ANTECEDENTS TO THE UNDERPRIVILEGED UNDERGRADUATE STUDENTS' INTENTION TO PARTICIPATE IN ONLINE CLASSES

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ABSTRACT

COVID-19 pandemic has forced educational institutions to use e-learning systems. Bangladesh is no exception; many students come from underprivileged families who are not well-off. This study aimed to explore the antecedents to the underprivileged undergraduate students' intention to participate in online classes in Bangladesh through the integration of the Technology Acceptance Model, Information Systems Success Model, and Theory of Planned Behaviour. We used confirmatory factor analysis (CFA) to test the hypotheses. The non-probability sampling method was used to select 394 respondents by dint of the subjective judgment of the researchers. Using smart PLS software, the data were analyzed with Structural Equation Modeling (SEM). It was divulged that e-Learning usage intention (BI) is influenced by attitude (ATT), perceived usefulness (PU), students' online learning satisfaction (SOS) and subjective norms (SN). But perceived ease of use (PEU) and system quality (SQ), internet service quality (ISQ) and perceived behavioral control (PBC) do not influence BI. Even ISQ does not influence SOS. It was also revealed that PEU mediated attitude and PU, and PEU and SQ also influenced SOS. The study contributes to e-Learning literature by incorporating three models which may guide policymakers in understanding how to integrate students from all social classes into e-learning systems to eliminate academic digital discrimination.

Keywords: Bangladesh, underprivileged undergraduate students, intention for e-learning.

INTRODUCTION

Bangladesh, a South-Asian country, reported the first COVID-19 case on March 8, 2020 (Shammi, Bodrud-Doza, Islam, & Rahman, 2020). Consequently, on March 17, 2020, the government was supposed to close all educational institutions and order students at all academic levels to stay home to ensure social isolation (Emon, Alif, & Islam, 2020). Subsequently, many Bangladeshi schools, colleges, and universities have switched to e-learning platforms (Al-Amin, Zubayer, Deb, & Hasan, 2021). As a result, the learning strategy has completely transformed from in-person learning to virtual classes (Khan, Rabbani, Thalassinos, & Atif, 2020) where being in different locations, the students and instructors can communicate using the internet and computers (Moore, Dickson-Deane, & Galyen, 2011; Sing & Thurman, 2019). It is also referred to as e-learning, computer-based, web-based, or virtual learning (Bartley & Golek, 2004), which is very expensive to most unprivileged rural people in a developing country like Bangladesh. Though this system has recently been employed as an alternate strategy to offset losses in the education sector (Al-Amin et al., 2021), there is a big question regarding the digital discrimination resulting from the shift (Adam, Kaye & Haßler, 2020; Jæger and Blaabæk, 2020). For example, Sintema (2020) described that the percentage of passing students significantly dropped in 2020 because of digital discrimination due to inequal family financial conditions.

Moreover, online class participants experience various other challenges. Because of the pandemic's unpredictability and rapid growth, online teaching platforms were developed quickly without adequate evaluation (Han & Sa, 2021). In addition, students and teachers have been facing problems due to power cuts, poor and unstable internet connection, especially in the rural areas of the country (Al-Amin et al., 2021), lack of appropriate electronic devices (Rouf, Hossain, Habibullah, & Ahmed, 2022), lack of separate/isolated home study environments (Al-Amin et al., 2021).

So, this study aims to identify the factors influencing underprivileged undergraduate students' intention to participate in online classes in Bangladesh. Although some researchers have explored the determinants of the student's satisfaction with/intention to use e-learning (Farahat, 2012; Liaquat, Siddiqui, & Iqbal, 2021; Li & Yu, 2020; Masrom, 2007; Rahman, Uddin, & Dey, 2021), this study expands the existing research in several ways.

Firstly, this study unearths the factors of underprivileged undergraduate students' intention to participate in online classes in a developing country like Bangladesh through a conceptual model combining three theoretical models, namely the Technology Acceptance Model (TAM), Information Systems Success Model (ISSM), and Theory of Planned Behaviour (TPB). Previous studies in this context did not use comprehensive theoretical models to identify the predictors of e-learning usage intention (Al-Amin et al., 2021; Rahman et al., 2021; Rouf et al., 2022; Sarkar, Das, Rahman, & Zobaer, 2021).

Secondly, the sample of this study consists of only underprivileged and marginalized undergrad-level university students. This population subgroup presents a unique research opportunity because of the disproportionately large impact of COVID-19 and related government interventions on this group, which has become even bigger due to the pandemic (Lata, 2022). Survey results claim that poverty rose to 42%, and extreme poverty rose to as high as 28.5% of the total population of Bangladesh during the COVID-19 pandemic (Raihan, Uddin, Ahmed, Nahar, & Sharmin, 2021). Moreover, a nationwide survey also reported a significant decrease in the education expenditure of poor households (Raihan et al., 2021). Therefore, the adoption of an online education system by poor students is specifically explored in this study.

