The Extended Technology Acceptance Model (ETAM): Examining Students' Acceptance of Online Learning During COVID-19 Pandemic

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Abstract—This study contributes to the existing literature on online learning during the COVID-19 pandemic in higher education by investigating the relationships between the cognitive variables and students' adoption of online learning. Based on Technology Acceptance Model (TAM), some hypotheses were formulated to test the links between TAM constructs and online learning anxiety as an antecedent. This study adopted structural equation modelling (SEM) to scrutinize technology adoption for a sample of 569 students in Oman. The results indicated that attitude towards online learning is a strong predictor of technology adoption during the COVID-19 pandemic. Furthermore, both perceived usefulness of online learning and perceived ease of online use yielded a significant contribution of the attitude construct. Besides, online learning anxiety affected both the perceived usefulness and perceived ease of online use negatively, in which perceived ease of use is largely predicted while perceived usefulness is moderately predicted. In the light of the previous findings, online learning anxiety should have more attention by tertiary lecturers, counsellors, academic advisors and policymakers when implementing online teaching and learning.

Keywords—COVID-19, online learning, Technology Acceptance Model

1 Introduction

During the COVID-19 pandemic, online education has become the only inevitable approach to education. Though it is not a novel concept, many educational institutions previously considered it supplemental, relying mainly on other education types. Online education can be constructive because it helps students learn in their own space, specifically from anywhere and anytime [1]. Still, the amendment of education mode to fully online, or perhaps 'online only', requires understanding students' acceptance of the new learning environment [2]. It is very decisive to identify how students perceive and take part in online learning platforms [3]. Also, the implementation of technology in learning should be in accordance with students' perceived attitudes [4].

Technology Acceptance Model (TAM) is deemed to be the most prevalent model employed to measure students' attitudes towards using emerging technologies in different circumstances and disciplines [5, 6]. TAM could be used to explore students' perceptions. It has six factors: perceived usefulness, perceived ease of use, attitudes towards the new technology, behavioural intention, actual system use, and external factors [7]. Therefore, it is a suitable instrument for assessing students' perceptions of online learning. However, some external factors can be included in the model in the era of COVID-19. This study proposed a significant factor which is online learning anxiety. Online learning anxiety is included in the previous studies because of its significance [6]. Therefore, this study explored students' perceptions towards online learning and investigated if the proposed factors affect students' actual usage of online learning. Our proposed model is depicted in Figure 1.

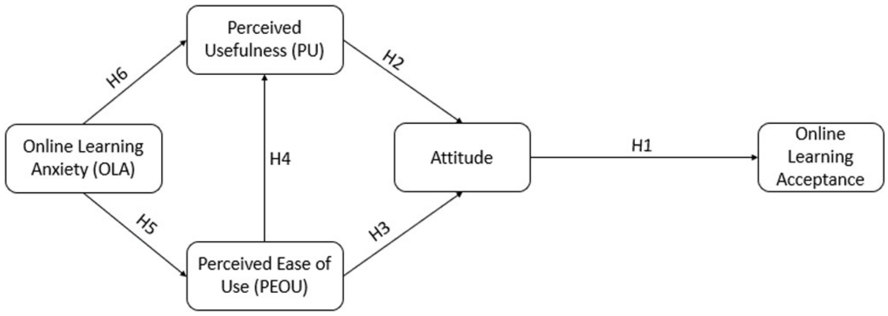

Fig. 1. Theoretical framework

Universities around the world have reacted differently to the onset of the COVID-19 pandemic. Some universities have adopted 'online only' mode, while other universities have implementing blended-learning systems. However, with the new variant of COVID-19, most governments worldwide have forced universities to adopt online learning. The unprecedented rapid shift in most cases in education delivery has urged developers and deliverers of online education to evaluate the education quality. Hence, empirical research is seriously needed to identify the usability of online learning systems. Many universities in Oman, if not all, have implemented online teaching and learning modes after the Supreme COVID-19 Committee announced the suspension of direct education in universities and colleges on March 15, 2020. Some Omani students are experiencing the first purely online learning. Therefore, this study aimed at constructing a cohesive theoretical framework of university students' online learning acceptance. The study attempted to deliver a key opportunity for the academic administrators and managers to advance understanding of students' technology acceptance. This research project provided an empirical analysis of university students' intention to use online learning with variables like students' attitude, perceived usefulness, perceived ease of use, and online learning anxiety. Some implications are discussed for academic administrators, managers, and educators to understand the use of online education better.

