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Résumé de l'article

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Technology Enabling the New Normal: How Students Respond to Classes

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Abstract

This cross-sectional study investigates the online education intention of undergraduate students in the largest and oldest public university in Bangladesh during the COVID-19 pandemic. Under convenient sampling, 843 undergraduate students with rural and urban backgrounds participated in an online self-administered questionnaire. Partial least squares structural equation modelling (PLS-SEM) was employed to examine the hypothesized relationships. We found that students' online class intention is significantly influenced by their attitude towards online classes (AOC), perceived usefulness (PU), and facilitating conditions (FC). We further identified that external antecedents have significant indirect effects on the outcome variables. Our findings provide new insights and contribute to a learners' community on online classes during the COVID-19 pandemic. This study extends the technology acceptance model (TAM) and the theory of planned behavior (TPB) to depict the factors influencing undergraduate students' intention to attend online classes (IOC) during the COVID-19 pandemic.

Keywords: COVID-19, online class intention, technology acceptance model, theory of planned behavior, Bangladesh

Introduction

In response to the worldwide emergency caused by the COVID-19 pandemic, many universities closed their on-campus academic activities and initiated online classes (Daniel, 2020; Murphy, 2020). Unlike adopting or accepting online learning as an alternative to face-to-face classes, the phenomenon of online learning during COVID-19 was merely a solution to address specific problems that the academic institutions were facing during the crisis (Dhawan, 2020). However, the rapid shift from a face-to-face classroom environment to online classes is creating various challenges (Crawford et al., 2020). Academics who normally conduct face-to-face lectures and communications may not be finding the new mode comfortable. Furthermore, students' adaptation capacity widely varies across countries. There remains ample scope for new research into the intention to use online education for both contextualization and theoretical extension.

During the COVID-19 pandemic, Bangladesh has been one of the most affected nations in the world (Bodrud-Doza et al., 2020). After detecting the first case in Bangladesh, authorities decided to shutdown academic activities on campuses in March 2020 (Anwar et al., 2020; Khan et al., 2020) to ensure social distancing as it is believed to be effective against transmission of the virus (Venkatesh & Edirappuli, 2020). Several months after the shutdown of on-campus academic activities, public universities in Bangladesh started using online education platforms with students (Al-Amin et al., 2021) though most academic institutions were yet to adopt well-established learning management systems (LMS) such as Moodle, Brightspace, WebCT, Blackboard, and Desire2Learn. Instead, online classes were conducted using Zoom, Google Meet, Webex, and other social media platforms that are not well developed LMSs.

Although the online class has been adopted globally as a tool during the crisis, the success of online learning largely depends on users' acceptance. Countries with limitations in technological advancement are not ready to implement online education (Sintema, 2020). Bangladesh does not belong among technologically developed countries as it was ranked 147th in the ICT Development Index among 176 countries in 2017 (Chowhan & Ghosh, 2020). The educational institutions of Bangladesh are at an early stage of adopting e-learning technologies for academic purposes, and the experience of using such technologies is new for both academics and students (Sarker et al., 2019). As online learning is a current phenomenon in Bangladesh, not much research has been conducted regarding the attitude and behavioral intention of students in the context of an online class. Since the online class during COVID-19 is not similar to a well-developed LMS, it is also essential to assess the experience of students and their attitudes about online academic activities. Therefore, we investigated the online class intentions of undergraduate students in a public university in Bangladesh, where online classes officially started several months after lockdown came into force in March 2020. The research was intended to extend available literature, incorporating new antecedents of online class intentions and unveiling the context of a lower middle income country where more than 3.2 million people are enrolled at the tertiary level of education (Mannan, 2017).

Literature and Hypotheses Development

Intention to Attend Online Classes (IOC)

Several factors affect behavioral intention. According to the technology acceptance model (TAM), attitude, perceived usefulness (PU), and perceived ease of use (PEU) influence behavioral intention (Davis, 1989). Aligned with the TAM, we investigated how attitude, PU, and PEU influenced students' intention to attend online classes during COVID-19. We also extended the TAM by adding four variables: personal innovativeness (PI), technological complexity (TC), expected performance (EP), and facilitating conditions (FC). Figure 1 summarizes our research model.