PURPOSE OF THE STUDY

Previous Literature on E-Learning Usage Intention

By the second quarter of 2020, COVID-19 has infected approximately 1.2 billion individuals, forcing the closure of numerous educational institutions (Dhawan, 2020) and the adoption of online learning (Chandra, 2021). Online learning often refers to organizing class sessions using applications such as Zoom, Microsoft Teams, Moodle, Google Meet, Adobe Connect, etc. (Liaquat et al., 2021). Various factors determine the effectiveness of and learners' intention to use this e-learning system (Aristovnik, 2020).

Studies exploring learners' intentions to use e-learning system span across different countries and regions (e.g. in the US (Lee, 2010) in Korea (Lee and Kim, 2009; Han and Sa, 2021; Kim, Kim, & Han, 2021; Li & Yu, 2020; Lee, 2010), in Malaysia (Masrom, 2007), in Egypt (Farahat, 2012), in Lebanon (Tarhini, Hone, & Liu, 2014), in Algeria (Mouloudj, Bouarar, & Stojczew, 2021), in Bangladesh (Rahman et al., 2021). The studies employed various theoretical models/lenses, e.g., TAM (Farahat, 2012; Han and Sa, 2021; Li & Yu, 2020; Masrom, 2007; Tarhini et al., 2014), TPB (Kim et al., 2021; Mouloudj et al., 2021).

The existing survey-based literature on the perception of online learning during the Covid-19 pandemic in Bangladesh is abundant, with evidence of challenges educators and learners face at different levels. However, no comprehensive conceptual/theoretical framework has been developed and tested (see Al-Amin et al., 2021; Rouf et al., 2022; Sarkar et al., 2021). Although Rahman et al. (2021) presented important evidence on the mediating role of online learning motivation on online learning satisfaction, a range of other factors, as suggested by many behavioural models, are still out of the picture. Therefore, this scarcity of research employing comprehensive behavioural models to identify the factors of online education usage intention in Bangladesh motivates this study. This study fills the gap said above. So, this study aims to explore the antecedents that play a pivotal role in upholding underprivileged undergraduate students' continuing intention to attend online classes.

Theoretical Framework

The preceding discussions and assessments of prior studies on students' acceptance behaviour and the linkages between variables serve as the foundation for developing a conceptual framework to investigate the elements influencing unprivileged students' intentions to participate in online classes. The intention is defined as how someone is willing to attempt to do a behaviour and how dedicatedly they intend to be in completing the behaviour.

According to the previously reviewed literature, significant research has been conducted using the Theory of Reasoned Action (TRA) model to discover online support service quality, online learning acceptance, and student satisfaction (Lee, 2010).

Aside from this theoretical framework, the Technology Acceptance Model (TAM) has been investigated to emphasize the link between variables. Davis (1989) proposed the TAM by expanding Fishbein and Ajzen's (1977) theory of reasoned action (TRA). TAM is the most effective methodology for analyzing information technology uptake (Gefen and Straub, 2000; Venkatesh & Davis, 2000; Wang, Wang, Lin, & Tang, 2003). The TAM of Davis (1989) is presented as a succinct and effective theoretical framework for examining how the perceived usefulness (PU) and perceived ease of use (PEU) of new technology or service affect its acceptance. As a result, TAM employs the two notions of "perceived ease of use" and "perceived usefulness" to explain users' intention to use information systems while embracing the causality of TRA (Davis, 1989).

In addition to this theory, the TPB has been studied to underline the relationship between attitude and intention. The TRA provides the foundation for the concept of planned behaviour. This theory adds perceived behavioural control as additional evidence of intention to attitude and subjective norms. Several researchers used TPB or an expanded version of TPB to look into students' intentions to use online learning (Chu & Chen, 2016; Lung-Guang, 2019; Ngafeeson & Gautam, 2021). Kim et al. (2021) and Akour, Alshurideh, Kurdi, Ali, & Salloum (2021) used both the TAM and the TPB to evaluate factors impacting students' intention to use online learning.

This study examines intention in terms of attitude, PU, PEU, subjective norm, system quality, online learning satisfaction, and service quality. Previous research has found that a new technology or service's perceived usefulness and ease of use influence its acceptability. On the other hand, subjective norms and attitudes are the most influential TRA factors in determining people's propensity to adopt online platforms as a learning medium. The factors of ISSM (Information Systems Success Model) model-System quality, service quality, online learning satisfaction, and IT competency are all new factors discovered in earlier studies that are being studied to see if there is a link between these factors and online learning platform adoption.

Based on a review of the existing literature and empirical evidence, the conceptual model for this study was constructed by integrating TPB, TAM, and ISSM from the perspective of Bangladesh to assess the antecedents to the marginalized undergraduate students' intention to participate in online classes in Bangladesh. Figure 1 depicts the conceptual model adopted in this investigation (conceptual framework).