2 Literature review

The technology acceptance model (TAM), proposed by Davis [7], is widely known as a valid theoretical scale for assessing user acceptance of a system [8]. TAM is mainly developed on two central elements, which are perceived ease of use (PEOU) and perceived usefulness (PU) [7]. PEOU and PU accentuate that a system will not be perceived as applicable if users do not feel comfortable using it. Based on the TAM framework, users' impressions about the ease of use and usefulness of a system mainly induce a behavioural intention (BI) and attitude to use or not to use the system [9]. Furthermore, a user's actual use (AU) of a system is primarily shaped by the three variables – perceived use, perceived and behavioural intentions [3]. TAM also suggests that external factors affect a user's acceptance of a technology system based on perceived usefulness and perceived ease of use [7]. This study expanded the original TAM framework to include external factors like online learning anxiety (OLA).

2.1 Behavioural intention

Behavioural intention (BI) to use a technology system is identified as "the degree of an individual's belief that he or she will continue to use the system" [10]. According to TAM, BI in acceptance of the new system is influenced by two main factors: perceived ease of use and perceived usefulness [11–13]. Previous research reports that PEOU and PU construct a positive impact on BI [14–16]. In learning contexts, this indicates that when students feel comfortable using the learning system and perceive benefits from it, they will show willingness to continue using the system. Thereby, system developers can direct one's behavioural intention by enhancing these two factors. Also, research proves that BI is directly and significantly associated with the actual use (AU) of a technology system [17]. However, actual use is excluded from the model in this study because students experienced using online learning for a short time and the university administration changed the learning mode from time to time. In this study, an online learning system was implemented in a higher education institution.

2.2 Attitude

Attitude to use a technology system refers to the user's positive or negative impressions towards taking part in the system [18]. A growing body of research indicates that attitude is an indispensable strand in exploring the use of technological innovations [19–21]. In learning settings, several studies, for example, Chang et al. [19] and Padilla-Meléndez et al. [20], revealed that perceived attitude influenced students' behavioural intentions positively to continue using technology. Mailizar et al. [22] emphasized that attitude toward online learning is the most influential construct to predict students' behavioural intention to utilize online learning. Thus, students are likely to continue using the technological innovations that are engaged in if they perceive approving views to these innovations. In this study, it is hypothesized that:

H1: Attitudes toward online learning will positively affect behavioural adoption to use online learning.

2.3 Perceived usefulness

Davis [7] defined perceived usefulness (PU) as "the degree to which a person believes that using a particular system would enhance his or her job performance" [7]. Moores [23] describes PU as the decreasing effort that a technology system provides to users. According to TAM, PU demonstrates a direct and significant influence on a technology system's users' attitude, consequently affecting users' behavioural intention to use the system [24]. For example, if students perceive benefits in being engaged in the online learning system, they will construct a positive attitude towards the system, and thereby they will be willing to continue using online learning [25, 26]. Thus, in this study, the next hypotheses were formulated:

H2: Perceived usefulness will positively predict perceived attitudes towards online learning.

2.4 Perceived ease of use

Perceived ease of use (PEOU) is defined by Davis [7] as "the degree to which a person believes that using a particular system would be free of effort" [7]. Several studies have proved that PEOU directly influences the attitude towards the use of a technological system [3, 27, 28]. In online learning, when students realize that the learning system is uncomplicated, effortless and easy to use, they will hold a positive attitude. Literature also reveals that PEOU affects PU, mainly positively, in the continued acceptance of a system [29]. This implies that the more the students perceive that the online learning system will be stress-free, the more they are inclined to continue using such system [30]. Promoting ease of use of any system enriches the perceived usefulness [12, 31]. Accordingly, this study hypothesized that:

H3: Perceived ease of use will positively predict students' attitudes towards online learning.
H4: Perceived ease of use will positively influence the perceived usefulness of online learning.