Figure 1

Research Model
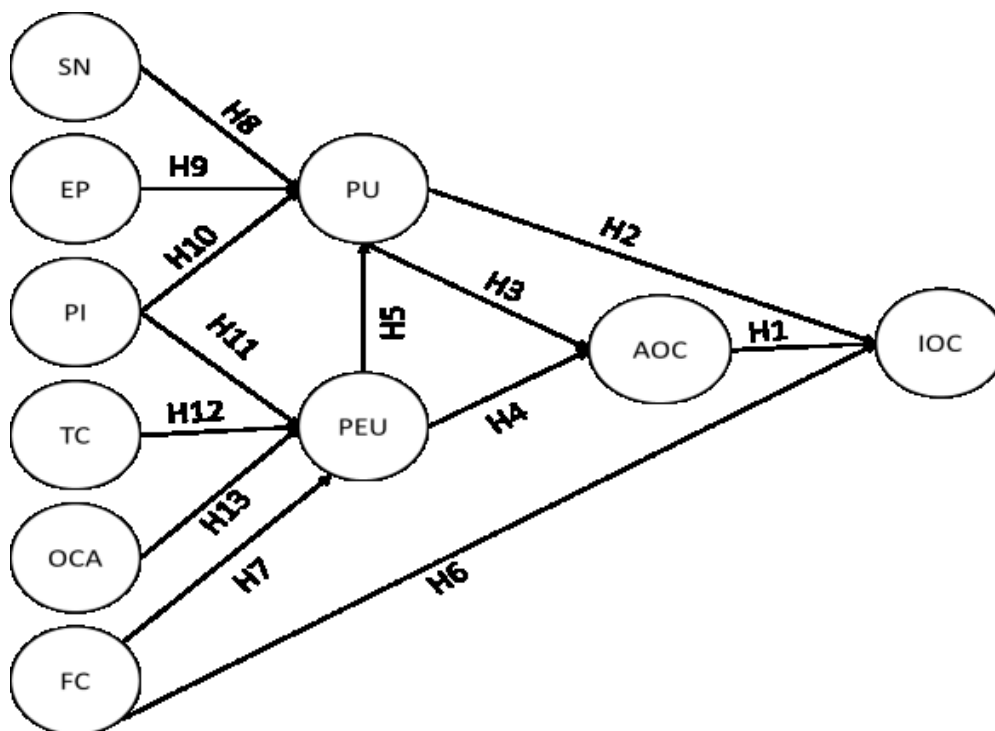
Note. SN = subjective norm; EP = expected performance; PI = personal innovativeness; TC = technological complexity; OCA = online class anxiety; FC = facilitating condition; PU = perceived usefulness; PEU = perceived ease of use; AOC = attitude towards online classes; IOC = intention to attend online classes; H = hypothesis.

Attitude Towards Online Class (AOC)

Attitude is widely held to be a person's positive or negative feeling about performing a target behavior (Fishbein & Azjen, 1980). Attitude deals with the possibility of performing and accepting a specific behavior (Davis, 1989; Hao, 2004). According to Kaplan (1972), the term attitude refers to the response tendency, favorable or unfavorable, to an event. In this study, attitude indicates whether students are interested in online classes, have positive feelings, and are willing to participate in an online class. Students' positive or negative attitude contributes to their online learning activities and their behavioral intention to use updated technology for learning (Venkatesh & Davis, 2000). Mailizar et al. (2021) identified that attitude positively influences the behavioral intention towards using online classes. Therefore, we set the following hypothesis:

H1: AOC positively influences IOC during COVID-19.

Perceived Usefulness (PU)

PU of technologies is one of the vital elements of the TAM. PU refers to the degree to which students using a particular system believe that it would improve their study performance and be more advantageous than earlier methods of study (Abdullah et al., 2016; Liu et al., 2009). PU influences a user's choice of whether to admit or refuse a particular technology. In accordance with the TAM (Davis, 1985), students' PU influences their attitude towards online learning through the use of technology. Moreover, PU has been consistently found to be a direct determinant of e-learning (Liu et al., 2009). With regards to the relationship between PU and IOC, Rizun and Strzelecki (2020) found that PU positively influences AOC. As such, we expect:

H2: PU positively influences IOC during COVID-19.

H3: PU positively influences AOC during COVID-19.

Perceived Ease of Use (PEU)

PEU refers to how quickly and confidently people believe that they can use a technology (Esteban-Millat et al., 2018). According to the TAM, PEU is one predictor of users' attitudes towards technology adoption (Davis, 1989). Studies suggest that PEU positively influences learning attitudes about online classes (Rizun & Strzelecki, 2020). Besides, earlier studies have confirmed that PEU could positively and significantly influence PU (Abdullah et al., 2016; Binyamin et al., 2019). Moreover, several studies (Al-Fraihat et al., 2020; Vanduhe et al., 2020) on online learning proved that PEU affects PU. In line with earlier evidence on PEU, it is likely that when students hold positive perceptions of the ease of using technologies, they consider virtual classes useful and embrace them without hesitation. Based on previous studies, the following hypotheses are postulated:

H4: PEU is positively related to AOC during COVID-19.