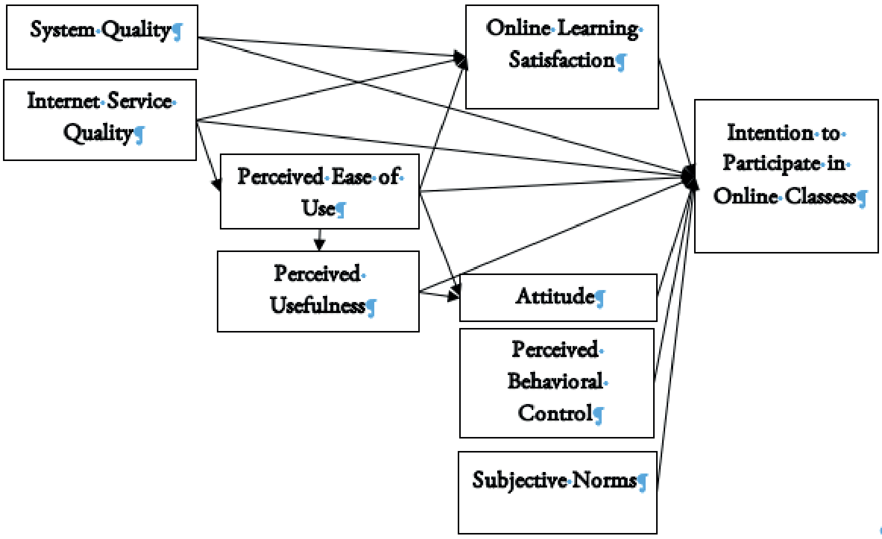

Figure 1. Proposed research model (Conceptual framework) of the study

Hypotheses Development

Attitude (ATT)

As per TPB, attitude is "the degree to which a person has a favourable or unfavourable evaluation or appraisal of the behaviour in question" (Ajzen, 1991). Here the researchers define attitude as "an overall positive or negative evaluation towards the behaviour of users of the online learning system." Because the learners' behavioural intention to use online learning systems is influenced by the response resulting from attitudes (Sukendro et al., 2020; Muhaimin et al., 2019). Several studies showed that attitude positively affects the intention to use e-learning platforms (Kim et al., 2021; Akour et al., 2021; Mailizar, Burg, & Maulina, 2021; Ndubisi, 2006, Chu and Chen, 2016). Consequently, the following hypothesis was developed:

H1: Students' attitudes positively and significantly affect their intentions to use online learning systems.

Perceived Usefulness (PU)

As per TAM, the degree to which the user believes using the technology would boost their productivity is termed PU (Masrom, 2007). In the context of e-learning, it is assumed that the availability of useful, efficient information and enhanced educational outcomes will result in the student's intention to use online learning platforms (Han & Sa, 2021; Lee, 2010). In the previous studies, it was seen that PU has a positive relationship with acceptance of and satisfaction with e-learning (Farahat, 2012; Han & Sa, 2021; Liaquat et al., 2021; Masrom, 2007; Tarhini et al., 2014); online learning acceptance, and student satisfaction (Lee, 2010; Kim et al., 2021). Thus:

H2a: Perceived usefulness positively and significantly affect the intentions to use online learning systems.

In the context of E-learning in different studies, it was seen that perceived usefulness has a positive relationship with attitudes toward online learning platforms (Farahat, 2012; Kim & Han, 2021; Li & Yu, 2020, Masrom, 2007). Thus:

H2b: Perceived usefulness positively and significantly affects attitudes towards online learning systems.

Perceived Ease of Use (PEU)

As per TAM, PEU is the degree to which users believe utilizing the system would require no effort or how simple it would be to learn and use (Davis, 1989). In the context of e-learning, if the students feel that they can clearly and easily understand and skillfully use the online learning system, it will result in a positive attitude toward the system through the satisfaction that will lead to the intention to use online learning system (Han & Sa, 2021). In the prior studies, it was seen that PEU influences students' attitudes toward online learning (Farahat, 2012; Kim et al., 2021; Li & Yu, 2020; Masrom, 2007), perceived usefulness of the learning system (Farahat., 2012; Masrom, 2007; Tarhini et al., 2014), online learning satisfaction of the students (Han & Sa, 2021) and finally the behavioural intention of the students to use the online learning system (Liaquat et al., 2021; Han & Sa, 2021; Tarhini et al., 2014). Thus:

H3a: PEU positively and significantly affects students' attitudes toward online learning systems.

H3b: PEU positively and significantly affects the PU of the learning system.

H3c: PEU positively and significantly affects students' perceived online learning satisfaction.

H3d: PEU positively and significantly affects the behavioural intention to participate in online classes.

Perceived Behavioural Control (PBC)

PBC is an individual's perceived ease or difficulty in performing a particular behaviour of interest (Ajzen, 1991). It describes a student's assessment of the perceived ease or difficulty of carrying out the desired conduct (Valtonen et al., 2015). In the context of e-learning, it is assumed that if the students have the ability and required resources to use the online learning system, they will be intended to use the e-learning system. Although in a former study, it was seen that students' PBC has no substantial influence on BI to use e-learning (Kim & Han, 2021), the following hypothesis has been developed to justify that finding:

H4: Students' PBC positively and significantly affects the BI participating in online classes.