2.5 Online learning anxiety

The current study integrated online learning anxiety (OLA) as an external factor. Igbaria and Iivari [32] defined anxiety as "the tendency of an individual to feel uneasy, apprehensive, or aversive at the prospect of using technology" [32]. Users of a technological system perceive anxiety when they feel frustrated and apprehended in using the system, thereby negatively affecting their technology acceptance [12]. Previous research findings into OLA have been consistent that it is one of the determinants of PEOU [12, 33]. Anxiety has a negative influence on ease of use [12, 33, 34]. From the learning perspective, if students feel the technology they are engaged in is challenging to use, they will be anxious to remain using the technology. Likewise, perceived usefulness is manipulated by anxiety, and that usually occurs when students respond nervously to what they feel impractical [35]. Thereby, it is predicted that:

H5: Online learning anxiety will negatively affect perceived ease of use.
H6: Online learning anxiety will negatively affect perceived usefulness.

3 Method

3.1 Research design

The nature of the current study is quantitative, and it follows the cross-sectional design using a questionnaire as a main data collection tool. The study focuses on the explanatory and predictive ability of the model in the Omani context.

The study employed a structural equation modelling (SEM) research design. In this research design, we proposed a particular model for online learning for students studying at applied and technological colleges and universities using TAM as a basis for designing the proposed model. Confirmatory factor analysis was run to make sure that the items were correlated to the constructs. Finally, we performed a structural equation model to approve the proposed model.

3.2 Sample and data collection procedures

Using random sampling procedures, the sample of the study was recruited from the University of Technology and Applied Sciences (Nizwa). The sample was from different departments (Foundation and post-foundation departments). The study was conducted at the outset of COVID-19 and students were not accustomed to learning online, although students were studying fully online.

The data was collected from students using Google Forms. The questionnaire was sent to 5600 students studying for a bachelor's degree at the University of Technology and Applied Sciences via emails. The respondents to the questionnaire were 569 students from different colleges at the university. The questionnaire was available for the students for one week. Since the number of respondents was not sufficient for the study, the period was extended to two weeks. After two weeks, the system stopped receiving more responses. Table 1 illustrates the demographic features of the respondents. Regarding gender, there are 249 males (43.8%) and 320 females (56.2%). In addition, 101 students use mobile devices only while learning online and 93 students use computers only and laptops when learning online, while the majority of students use both 375 (65.9). Concerning time spent learning online, 246 students (43.2%) spend around 5–6 hours studying online. Finally, 64% of the students are studying science fields (Engineering and IT) whereas the rest are studying art stream (business and foundation).

Table 1. Demographic information about the participants

Item	Category	Frequency	Percent
Gender	Male	249	43.8%
	Female	320	56.2%
	Total	569	100%
Devices used for Online Learning	Mobile devices	93	16.3%
	Computers & Laptops	101	17.8%
	Both	375	65.9%
	Total	569	100%
Time spent on learning online per day (hours)	Less than 2	42	7.4%
	3–4	135	23.7%
	5–6	246	43.2%
	7–8	89	15.6%
	More than 8	57	10.0%
	Total	569	100%
Specialization	Engineering	248	43.6%
	IT	116	20.4%
	Foundation	64	11.2%
	Business	141	24.8%
	Total	569	100%

3.3 Research instrument

Technology acceptance model (TAM) [7] was adapted for this study and it was employed during the COVID-19 pandemic. The questionnaire contains three main parts. Part A sought the participants' demographical information, including gender, specializations, time spent online weekly and the devices used for online learning. The second part of the questionnaire encompassed five variables which were online learning anxiety (5 items), perceived usefulness (6 items), perceived ease of use (6 items), attitudes towards online learning (6 items), behavioural intention (5 items). Examples of online learning anxiety items are "*I have difficulties using technological devices for online learning*", "*I feel apprehensive about using an online platform*", and "*Online education terminology sounds like confusing jargon to me*". 5 Likert-scale was employed in the scale ranging from 1 = strongly disagree to 5= strongly agree for all constructs. The questionnaire was used in many studies [36, 37], and it was found to be reliable and valid. However, we measured the validity and reliability of the questionnaire in the Omani context. The research instrument was piloted (N=105) in a different university in Oman.

3.4 Analysis procedures

To test the proposed model, partial least squares structural equation modelling (PLS-SEM) was performed using SmartPLS 3. PLS-SEM was used for two reasons. First, PLS can handle incremental studies, as in the current study, where new constructs and new paths are added to an existing model [38]. Second, PLS-SEM is a suitable technique to manage single-level models with cross-sectional design [39].

4 Results

4.1 Preliminary analysis

Before assessing the model, the multivariate normality test was examined using WebPower. Specifically, Mardia's coefficient procedure was used, and it was found that the kurtosis coefficient is 74.665. This result indicates that the data is not distributed normally because it is above the threshold score, which is 20 [40, 41]. Hence, PLS-SEM is an appropriate statistical inferential technique for this non-normality distributed data.