H5: PEU is positively related to PU of online learning during COVID-19.

Facilitating Condition (FC)

The term facilitating condition refers to whether an individual believes that sufficient infrastructure is available to use a specific system (Venkatesh et al., 2003). FC indicates the state where all the required facilities, tools, equipment, and assistance are supplied to an individual to use a system. Prior studies reveal that FC significantly influences students' intention to use interactive e-learning systems in a learning environment (Teo, 2010; Wong et al., 2013). Earlier research also demonstrated that FC predicted the PEU of web-based learning and assessment (Nikou & Economides, 2017). Sukendro et al. (2020) identified a positive relationship between FC and PEU in e-learning during COVID-19. Thus, we expect:

H6: FC positively influences IOC during COVID-19.

H7: FC positively influences PEU of online classes during COVID-19.

Subjective Norm (SN)

According to Fishbein and Ajzen (1975), SN refers to the degree of individual attention affected by other societal members' views while taking a specific decision. It assumes that an individual's belief about whether to carry out a specific behavior is significantly influenced by the judgment of others. Several studies have indicated that SN is one of the vital factors in the uptake of technology-based services (Venkatesh & Davis, 2000; Yang et al., 2012). Moreover, favorable opinions of relatives, friends, peers, and family members induce an individual to take up new services, and the individual begins to perceive that these services are useful (Schepers & Wetzels, 2007). Venkatesh and Bala (2008) and Teo et al. (2019) suggested that SN has a significant influence on PU. In the case of students, their teachers, friends, peers, and family members are regarded as significant influencers on adopting technology to assist with attending online classes (Teo, 2012). Based on this discussion, the following hypothesis has been developed:

H8: SN has a positive influence on PU of online classes during COVID-19.

Expected Performance (EP)

Expected performance is often seen as an individual's perception of completing a task successfully. Venkatesh and Davis (2000) stated that EP indicates whether a system accomplishes the given tasks effectively and efficiently. In this paper, EP refers to students' perception(s) regarding the quality of learning in online classes and whether it increases their skill(s) and academic performance and effectively equips them. Moreover, Venkatesh and Davis (2000) mentioned a correlation between output quality and PU, which was later empirically tested in the TAM (Jan & Contreras, 2016; Venkatesh & Bala, 2008). These studies indicated that the PU of a system is formed by an individuals' perception of how well the system might accomplish the given tasks and their mental assessments of the performance from applying that system (Venkatesh & Bala, 2008). We hypothesize that EP may influence students' PU of technology.

H9: EP positively influences PU of online classes during COVID-19.

Personal Innovativeness (PI)

Personal innovativeness denotes the traits that explain a person's willingness to find and adopt new technology and search for ways to experiment with it. In a broader sense, PI indicates whether a person is willing to adopt technologies or ideas that surpass the extent of their familiarity (Aldás-Manzano et al., 2009). Moreover, PI indicates an inherent side of an individual's personality, and the degree of innovativeness differs from person to person (Yang et al., 2012). Area-specific innovativeness helps users regarding the acceptance of technological innovation (Yi et al., 2006). However, an individual with a greater degree of PI in information technology in general might build up more favorable perceptions of the innovation and a better behavioral intention to accept it (Agarwal & Prasad, 1998). Thus, it is important to ascertain the role of personal innovativeness in the broader area of information technology research and technology adoption in online classes. Based on the earlier literature, we posit the following hypotheses:

H10: Students' PI positively influences their PU of online classes during COVID-19.

H11: Students' PI positively influences their PEU of online classes during COVID-19.

Technological Complexity (TC)

Technological complexity refers to the technological level that an individual requires to get familiar with a new technology and perform task(s) with it more effectively. Thompson et al. (1991) stated that TC refers to users' belief in the extent to which a technology is complicated to use. Moreover, considering human information processing capacity confines, Venkatesh and Bala (2008) recommended that TC largely influences technology users' PEU. They stated that when users find a technology is too complex, they might perceive it as challenging to use. In educational settings, TC was found to have an opposite association with students' PEU (Cigdem & Topcu, 2015; Teo, 2009). It is reasonable to expect that when students taking online classes use a technology with a greater TC than the commonly used technologies (e.g., e-mail and Microsoft Office applications), they might perceive that technology is not easy to use and more effort is required. Therefore, the following hypothesis is formulated:

H12: Students' perceived TC negatively influences PEU of online classes during COVID-19.