System Quality (SQ)

System quality refers to how well an e-learning system performs its functions and how well users rate the system in terms of the information it provides and the efficiency of information transmission (Rui & Lin, 2018). In the context of e-learning, if the students are satisfied with the e-learning system functions, internet speed, and e-learning content, it will result in their satisfaction with the platform and will lead to the intention to use the e-learning system. Several research findings (Islam, 2010; Zeithaml, Parasuraman, & Malhotra, 2000) show that system quality influences students' perceived online learning satisfaction (SOS), which affects behavioural intention (Ajzen, 1991; Al-Maroof, Salloum, AlHamadand, & Shaalan, 2020; Cheng, 2012; Davis, 1989). Thus:

H5a: SQ positively and significantly affects the SOS.

H5b: SQ positively and significantly affects the BI participating in online classes.

Internet Service Quality (ISQ)

In the case of the online learning system, service quality refers to the internet service with the innovative and advanced technology with strong and high-quality network signals ensuring quick communication service more efficiently (Joudeh & Dandis, 2018). In this study, it is assumed that if the internet service is competent and efficient with strong and high-quality network signals providing easy access to the students during busy times, then it will be easy for the students to handle, ensuring satisfaction resulting in the intention to use the e-learning systems. Several research (Cristobel and Guinaliu, 2007; Gounaris & Dimitriadis, 2008; Zeithaml et al., 2000) demonstrated that service quality influences satisfaction, which in turn affects behavioural intention (Ajzen, 1991; Davis and Venkatesh, 1991; Fishbein and Ajzen, 1975). The following hypotheses have been offered based on ideas, concepts, and evidence from various empirical studies, namely:

H6a: ISQ positively and significantly affects the BI for participating in online classes.

H6b: ISQ positively and significantly affects the PEU of online classes.

H6c: ISQ positively and significantly affects the SOS.

Students' Online Learning Satisfaction (SOS)

Satisfaction is key to improving user continuity intention and enhancing e-learning's competitive advantage (Paramadini and Suzianti. 2021). In this study, it is assumed that if the students are satisfied with the online instructional styles of the instructors, the learning contents and course structure, the assignment submission process, and online exams, they will be motivated to attend and continue the online classes. Previous research suggested that PU and satisfaction can directly affect continuance intention (Al-Maroof et al., 2020; Chen, Lai, and Ho, 2015; Venter and Swart, 2018). Thus:

H7: SOS positively and significantly affects BI to participate in online classes.

Subjective Norm (SN)

Subjective norm, as the social pressures on an individual to do or not to execute a specific activity, regulates conduct motivated by a desire to act as others expect (Ajzen,1991). In this study, it was assumed that if the people important to the students influence them and want them to use online classes, and if most of their friends use online classes, they will be motivated to use them. Previous studies showed that subjective norms directly impact behavioural intention (Kim et al., 2021; Mouloudj et al., 2021; Tarhini et al., 2014). Thus:

H8: SN positively and significantly affects BI to participate in online classes.

Mediation Relationships

This study explores the mediation effect of attitude, perceived ease of use, perceived usefulness, and students' online learning satisfaction on e-learning usage intention. Therefore the following hypothesis is also tested.

H9: Attitude mediates the impact of ISQ, PEU, PU and SQ; PEU mediates the effects of ISQ; PU mediates the impact of PEU, and SOS mediates the impact of PEU, ISQ, and SQ on the intention to use online learning systems.

METHOD

Research Design and Participants

This study aims to determine the antecedents to the online learning intention of Bangladesh's unprivileged marginalized undergraduate students. The target respondents for this study are unprivileged students who go through socioeconomic conditions where there is a lack of proper logistic support that facilitates online learning systems. The students of Jashore University of Science and Technology, Bangabandhu Sheikh Muzibur Rahman Science and Technology University of Gopalgang, and Khulna University, which are situated in the bordering zone of Bangladesh, were focused. After selecting the population and respondent category, we select the minimum sample size using the following formula(Saunders, Lewis and Thornhill, 2019):

$$n = \frac{Z^2 p(1-p)}{\epsilon^2} = \frac{Z^2 pq}{\epsilon^2} = 384$$

Here, n = sample size, Z = tabulated value = 1.96 (for a large sample at a 5% significance level), p = proportion of success, q = 1– p = proportion of failure, ϵ = margin of error = 0.05. Based on the formula, the sample size is 384. But this paper used 394 respondents as the sample for better results of the data analysis.

Here the population was known., but as the sampling frame was unknown, the non-probability sampling method was used to select the respondents by the subjective judgment of researchers (Saunders, Lewis, & Thornhill, 2019). We used the judgmental sampling technique (i.e., purposive sampling) to lessen the sampling error arising from the random sampling technique in this situation where the marginalized students are to be found. Besides, judgmental sampling enables us to minimize the cost and time of data collection (Hair, Hult, Ringle, & Sarsstedt, 2017).

The questionnaire was of two parts- (i) one was for demographic information, and (ii) another one was for measurement items. Following the back-translation method (Brislin, 1976), we translated the English questionnaire into Bengali, the mother tongue of Bangladeshis, for better comprehension by the students. Two bilingual professors of marketing checked the Bengali version of the questionnaire. Then pilot survey was conducted among 25 students, and the study result showed that they appropriately comprehended the measurement items, and then it was accepted for data collection.

