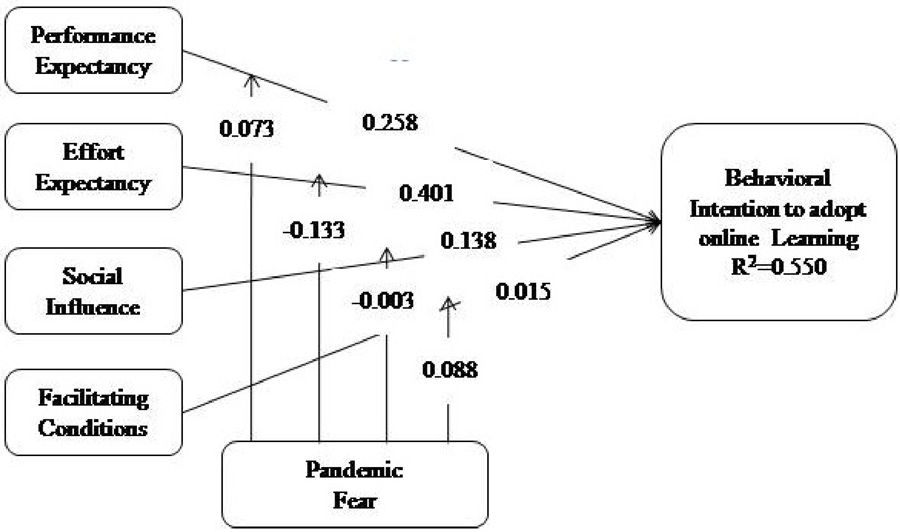

Figure 2
Path coefficients are computed structural model path relationships
Source. Own research.

When the Q^2 value exceeds zero, exogenous constructs are found to be predictive of endogenous constructs (Hair et al., 2013). As the Q2 value is 0.439, the model is statistically highly predictive. The findings of Table 8 indicate that the model is predictively relevant.

Table 9
Predictive Relevance of the Exogenous Constructs

Construct	*R^2*	*Q^2*
BI	0.550	0.439

Source. Own research.

Discussion

Presently educational institutions in Bangladesh are improving the interface and ensuring that the new technology introduces learning continuity functionality to increase student success. When students' learning efficiency increases, they are more likely to succeed in their studies, especially during an outbreak such as PF. Students are improving the online learning system concerning the effort needed to ensure learning continuity. When students perceive technology as easy and beneficial, they are more likely to adopt it. As a result, students will remain flexible in the future because of learning continuity during pandemics when institutions are closed.

The first findings from the present study found that PE and BI showed a significant correlation with a solid positive path coefficient. As a result, PE is one of the strongest determinants of whether an individual will accept or reject OL. When perceived as beneficial, it will be more likely to be adopted. Based on such a finding, it is suggested that PE should be enhanced to increase students' engagement with OL and, thereby, learning continuity. The second important finding was that EE significantly influenced BI. Students found it easy to use to continue their OL as a result of this study. The result indicates that learning to be skillful in using OL is easy. To measure EE, it is essential to consider whether OL is perceived as easy or complicated. OL will be more likely to be used by students if they expect it to perform well during COVID-19. The third significant finding is that SI is significantly associated with the BI of students who adopt online learning. SI and BI were found to be significantly correlated, with a significant positive path coefficient. The fourth important finding is that FC does not significantly influence BI. Since OL students use their facilities outside of the campus, such as their homes or offices, campus facilities do not have an impact in this context, as they use their facilities. A previous study also found that FC does not influence learners' BI to adopt OL in Bangladesh (Amin & Zaman, 2021).

The moderating effect of PF does not support PE and BI in adopting OL. Using a specific technology is an individual's goal, and students believe it will allow them to perform better in class. If students believe that online learning enhances their performance in class, they are more likely to use it in the future. The PF determines a negative path coefficient that moderates the relationship between EE and BI to achieve OL adoption. In addition, the relationship between EE and BI is found to vary according to a student's PF level. Based on the highly collective culture of the population, it is likely that university students may use OL to the extent that their peers or instructors inform them that it is simple to use. The relationship between SI and BI is not affected by whether students are in the low-fear or high-fear group. Instead, this relationship is the same for both groups of PF. This study found that students who experience less fear of COVID-19 are more likely to adopt OLS due to SI after listening to the perspectives of their peers, friends, instructors, and fellow students. Finally, the PF moderates the association between FC and the BI to adopt OL with a significant positive path coefficient. It reveals that the relationship is stronger for the high group of PF, suggesting that FC should be enhanced with more attention given to the high-fear group of students.

Implication

The study integrates pandemic fear with the UTAUT model while measuring the students' behaviour towards online learning. In this pioneering effort, the study also records the gradually receding fear of the pandemic among the students while resiliently returning to normalcy. There are several practical implications of the study for faculty members, decision-makers of tertiary education, and offices of teaching and learning. OL adoption in PE, EE, SI, FC, and BI is examined and PF acts as a moderator between PE, EE, SI, FC, and BI in this study. When implementing OL to promote learning continuity in Bangladesh's higher education sector, decision-makers must consider students' objectives and duties. By considering these responsibilities and priorities, decision-makers can make a more informed decisions regarding OL and enable students to utilise OL elements that are appropriate to their needs.

Conclusion

The study addresses the potential challenges of providing accountable and open information to the public (Schreiber et al., 2021). This pandemic has disrupted higher education faculty, academics, and university professionals. It is imperative that they work together to assess the disruption caused by it, document the best practices, note the increase in evidence-based practices, and simultaneously increase university students' learning experiences.

The present study examines how OL is accepted in a specific context of learning continuity, particularly during times of lockdown due to pandemics. This research indicates that students had a strong intention to adopt online learning, and their BI was driven by their opinions of online learning's efficacy in enhancing their class performance. In light of this, future research should focus on studying students' BI regarding the voluntary usage of OL regularly. A qualitative or mixed methodology may be used in future research to improve generalizability; this study used a quantitative methodology. The BI of students to accept OL can also be investigated using alternative frameworks and theories. In the future, OL acceptance may be examined using other constructs such as trust, culture, and experiences. Faculty perspectives may be explored in future research as the latest research focuses exclusively on learners.

Switching to emergency remote teaching (ERT) during the pandemic from physical classes was difficult for the students and teachers. However, the students exhibited the utmost grit and determination to overcome the teething challenges and resolutely subscribed that online learning was a valuable method for ensuring learning continuity, and the subsequent successful implementation is the way forward. This study offers a clear understanding how online learning is adopted in challenging times to improve learning. Students' perceptions of online learning may prove helpful to university administrators in improving existing installations and customising future deployments to meet students' needs and expectations. Additionally, universities must ensure that online learning platforms are practical and efficient and achieve students' best performance during this pandemic. Some limitations are associated with this study. The selected study samples were from a limited number of universities in Bangladesh, namely five public and five private. Future research should be conducted at universities and colleges throughout the country. Online learning will be intensified in tertiary education, and systematic coordination is needed across the universities to explore the most valuable aspects of professional development. Every organisation will benefit from the designed frameworks the ecosystem will place before the policymakers to continue its training and education missions in times of crisis.

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