Online Class Anxiety (OCA)

Online class anxiety is analogous to computer anxiety and is an external antecedent to PEU. According to Hajiyev (2018), computer anxiety is characterized as the supplication of anxious or emotional reactions when accomplishing any task on a computer. Earlier research evidenced that users may feel nervous and anxious at preliminary stages of their interfaces with computers, and that such anxiety negatively influences PEU (Rizun & Strzelecki, 2020). In this study, OCA refers to students' nervousness or intimidation when attending online classes. Thus, we propose the following hypothesis:

H13: Students' OCA negatively influences PEU of online classes during COVID-19.

Method

Sample and Data

Our data comes from a convenience sample of undergraduate business students from year one to four at the University of Dhaka in Bangladesh. The University of Dhaka is Bangladesh's century-old premier public university in which students from all social strata and all geographic locations are enrolled. An online questionnaire was sent to 1700 students in May 2021 with a request to participate voluntarily and anonymously. Students were assured of the use of their responses only in aggregate. They were also given the option to withdraw from the survey at any point. The response rate was 50.17%. Over half of the respondents (52.8%) were male and from metropolitan cities (55%). In relation to the education level of the respondents' parents, it was found that 24.4% of students had a parent who had completed five years of primary education, 18% had a parent who had gone to study at the secondary level, and 18.9% had a parent who had studied at the higher-secondary level. However, the largest proportion (38.7%) had a parent who had earned a diploma or above.

Measures

All measures used a five-point Likert-type scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Most of the measurement scales, shown in Table 1, were adapted from the existing literature, with modifications to address intention to use online classes during the pandemic. We developed some of the measures based on theoretical and empirical literature on the extended TAM and the theory of

planned behavior (TPB). The instrument was developed in English, and the final instrument was designed based on feedback from a pilot test on 20 students.

Table 1

Measurement Scales

Construct	Measurement Item	Source
Intention to attend online class	I intend to attend all online classes.	Adapted from Zia (2020)
	I encourage my friends to attend online classes.	Developed by researchers
	I am ready to attend an examination/test online.	
	I plan a learning schedule for online classes.	Lee et al. (2019)
Attitude towards online class	The online classes are attractive to me.	Adapted from Liñán & Chen (2009)
	I am happy with online classes.	
	I am willing to participate in online class activities.	Adapted from Teo et al. (2019)
	I have positive feelings towards online classes.	
Perceived usefulness	Attending online classes has been more advantageous to me.	Adapted from Liñán & Chen (2009)
	Attending online classes helps me complete my courses.	Developed by researchers
	Attending online classes is beneficial.	
Perceived ease of use	I can easily use online class platforms.	
	I know how to use online class platform features.	
	Online classes allow flexibility.	
Subjective norm	People who influence my behavior think that I should attend online classes.	Adapted from Teo et al. (2019)
	People who are important to me think that I should attend online classes.	
	People whom I respect support me to continue online classes.	
Expected performance	The quality of learning via online classes is the same as physical classes.	Developed by researchers
	Online classes increase my skills.	
	My academic performance will not be affected by online classes.	
	Online classes offer more learning opportunities.	

Technological complexity	I have problems with the technical aspects of online classes.	Adapted from Teo et al. (2019)
	I take a long time to become familiar with the online classes tool.	
	Attending online classes is a complex activity.	
Online class anxiety	I feel nervous about online classes.	
	I hesitate to respond in online classes for fear of making mistakes.	
	Attending online classes leads to stress and anxiety for me.	
Personal innovativeness	I like to experiment with new technology.	Saadé & AlSharhan (2015)
	If I hear about new technology, I will look for ways to explore it.	
	In general, I am hesitant to try out new technology.	
	Among my peers, I am the first to try out new technology.	Yi et al. (2006)
Facilitating condition	I have the gadgets (laptop, mobile, tablet) to attend online classes.	Developed by researchers
	I have a good Internet connection.	
	I have a good Internet speed.	

Results

Analytical Framework

Apart from descriptive statistical analysis, this study implemented structural equation modeling using SmartPLS3. Mardia's multivariate test of data normality indicated significant values of skewness (β = 6.33, $p \leq$ 0.00) and kurtosis (β = 144.49, $p \leq$ 0.00), and therefore, PLS-SEM was suited to this data (Hair et al., 2017). Reliability and validity (convergent and discriminant) in the measurement model were tested based on the results of the PLS algorithm by using multiple indicators. The values of R^2 and f^2 are used to judge the explanatory power and effect size of the model. Using the blindfolding technique in PLS-SEM, the Stone-Geisser test was performed to ascertain the model's predictive power.