In this vein, a two-stage analytical approach was used, which is suggested by Anderson and Gerbing [42]. In the first stage, we examined the measurement model, and in the second stage, we examined the structural model, as the following section shows.

4.2 Measurement model

The measurement model consists of several procedures to maintain the psychometric properties of the constructs. The first property is the estimation of the internal consistency which is assessed using Cronbach's alpha and composite reliability. The second property is the estimation of the convergent validity which is measured using factor loadings of the items and average variance extracted (AVE) of the constructs. The third property that was evaluated in the measurement model is discriminant validity. Previously, discriminant validity was assessed using the Fornell-Larcker criterion and cross-loading, yet it was found that the HTMT criterion is more precise in gaining precise results regarding discriminant validity [43]. Therefore, the HTMT criterion was adopted in this study to measure the discriminant validity, and cross-loadings was used for remedy purposes.

Table 2 shows the results of the factor loadings, Cronbach's alpha and composite reliability and AVE for all constructs. According to Hair, Risher, Sarstedt, and Ringle's [44] suggestions and criteria, all the constructs passed the cut-off value for construct convergent validity because the AVE is more than 0.5 and the factor loadings are more than 0.708 for all items. However, three items (PEOU3, PEOU4 and PU4) were deleted because of the low factor loadings. Furthermore, Cronbach's alpha and composite reliability for all the constructs are higher than the threshold value of 0.7, which is an indication of the high reliability of the constructs [44].

Table 2. Factor loadings, composite reliability, Cronbach alpha and AVE

Construct	Items	FL	CR	CA	AVE	Mean	SD
Behavioral Intention	BI1	0.919	0.963	0.971	0.871	2.717	1.4
	BI2	0.909					
	BI3	0.954					
	BI4	0.945					
	BI5	0.938					
Online Learning Anxiety	OLA1*	0.841	0.818	0.863	0.560	2.789	1.1
	OLA2*	0.824					
	OLA3	0.662					
	OLA4	0.673					
	OLA5	0.722					
Attitude	PA1	0.904	0.956	0.965	0.821	2.657	1.4
	PA2	0.936					
	PA3	0.912					
	PA4	0.907					
	PA5	0.858					
	PA6	0.919					
Perceived Ease of Use	PEOU1	0.869	0.848	0.908	0.767	3.048	1.2
	PEOU2	0.888					
	PEOU5	0.870					
Perceived Usefulness	PU1	0.912	0.941	0.955	0.809	2.696	1.4
	PU2	0.930					
	PU3	0.918					
	PU5	0.829					
	PU6	0.904					

Note: FL, factor loadings; CR, composite reliability; CA, Cronbach alpha; AVE, average variance extracted; SD, standard deviation.
Source: Items PEOU3, PEOU4 and PU4 were deleted because of low factor loadings.
*Items are reversed coded.

To measure discriminant validity, we employed HTMT. Some of the results are higher the threshold (> 0.9) as shown in Table 3 so we perform complete bootstrapping HTMT inferences as suggested by Franke and Sarstedt [45]. The results of the upper bounds of the interval confidence are less than 1 [39, 45]. Therefore, the discriminant validity for the constructs was established.

Table 3. HTMT results for discriminant validity

Constructs	1	2	3	4	5
1 – Attitude					
2 – BI	0.963				
3 – OLA	0.761	0.722			
4 – PEOU	0.905	0.872	0.805		
5 – PU	0.956	0.908	0.774	0.914	

4.3 Structural model: hypotheses testing

The structural model assessment follows five steps. The first step is the multicollinearity, variance inflation factor (VIF), between all the endogenous constructs [46], which should be less than 5. The second part is checking the t-value and the p-value. The third component is examining the Coefficient of Determination (R^2). The fourth assessment is the effect size (f^2) and the last one is the predictive power ability of the model [47].

To start with, all the results VIF of the exogenous constructs in the model is less than five, which is suitable for assessing the model and there is no multicollinearity issue in the model [46, 48]. The inner VIF scores were used because all the constructs are reflective, not formative. Table 4 displays the results of the inner VIF scores of the exogenous constructs in the model.