Measurement Scale

A Likert scale with a maximum of five points was employed for all of the constructs, with '1' being "strongly disagree" and '5' being "strongly agree." The existing researches are the source of all the measurement items. The items with sources are not reported but are available on demand.

Data Collection and Data Analysis

The researchers collected data from April 2021 and June 2021. During the pandemic situation, to maintain social distance, the universities introduced online learning systems. At that time, the students faced some difficulties in attending online classes. An email containing a cover letter and a questionnaire was sent to each respondent's email address following Dillman's (2000) suggestion to guarantee optimal convenience for responding to the survey. Email requests to complete the survey were repeatedly made to the responders. The prospective respondents received 700 questionnaires, and 425 responded with their opinions. 394 replies (56.29%) were kept after the incomplete ones were discarded. 35.3% (139) of them were female, and 64.7% (255) were men.

We applied structural equation modelling (SEM) to evaluate the data, which simultaneously analyzes several dependent variables, causal models, or equations (Chin, 1998; Cohen, 2018; Wang. Lew, Lau, & Leow, 2019). The SEM can be divided into two categories: partial least square SEM (PLS-SEM) and covariance-based SEM (CB-SEM) (Wang et al., 2019). While PLS-SEM analyzes independent and dependent factors to forecast and estimate the maximum explained differences, CB-SEM examines whether the observed variables in the covariance matrix are suitable (Wang et al., 2019). Additionally, PLS-SEM can forecast how much an ensemble of exogenous variables will affect the endogenous variables' fluctuations (Al Amin et al., 2021). The current study followed the recommendations of Hair et al. (2017) and used SMART PLS 3.0 software for confirmatory factor analysis (CFA).

Table 1. Demographic profile of the respondents

Variable	Number	Percentage
Gender		
Male	255	64.7
Female	139	35.3
Living Area		
Urban	255	64.7
Rural	139	35.3
Devices		
Smart Mobile	291	73.9
Laptop	99	25.1
Desktop	4	1.0
Internet Users		
Wifi	176	44.7
Mobile Data	218	55.3

Research Validation and Results

Validating Measurement Model

As per the suggestion of Hair et al. (2017), the outer measurement model was tested to validate the research model. We used rohA, CR, and Cronbach Alpha to assess the model's construct reliability. AVE and factor loadings were used to validate the model's convergent validity, while the Fornell and Lacker criteria and the HTMT ratio were used to assess the model's discriminant validity.

Construct Reliability and Convergent Validity

As per the suggestion of Hair et al. (2017)), we have ensured the construct reliability. They proposed that composite reliability (CR) should be more than 0.7, explaining 70% of the variation in the measurement model. Additionally, the reference range for Cronbach's alpha and rohA provided by Hair et al. (2017), which ranges from 0 to 1, was used in our research to validate the measurement model. Greater consistency is explained by the value that is closer to 1. The cut-off value was said to be 0.7 (: >0.7; rohA: >0.7). Additionally, the convergent validity was confirmed by dint of cross-loadings and average variance extracted (AVE). The cut-off value for AVE for each construct was more than 0.5, explaining 50% of the variance in the research model (Hair et al., 2017). Each construct met the prerequisites for rohA, CR, Cronbach Alpha, AVE, and factor loadings in table 2. Fornell and Lacker criteria and heterotrait-monotrait (HTMT) Ratio of correlations were used to ensure the discriminant validity of the measurement model. As per the suggestion of Hair et al. (2017), the diagonal values resembling the squared root of AVE should be greater than off-diagonal values, which were ensured by The Fornell and Lacker criterion (table 3). The HTMT correlation ratio, shown in table 4, must be less than 0.85 (HTMT < 0.85) to be considered legitimate (Henseler, Ringle, &, Sarstedt, 2015).

Table 2. Construct reliability (rohA, CR, and Cronbach Alpha), AVE, and cross-loading.

Constructs	Items	Loadings	CR>0.7	Cranach's alpha> 0.7	rhoA> 0.7	AVE> 0.5
Attitude (ATT)	ATT1	0.853	0.885	0.827	0.835	0.660
	ATT2	0.843				
	ATT3	0.796				
	ATT4	0.754				
Intention (INT)	INT1	0.910	0.964	0.954	0.954	0.844
	INT2	0.933				
	INT3	0.945				
	INT4	0.904				
	INT5	0.900				
Internet Service Quality (ISQ)	ISQ1	0.858	0.953	0.942	0.943	0.742
	ISQ2	0.874				
	ISQ3	0.892				
	ISQ4	0.777				
	ISQ5	0.877				
	ISQ6	0.842				
	ISQ7	0.904				
Perceived Behavioral Control (PBC)	PBC1	0.839	0.876	0.824	0.890	0.642
	PBC3	0.814				
	PBC4	0.887				
Perceived Ease of Use (PEU)	PEU1	0.849	0.916	0.878	0.885	0.732
	PEU 2	0.891				
	PEU 3	0.863				
	PEU 4	0.818				

Perceived Usefulness (PU)	PU 1	0.810	0.938	0.922	0.924	0.682
	PU2	0.814				
	PU 3	0.837				
	PU 4	0.822				
	PU 5	0.851				
	PU 6	0.807				
	PU 7	0.839				
Subjective Norm (SN)	SN1	0.891	0.929	0.897	0.909	0.767
	SN2	0.928				
	SN3	0.924				
	SN4	0.749				
Student's online learning satisfaction (SOS)	SOS1	0.791	0.905	0.867	0.877	0.658
	SOS2	0.893				
	SOS3	0.868				
	SOS4	0.876				
System quality (SQ)	SQ 1	0.878	0.895	0.843	0.861	0.681
	SQ2	0.703				
	SQ3	0.844				
	SQ4	0.864				

Table 3. Fornell and Lacker criteria.