Assessment of the Measurement Model

All measurement items strongly load on the constructs and fulfill the convergent validity (Table 2). Cronbach's alpha values range from 0.74 to 0.92, and henceforth, reliability of the construct is established. Composite reliability (CR) is attained as all the values are above the threshold value of 0.7 (Hair et al., 2011). The estimated values of the average variance extracted are much greater than the threshold value of 0.5 (Sarstedt et al., 2017). Thus, there is adequate evidence of the convergent validity of the measurement model (Lin & Bautista, 2017; Venkatesh, 2000). Discriminant validity is confirmed

using HT-MT$_{0.90}$, the heterotrait-monotrait ratio of correlations criterion suggested by Henseler et al. (2015). See Table 3.

Table 2

Reliability and Validity Measures

Latent variable	Item	Loading	α	AVE	CR
AOC	AOC1	0.886	0.92	0.81	0.95
	AOC2	0.89			
	AOC3	0.90			
	AOC4	0.93			
IOC	IOC1	0.88	0.85	0.69	0.90
	IOC2	0.87			
	IOC3	0.79			
	IOC4	0.78			
OCA	OCA1	0.89	0.83	0.75	0.90
	OCA2	0.87			
	OCA3	0.84			
EP	EP1	0.75	0.86	0.70	0.90
	EP2	0.87			
	EP3	0.85			
	EP4	0.88			
PEU	PEU1	0.84	0.82	0.74	0.90
	PEU2	0.89			
	PEU3	0.85			
PI	PI1	0.95	0.89	0.90	0.95
	PI2	0.95			
PU	PU1	0.85	0.82	0.74	0.90
	PU2	0.86			
	PU3	0.88			
SN	SN1	0.88	0.89	0.82	0.93
	SN2	0.94			
	SN3	0.90			
FC	FC1	0.83	0.74	0.66	0.85
	FC2	0.79			
	FC3	0.82			
TC	TC1	0.86	0.86	0.78	0.91

TC2	0.89	
TC3	0.89	

Note: CR = composite reliability; AOC = attitude towards online classes; IOC = intention to attend online classes; OCA = online class anxiety; EP = expected performance; PEU = perceived ease of use; PI = personal innovativeness; PU = perceived usefulness; SN = subjective norm; FC = facilitating condition; TC = technological complexity.

Table 3

Discriminant Validity (Heterotrait-Monotrait)

	AOC	IOC	OCA	PEU	PU	EP	PI	SN	TC	FC
AOC										
IOC	0.89									
OCA	0.41	0.43								
PEU	0.57	0.67	0.53							
PU	0.84	0.82	0.38	0.62						
EP	0.77	0.74	0.33	0.50	0.73					
PI	0.31	0.39	0.28	0.49	0.30	0.27				
SN	0.64	0.72	0.26	0.53	0.67	0.57	0.37			
TC	0.44	0.48	0.67	0.59	0.43	0.35	0.20	0.31		
FC	0.47	0.62	0.46	0.83	0.48	0.43	0.45	0.57	0.51	

Note. AOC = attitude towards online classes; IOC = intention to attend online classes; OCA = online class anxiety; PEU = perceived ease of use; PU = perceived usefulness; EP = expected performance; PI = personal innovativeness; SN = subjective norm; TC = technological complexity; FC = facilitating condition.

Assessment of the Structural Model

There is no evidence of multicollinearity as the variance inflation factor (VIF) scores as shown in Table 4 are much lower than the threshold value 3.3 (Hair et al., 2011). Stone-Geisser's test indicates all the endogenous latent variables have high predictive power as all the Q^2 values (Table 5) exceed the threshold limit of 0.35 (Chin, 2010). The model also has high explanatory power as it yielded high R^2 values.

Table 4 and Figure 2 indicate that 12 hypotheses were supported. IOC is positively determined by AOC ($\beta = 0.573$; $p < 0.00$), PU ($\beta = 0.192$; $p < 0.00$), and FC ($\beta = 0.199$; $p < 0.00$). Thus, H1, H2, and H6 are supported. Both PU ($\beta = 0.647$; $p < 0.00$) and PEU ($\beta = 0.168$; $p < 0.00$) are significant predictors of AOC that in turn support H3 and H4. Three variables, namely PEU ($\beta = 0.221$; $p < 0.00$), SN ($\beta = 0.297$; $p < 0.00$), and EP ($\beta = 0.386$; $p < 0.00$) have positive and significant relationships with PU. Thus, H5, H8, and H9 are supported. The relationship between PI and PU is insignificant as $p = 0.129$ and hence, H10 is not supported. Finally, PEU is negatively affected by TC ($\beta = -0.214$; $p < 0.00$) and OCA ($\beta = -0.102$; $p < 0.00$) while it is positively affected by PI ($\beta = 0.189$; $p < 0.00$) and FC ($\beta = 0.462$; $p < 0.00$). As all four predictors of PEU show significant results with expected signs, H11, H12, H13, and H7 are also supported. We also observed that f^2 values of the significant paths ranged from 0.014 to 0.701. Following the benchmark suggested by Cohen (1988), we found a significant effect size of two paths, a medium effect size of two paths, and a small effect size of eight paths.