Table 4. Inner VIF for exogenous constructs

Constructs	Attitude	BI	OLA	PEOU	PU
Attitude		1.000			
BI					
OLA				1.000	2.228
PEOU	3.049				2.228
PU	3.049				

Furthermore, in the current study, the hypotheses of the structural model were investigated by deploying a bootstrapping sampling technique of 5000 iterations of a subsample which is recommended by Hair et al. [39]. Table 5 shows the results of the structural model. The results showed that Attitude has a positive impact on Behavioral Intention of using online learning during COVID-19 (H1: $\beta = 0.925$, $p < 0.001$), and Perceived Usefulness (H2: $\beta = 0.721$, $p < 0.001$) affect attitude towards online learning during COVID-19 positively. Next, Perceived Ease of Use (H3: $\beta = 0.227$, $p < 0.001$) affects Attitude towards learning online positively and the same construct positively influences Perceived Usefulness while students learn online (H4: $\beta = 0.579$, $p < 0.001$). However, online Learning Anxiety negatively affects the Perceived Ease of Use (H5: $\beta = -0.742$, $p < 0.001$) and Perceived Usefulness (H6: $\beta = -0.324$, $p < 0.001$).

Table 5. Hypotheses testing

					BC-CI (95%)	
Hypo	**Paths**	**Beta**	**T-Value**	**P-Values**	**LB**	**UB**
H1	Attitude -> BI	0.925	133.736	p < 0.001	0.912	0.935
H2	PU -> Attitude	0.721	23.283	p < 0.001	0.669	0.771
H3	PEOU -> Attitude	0.227	6.654	p < 0.001	0.172	0.284
H4	PEOU -> PU	0.579	16.374	p < 0.001	0.521	0.638
H5	OLA -> PEOU	–0.742	41.653	p < 0.001	–0.769	–0.710
H6	OLA -> PU	–0.324	8.873	p < 0.001	–0.383	–0.263

Next, the coefficient of determination (R^2) is tested to examine the in-sample predictive power as shown in Table 6. R^2 is calculated for the endogenous variables, and it is considered weak, moderate and substantial if the value of the R^2 is 0.25, 0.50 and 0.75, respectively [39]. The results display that all the endogenous variables have substantial power. Specifically, the results show 85.5% of the variance in BI is explained by Attitude while 84.1.9% of the variance in Attitude is explained by PU and PEOU. In addition, only 55.1% of the variance in the Perceived Ease of Use is explained by PEOU and OLA. Furthermore, 71.9% of the variance in PU is explained by OLA.

Table 6. R square of the endogenous variables

Construct	Attitude	BI	PEOU	PU
R Square	0.841	0.855	0.551	0.719

Regarding the effect size (f^2), Cohen [49] posited that the ES is considered small, medium and large if the values are over 0.02, 0.15 and 0.35, respectively. Hence, as shown in Table 7, Online Learning Anxiety ($f^2 = 1.228$) represented a large effect size on Perceived Ease of Use while it demonstrated a medium effect size on Perceived Usefulness ($f^2 = 0.167$). However, Perceived Ease of Use ($f^2 = 0.106$) portrayed a small or trivial effect size in generating R^2 for Perceived attitudes, whereas it displays a large effect size for Perceived Usefulness ($f^2 = 0.537$). In contrast to Perceived Ease of Use on Perceived attitudes, Perceived Usefulness ($f^2 = 1.070$) depicted a large effect size in yielding R^2 for Perceived attitudes. Finally, Perceived attitudes ($f^2 = 5.919$) exhibited a large effect size in producing R^2 for Behavioral Intention.

Table 7. Effect sizes

Construct	Attitude	BI	PEOU	PU
Attitude		5.919		
BI				
OLA			1.228	0.167
PEOU	0.106			0.537
PU	1.070			

In terms of the predictive power ability of the model, we used the blindfolding technique suggested by Geisser [47]. It can be noticed that the structural model has a predictive power because Q^2 of all the endogenous constructs are more than 0 [47, 50] as displayed in Table 8.

Table 8. Blindfolding results for predictive power

Construct	Attitude	BI	PEOU	PU
Q^2	0.686	0.74	0.419	0.577

5 Discussion

The study's main purpose was to investigate the behavioural intention of using online learning by university students in Oman during COVID-19 using the extended TAM. The results of the model indicated that the extended TAM could adequately explain the acceptance of using online learning during COVID-19, and the behavioural intention of using online learning can be predicted in Omani scientific universities. The results also displayed that the extended TAM has a predictive power because all the values of the Q-square for the endogenous variables are more than 0. Precisely, online learning anxiety, perceived usefulness, perceived usefulness and perceived attitudes can well predict the behavioural intention of using online learning during COVID-19. The model can explain 85.5% of the variance of the combined effects in behavioural intention.