	ATT	BI	ISQ	PBC	PEU	PU	SN	SOS	SQ
ATT	0.812								
BI	0.750	0.919							
ISQ	0.415	0.472	0.862						
PBC	0.584	0.573	0.493	0.847					
PEU	0.433	0.363	0.324	0.583	0.856				
PU	0.770	0.745	0.452	0.550	0.436	0.826			
SN	0.727	0.751	0.462	0.590	0.373	0.698	0.876		
SOS	0.642	0.697	0.512	0.563	0.408	0.668	0.635	0.858	
SQ	0.561	0.641	0.663	0.552	0.375	0.615	0.593	0.757	0.825

Table 4. Heterotrait-monotrait ratio of correlations (HTMT).

	ATT	BI	ISQ	PBC	PEU	PU	SN	SOS	SQ
ATT									
BI	0.843								
ISQ	0.466	0.497							
PBC	0.703	0.632	0.573						
PEU	0.499	0.391	0.351	0.700					
PU	0.871	0.790	0.480	0.624	0.476				
SN	0.847	0.810	0.502	0.688	0.411	0.762			
SOS	0.747	0.757	0.561	0.652	0.458	0.736	0.714		
SQ	0.659	0.709	0.764	0.659	0.431	0.687	0.679	0.869	

Validating structural model. We have used multiple correlations (R2) to validate our structural model, according to Henseler et al. (2015). Using the SMART PLS3 software, we determined the path coefficient for validating our proposed model, assessing the *t*-test value by the routine bootstrapping of 5000 resamples. Path coefficient results and hypotheses have been depicted in table 5. H1 was supported and ATT had an impact on BI (β= 0.232, *t*-statistics = 3.357, $p < 0.001$) (table 5). In case of H2a, and H2b, it was seen that PU influenced ATT (β = 0.717, *t*-statistics = 25.747, $p < 0.000$) and BI (β = 0.211, *t*-statistics = 3.783, $p < 0.000$) in supporting H2a and H2b in a significant and positive manner. BI is also influenced by SOS (β = 0.161, *t*-statistics = 2.584, $p < 0.010$) and SN (β = 0.267, *t*-statistics = 4.229, $p < 0.000$) supporting H8 and H9 in the model. Besides, in the context of H3a, H3c and H3d, ATT (β = 0.120, *t*-statistics = 3.321, $p < 0.001$),

Table 5. Path coefficient and hypotheses test result.

Hypotheses	Relationship	Path Coefficient	Standard Deviation	T Statistics (|O/ STDEV|)	P Values	Result
H1	ATT -> BI	0.232	0.069	3.357	0.001	Supported
H2a	PU -> ATT	0.717	0.028	25.747	0.000	Supported
H2b	PU -> BI	0.211	0.056	3.783	0.000	Supported
H3a	PEU -> ATT	0.120	0.036	3.321	0.001	Supported
H3b	PEU -> BI	-0.065	0.045	1.422	0.155	Not supported
H3c	PEU -> PU	0.436	0.045	9.617	0.000	Supported
H3d	PEU -> SOS	0.145	0.042	3.475	0.001	Supported
H4	PBC -> BI	0.059	0.052	1.136	0.256	Not supported
H5a	SQ -> BI	0.086	0.063	1.371	0.171	Not supported
H5b	SQ -> SOS	0.703	0.053	13.169	0.000	Supported
H6a	ISQ -> BI	0.009	0.041	0.219	0.826	Not supported
H6b	ISQ -> PEU	0.324	0.052	6.295	0.000	Supported
H6c	ISQ -> SOS	-0.001	0.052	0.021	0.983	Not supported
H7	SOS -> BI	0.161	0.062	2.584	0.010	Supported
H8	SN -> BI	0.267	0.063	4.229	0.000	Supported

PU (β= 0.436, *t*-statistics = 9.617, $p < 0.000$), and SOS (β = 0.145, *t*-statistics = 3.475, $p < 0.001$) are influenced by PEU in the model. On the other hand, PEU is influenced by ISQ (β = 0.324, *t*-statistics = 6.295, $p < 0.000$) supporting H6b. But BI is not influenced by PEU (β= -0.065, *t*-statistics = 1.422, $p < 0.155$), PBC (β= 0.059, *t*-statistics = 1.136, $p < 0.256$), SQ (β= 0.086, *t*-statistics = 1.371, $p < 0.171$) and ISQ (β= 0.009, *t*-statistics = 0.219, $p < 0.826$) in the model that means H3b, H4, H5a and H6a are not supported.