Table 4

Results of the Structural Model

Hypothesis	Path	Path coefficient	*p*-value	f^2	CI (%)		VIF
					UL	*LL*	
H1	AOC→IOC	0.573	0.00	0.467	0.52	0.62	2.24
H2	PU→IOC	0.192	0.00	0.053	0.14	0.24	2.21
H3	PU→AOC	0.647	0.00	0.701	0.61	0.68	1.35
H4	PEU→AOC	0.168	0.00	0.047	0.12	0.21	1.35
H5	PEU→PU	0.221	0.00	0.067	0.17	0.27	1.50
H6	FC→IOC	0.199	0.00	0.104	0.16	0.24	1.21
H7	FC→PEU	0.462	0.00	0.335	0.41	0.51	1.36
H8	SN→PU	0.297	0.00	0.12	0.24	0.35	1.52
H9	EP→PU	0.386	0.00	0.216	0.33	0.44	1.43
H10	PI→PU	-0.033	0.12	0.002	-0.08	0.02	1.25
H11	PI→PEU	0.189	0.00	0.065	0.14	0.23	1.69
H12	TC→PEU	-0.214	0.00	0.062	0.27	0.15	1.58
H13	OCA→PEU	-0.102	0.00	0.014	-0.15	-0.04	1.54

Note. CI= confidence interval; VIF = variance inflation factor; H = hypothesis; AOC = attitude towards online classes; IOC = intention to attend online classes; PU = perceived usefulness; PEU = perceived ease of use; FC = facilitating condition; SN = subjective norm; EP = expected performance; PI = personal innovativeness; TC = technological complexity; OCA = online class anxiety.

Figure 2

Research Model with Coefficients
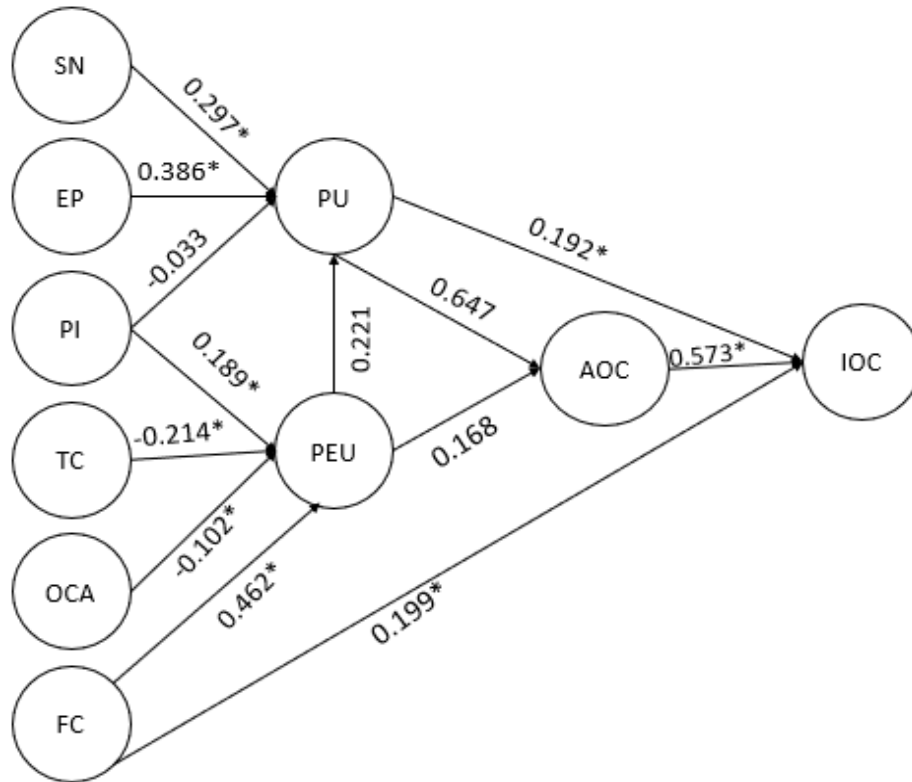
Note. SN = subjective norm; EP = expected performance; PI = personal innovativeness; TC = technological complexity; OCA = online class anxiety; FC = facilitating conditio; PU = perceived usefulness; PEU = perceived ease of use; AOC = attitude towards online classes; IOC = intention to attend online classes. *$p < 0.001$.

Results in Table 5 show that AOC is the most significant variable influencing intention, with a total effect of 0.57, followed by PU (0.56) and FC (0.30). PU exerts the highest direct effect on attitude. Although EP and SN positively predict PU, EP has a higher total impact ($\beta = 0.39$) than SN ($\beta = 0.30$). Results also demonstrate that among all the paths to PEU, the largest direct effect comes from FC ($\beta = 46$).

Table 5

Direct, Indirect, and Total Effects of the Research Model

Outcome	Determinant	Standardized estimate			R^2	Q^2
		Direct effects	Indirect effects	Total effects		
Intention to attend online classes	AOC	0.57		0.57	0.69	0.47
	PU	0.19	0.37	0.56		
	FC	0.20	0.10	0.30		
	EP		0.22	0.22		
	SN		0.17	0.17		
	OCA		-0.02	-0.02		
	PEU		0.22	0.22		
	TC		-0.05	-0.05		
	PI		0.02	0.02		
Attitude towards online classes	PU	0.65		0.65	0.56	0.45
	PEU	0.17	0.14	0.31		
	FC		0.14	0.14		
	OCA		-0.03	-0.03		
	EP		0.25	0.25		
	PI		0.04	0.04		
	SN		0.19	0.19		
	TC		-0.07	-0.07		
Perceived ease of Use	FC	0.46		0.46	0.53	0.39
	OCA	-0.10		-0.10		
	TC	-0.21		-0.21		
	PI	0.19		0.19		
Perceived usefulness	PEU	0.22		0.22	0.52	0.38
	SN	0.30		0.30		
	EP	0.39		0.39		
	OCA		-0.02	-0.02		
	TC		-0.05	-0.05		
	FC		0.10	0.10		
	PI	-0.03	0.04	0.01		

Note. AOC = attitude towards online classes; PU = perceived usefulness; FC = facilitating condition; EP = expected performance; SN = subjective norm; OCA = online class anxiety; PEU = perceived ease of use; TC = technological complexity; PI = personal innovativeness.

Discussion

To explore antecedents of students' intention to use online classes during the period of COVID-19, we set 13 hypotheses, of which 12 were found statistically significant. These results support the TPB (Fishbein & Ajzen, 1975, 1980), TAM2, and TAM3 (Venkatesh, 2000; Venkatesh et al., 2003; Venkatesh & Bala, 2008). We found that AOC, PU, and FC positively affect the online class intention of undergraduate students in business school. Among these variables, AOC exerts the most dominant influence on intention. This result is consistent with the studies of Sánchez and Hueros (2010) and Teo et al. (2019). Similar to the perceived behavioral control in the TPB, this study confirms the significant direct impact of FC on IOC. Prior studies did not examine the role of FC in determining students' intention to attend online classes. The effect of FC on IOC is evident given that the students participating in this study were located in diverse locations including villages, towns, and metropolitan areas where the availability of devices and quality of internet service vary to a great extent and students need to attend online classes using free versions of Zoom and Google Meet since the institution lacks an online learning management system.

In line with the assertion of the TAM and prior empirical evidence i.e., Schepers and Wetzels (2007), Teo et al., (2019), Venkatesh (2000), and Venkatesh and Bala (2008), this study finds that there is significant impact of PU and PEU on AOC. The results underscore that students are more likely to support online classes and examinations if they feel that online classes are helpful and accessible. However, the relative impact of PU is much higher than PEU, which signifies that PU has a more substantial determining effect on attitude than PEU. This result can partly be attributed to the fact that university students are familiar with online platforms and feel a degree of ease in using those technologies.

The extended TAM of this study finds that EP positively contributes to students' PU of an online class. The result implies that many students might have a negative attitude to online classes, with an apprehension that they might not perform satisfactorily, that negatively impacts their academic performance, employment opportunities, and career advancement. Similar to prior studies on the extended TAM by Jan and Contreras (2016) and Venkatesh and Bala (2008), this study supports the relationship between EP and PU in online class intention of tertiary level students. Besides, in line with the earlier evidence of the TAM by Venkatesh and Davis (2000), Schepers and Wetzels (2007), Venkatesh and Bala (2008), and Teo et al. (2019), this study confirms that the people who surround the students positively influence PU.