Coefficient of determination (r2) and strength of the effect. It was seen that the R2 values for BI and ATT were 0.714 and 0.604, respectively, which explains 71.4% and 60.4% variation in BI and ATT caused by independent variables. Besides, the R2 value for PEU = 0.105, PU = 0.190 and SOS = 0.591 which are accounted for 10.5 %, 19.0% and 59.1% variation in PEU, PU and SOS by the independent variables in the model (table 6).

Table 6. Coefficient of determination (R2) and strength of the effect.

	R2	Adjusted R2	f2	Effect Size
Effect of BI				
ATT -> BI	0.714	0.708	0.060	Small
PU -> BI			0.051	Small
PEU -> BI			0.009	Small
PBC -> BI			0.006	Small
SQ -> BI			0.008	Small
ISQ -> BI			0.000	Small
SOS -> BI			0.031	Small
SN -> BI			0.094	Small
Effect of ATT				
ATT -> BI	0.604	0.602	0.060	Small
PU -> ATT			1.052	Large
PEU -> ATT			0.029	Small
Effect of PEU				
PEU -> ATT	0.105	0.103	0.029	Small
PEU -> PU			0.235	Moderate
PEU -> SOS			0.043	Small
ISQ -> PEU			0.118	Small
Effect of PU				
PU -> ATT	0.190	0.188	1.052	Large
PU -> BI			0.051	Small
PEU->PU			0.235	Moderate
Effect of SOS				
PEU -> SOS	0.591	0.587	0.043	Small
SQ -> SOS			0.642	Large
ISQ -> SOS			0.000	Small

Effect sizes (f2) of independent variables were categorized into small, medium, and large by Chin (1998), with values of 0.02, 0.15, and 0.35, respectively. The effect size for this research model ranges from 0.0 to 1.05 (table 6).

Table 7. Indirect effect.

Hypotheses	Relationship	b	t-statistics	P Values
H9a	ISQ -> PEU -> ATT	0.039	2.861	0.004
H9b	PEU -> PU -> ATT	0.313	9.000	0.000
H9c	ISQ -> PEU -> PU -> ATT	0.102	4.564	0.000
H9d	PEU -> ATT -> BI	0.028	2.144	0.032
H9e	ISQ -> PEU -> ATT -> BI	0.009	1.978	0.048
H9f	PU -> ATT -> BI	0.166	3.351	0.001
H9g	PEU -> PU -> ATT -> BI	0.073	3.164	0.002
H9h	ISQ -> PEU -> PU -> ATT -> BI	0.024	2.686	0.007
H9i	ISQ -> PEU -> BI	-0.021	1.307	0.191
H9j	PEU -> PU -> BI	0.092	3.575	0.000
H9k	ISQ -> PEU -> PU -> BI	0.030	2.843	0.004
H9l	ISQ -> SOS -> BI	0.000	0.020	0.984

H9m	PEU -> SOS -> BI	0.023	1.869	0.062
H9n	ISQ -> PEU -> SOS -> BI	0.008	1.841	0.066
H9o	SQ -> SOS -> BI	0.113	2.544	0.011
H9p	ISQ -> PEU -> PU	0.142	4.709	0.000
H9q	ISQ -> PEU -> SOS	0.047	3.084	0.002

Mediation analysis. The current study bootstrapped 5000 times to analyze the indirect effects, which checked PEU's and PU's mediation effect on ATT. We tried to see the mediating effect of PEU between ISQ and ATT/BI/PU/SOS and the mediating effect of ATT between BI and PEU/PU. We also found the mediating impact of PU between PEU and ATT/BI; the mediating effect of SOS between BI and ISQ/PEU/SQ. Besides, the combined impact of PEU and PU between ISQ and ATT/BI; the combined effect of PU and ATT between PEU and BI; the combined effect of PEU and ATT between ISQ and BI; the combined effect of PEU and SOS between ISQ and BI and the combined effect of PEU, PU, and ATT between ISQ and BI were divulged in the model. It was seen that there was significant mediation of 13 hypotheses with a *p*-value less than 0.05 ($p < 0.05$) (table 7). The results proposed BI's partial (complementary) mediation effect among all equations (Hair et al., 2017).

DISCUSSION

The research focused on incorporating TAM, ISSM, and TPB to explore Bangladeshi marginalized university students' BI to use e-learning platforms. Here we have combined three models to examine the intention of using an e-learning platform. We have shown whether there is an association between the determinants of TPB and other models. In hypothesis H1, ATT positively influences the BI for online learning. This finding agrees with previous studies (Akour et al., 2021; Chu and Chen, 2016; Kim et al., 2021; Mailizar et al., 2021; Ndubisi, 2006). This might be due to the COVID 19 pandemic, which forced the students to maintain physical distance, having shaped positive attitudes towards online classes, which is considered a better alternative to class on-campus maintaining a physical distance.