The PEU of an online class is predicted by four variables that PI and FC determine positively while OCA and TC affect negatively. No prior evidence on the relationship between PI and online class intention exists. However, Saadé & AlSharhan (2015) have found no impact of PI on students' motivation when using an online learning tool, while other studies (Bauer et al., 2005; Shankar & Datta, 2018) have identified PI as an important factor in technology adoption intention of customers in different cultures.

Our results indicate the positive influence of FC on PEU, and this finding is both theoretically and empirically supported by Venkatesh (2000), Venkatesh et al. (2003), and Venkatesh and Bala (2008). Besides, results demonstrate that among all the paths to PEU, the largest direct effect comes from FC. This result underscores the heightened importance of FC in the perception of ease. Thus, to promote students' PEU, the focus needs to be given to improving facilitating conditions. Moving away from the physical classroom to a virtual class is a new experience for many students. Since the new class format

is a technology-enabled learning system, TC is negatively related to PEU. Teo et al. (2019) also found a negative association between TC and PEU. OCA is identified as another significant determinant of PEU, and the relationship between them is negative. Although the relationship between PEU and OCA was first examined in relation to online classes during COVID-19, our result echoed the findings of Chuo et al. (2011) and Teo et al. (2019).

Theoretical and Practical Contributions

Our research offers contributions to knowledge about online class intention. We extended the prevailing literature by adding new antecedents to the TAM (Venkatesh, 2000; Venkatesh et al., 2003; Venkatesh & Bala, 2008) and the TPB (Fishbein & Ajzen, 1975, 1980). We have extended the existing TAM in three significant ways. First, we found new variables, including OCA and PI, to be determinants of PEU of online classes while EP determines PU. Second, we developed a valid and reliable measurement of EP in online classes, which also significantly predicts PEU. Third, we have extended the measurement scales of AOC, PU, and PEU to the COVID-19 context. Altogether, our analysis has increased the predictive power and explains 69% of students' intention to accept online classes during COVID-19. As a result, this study has broadened the understanding found in the growing body of literature relating to students' intention to use online classes. In relation to the TPB, this study adds facilitating conditions as a new variable that directly impacts attitude towards online classes. FC acts as an external antecedent of PEU.

From the practical side, this study carries valuable insights for academic institutions and policymakers since there remains an ample gap in the contextual understanding of students' intentions. The underlying antecedents vary due to wide gaps in their socioeconomic contexts and institutional practices. Among the variables that determine attitude, PU is the most dominant. It implies that students will be more interested in attending online classes if PU is adequately conveyed. This is critically important in the context of Bangladesh and in many other developing countries where students show disinterest in online classes and even put pressure on authorities to open dormitories, defying the requirement of social distancing. The external antecedents also have significant indirect effects on the outcome variable. TC and OCA exert a negative impact on PEU. Thus, students who perceive online classes as complex and suffer from anxiety might have strong negative IOC. This result carries insights for future research on attitude and behavioral intention in a new normal world.

High PEU and PU will reduce resistance from students to online classes and tests. These findings underscore that educational institutions need to interact with students' communities to identify the problems of attending online classes, such as unavailability of devices, weak network speed, electricity failures, and family hardship, so that relevant agencies can design programs for underprivileged students who otherwise might be excluded as a result of the sudden adoption of online classes. Hence, policymakers need to consider the long-lasting effect of regional disparity in terms of access to online education.

Besides, students' AOC will be favorable if their performance expectations are met. If students perceive that their performance will degrade as a result of online classes, their attitude will be negatively affected. TC has the strongest negative effect on PEU, which implies that to increase students' motivation to use an online class, TC needs to be minimized. Academic institutions can organize training programs for students, develop video tutorials that students can access at their convenience, and design an online

LMS. Otherwise, organizing online assessments might go in vain, eventually paralyzing online classes in the new normal.

Limitations and Future Directions

Our study is not without limitations. This study has analyzed behavioral intention rather than actual behavior. Analyzing actual behavior by taking into account students' participation and performance indicators might show a different result from the antecedents of behavioral intention. Future studies can explore this relationship by looking at actual performance data. We have collected data from students attending business school. However, the views of students in other schools and results derived from another unit of analysis in a similar context might be different. Future studies can accommodate students' diversity in terms of their fields of study and levels of study, for example, undergraduate and graduate programs. Fresh insights can also be derived by exploring the intention of students to sit for online assessments that can help academic institutions and policymakers address students' concerns. This will guide the investment decision of the government in allocating funds for developing essential educational infrastructure in a new normal.

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