In H2a and H2b, PU, a determinant under TAM, positively influences ATT and BI. Former research works also found a similar relationship between PU and BI (Han & Sa, 2021; Lee, 2010; Li & Yu, 2020; Liaquat et al., 2021; Kim et al., 2021) and between PU and ATT (Farahat, 2012; Kim & Han, 2021; Li & Yu, 2020; Masrom, 2007). As the students' learning performance was hampered due to having been kept in quarantine for a long time due to COVID-19, they believed using online learning technology might improve their performance.

In H3a, H3c, and H3d, PEU, a TAM determinant, significantly influences ATT, PU, and SOS. The former research works also found a similar relationship between PEU and ATT (Farahat. 2012; Kim et al., 2021; Li & Yu, 2020; Masrom, 2007), PEU and PU (Farahat, 2012; Masrom, 2007; Tarhini et al., 2014) and between PEU and SOS (Han & Sa, 2021) which is a determinant of ISSM model. This study is confined to students who are from marginalized families. Any technology to which they have easy access and which is easy to use will benefit them, resulting in positive attitudes towards the technology through satisfaction.

But in hypothesis H3b, we see that PEU does not influence BI, which disagrees with previous studies' findings (Han & Sa, 2021; Liaquat et al., 2021; Tarhini et al., 2014). This might be because an online learning platform requires mobile data or a Wi-Fi connection, and the marginalized students lack money. This is why, although they have positive attitudes toward e-learning, it will not result in the intention to use it because if they get the chance, they will attend in-house classes. And it might be for this reason, in hypothesis H4, we see that PBC does not affect BI, which agrees with the findings of former studies (Kim & Han, 2021).

In H5a, we see that SQ, a factor ISSM, does not influence BI, which disagrees with the former studies (Al-Maroof et al., 2020). As higher SQ requires higher investment in hardware and software, which underprivileged students cannot afford, the variability in SQ in our study sample is not adequately high and therefore, SQ could not explain differences in BI. In H5b, SQ substantially influences SOS, which agrees with the former studies (Cheng, 2019; Salam and Farooq, 2020).

As the students are not from well-off families, SQ will not result in BI but might enhance their satisfaction. And so, in H5b, we see that SQ results in SOS, and for the same reason, in H7, we see that SOS influences BI. The previous studies also found similar findings between SOS and BI (Al-Maroof et al., 2020; Chen et al., 2015; Venter and Swart, 2018). In H8, we see that SN influences BI, which agrees with the previous studies (Kim et al., 2021; Mouloudj et al., 2021; Tarhini et al., 2014). This indicates that when peers attend online classes during COVID-19, the students from unprivileged, especially marginalized families, also feel motivated to attend online classes.

In hypotheses H6a, H6b, and H6c, we see that ISQ does not influence BI, PEU and SOS. These findings disagree with the previous studies (Ajzen, 1991; Cristobel & Guinaliu, 2007; Davis and Venkatesh, 1991; Fishbein & Ajzen, 1975; Gounaris & Dimitriadis, 2008; Zeithaml et al., 2000). This implies that the quality of the internet across the study sample is homogenous. The experienced ISQ is necessarily low and, due to insufficient variability across the sample, cannot explain the variability in BI, PEU, and SOS. The higher the ISQ, the larger the internet expenditure required in Bangladesh. A broadband connection is required to get a stable high-speed internet service, which requires a large initial investment and additional monthly expenditure. This is beyond the affordability/availability of some underprivileged undergraduate students (who use mobile data) while inefficient for others (who avail broadband but experience unstable and low-speed internet due to low-cost packages and/or unstable electricity supply). This is why digital discrimination must be alleviated to ensure the continuing intention of underprivileged undergraduate students to attend online classes.

CONCLUSION AND IMPLICATIONS

This research work has validated an integrated research model to identify the determinants of Bangladeshi unprivileged university students' behavioural intention to use e-learning platforms. Given that online learning was the only way to continue education, students perceived it to be useful, although the perception was varied and could explain the variation in intention to use e-learning. However, ease of use, internet service quality and system quality were perceived to be low as these require resources and investments which poor students could not afford. Therefore, these variables could not explain the variability in the underprivileged university students' intention to use the e-learning approach. Our findings contrast with those of previous literature (based on participants from broader classes and income groups as opposed to our sample of specific groups, namely underprivileged university students) and have significant practical implications for a number of audiences.

This study corroborates previous research showcasing evidence of the digital divide in higher education, which was further exacerbated during the COVID-19 pandemic (Rouf et al., 2022; Sarkar et al., 2021; Emon et al., 2020). The educational institutions, government organizations, non-government organizations (NGOs) and private sector organizations working in the education sector will be benefited from our findings. Universities and other authorities that strive to design and implement wholly or partially online education delivery systems will realize the importance of paying attention to the severe digital divide (that makes poor students show little interest in e-learning) during such design and implementation process (Sarkar et al., 2021). Local and international financial institutions and development organizations, e.g. (the World Bank) and regulatory authorities shall realize the need for financing schemes that narrow the digital divide (e.g. to ensure low-cost and stable internet connectivity and appropriate electronic gadgets for all learners) in an emerging economy like Bangladesh (Emon et al., 2020).

Further research should be undertaken to explore the challenges faced by the teachers who conduct online classes in an emerging economy like Bangladesh.

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