5.1 Theoretical contribution

This study contributes to the field of technology acceptance while studying online in various aspects. First, although TAM was developed many years ago to predict users' acceptance in easy situations, it can also be used as a predictable model when learning online in challenging times, as in the case of the COVID-19 pandemic. All the paths between the constructs of the original model (perceived usefulness, perceived ease of use, attitudes and behavioural intentions) were significant and can be predictors of their antecedents.

Second, as suggested by Davis [7], TAM, specifically perceived usefulness and perceived ease of use, can be preceded by external constructs according to the current situation during the conducted study. In the current study, online learning anxiety was integrated into the model as many studies confirmed that it could influence students' acceptance of online learning during COVID-19. This study proves that online learning anxiety could be an antecedent that should be manipulated and dealt with effectively when teaching students online during COVID-19.

5.2 Practical implications

This study has many practical implications to be applied to tertiary education. First, students' attitudes in Omani universities predicted behavioural intention to using online learning largely. This result is consistent with many previous results in the previous studies such as Park [3], Padilla-Meléndez, et al. [20] and [21]. Therefore, it is necessary to promote students' perceived attitudes towards online learning so that tertiary students can hold a strong behavioural intention for utilizing online learning effectively.

Students' attitudes towards online learning during the COVID-19 pandemic in the Omani universities were predicted by the ease of use and perceived usefulness. However, perceived usefulness can explain much more variance in the perceived attitudes construct than perceived ease of use. This is an indication that Omani university students in this study perceived online learning as a useful tool of learning, but they conceived online learning in this situation as a difficult task to perform. However, this finding contradicts with Chang et al. [27], [28] and [3]. This could be because students don't deal with the situation with ease during COVID-19, as it is the first time they have fully experienced online learning. Moreover, perceived ease of use affected perceived usefulness positively and largely, which implies that university administration should provide students with more training for online learning so that students feel satisfied with the situation. This result echoes with seminal research that was conducted in this area, such as Elkhani et al. [31] and Venkatesh and Davis [12].

Moreover, online learning anxiety played an essential role in the current model. As hypothesized, online learning anxiety prognosticated perceived usefulness and perceived ease of use negatively and perceived ease of use explained more variance than perceived usefulness. Examples of the studies that echoed with these findings are Chen and Tseng [34], Pedersen and Nysveen [33] and Venkatesh and Davis [12]. This indicates that online learning anxiety should be the primary focus when teaching tertiary students online. This finding implies that university counsellors and academic advisors should deal with students' online anxiety carefully so that students can feel the ease of use while learning online.

6 Conclusion

This paper implemented an extended TAM that included online learning anxiety in online learning during the COVID-19 pandemic. Similar to previous studies, the study proved that TAM is a competent theoretical model in understanding and defining students' acceptance and behavioural intention in online learning. The study revealed that perceived attitude towards online learning is a strong predictor of behavioural intention during the COVID-19 pandemic. This study contributes to the present literature on TAM that both perceived usefulness of online learning and ease of online learning use generated significant contributions to students' perceived attitude. The study also indicated that online learning anxiety demonstrated a negative effect on both perceived usefulness of online learning and perceived ease of online use; where perceived ease of use is predicted largely while perceived usefulness is predicted modestly.

6.1 Limitations and future directions

The present study investigated university students' technology acceptance using an extended TAM. Yet, the design of this study is subjected to some limitations and future directions. First, the sample of the study was attained from only one university in Oman.

Hence, future investigations are needed to expand the sample using a cross-country scheme, and thereby the findings can be generalized to a larger context. Second, this study described the use of online learning from the students' perception. So, further work is required to triangulate different perceptions, such as professors and lecturers, to understand the technological system acceptance better. Third, much of the current literature on TAM pays particular attention to technology actual use. However, the extended TAM employed in this research did not include perceived actual use. Therefore, further studies should focus on adding perceived actual use as one variable of this extended model to highlight any potential association with the perceived attitude and behavioural intentions. Finally, the proposed ETAM in this study considers only when students learn fully online. As some universities move to use the hybrid method of teaching, it is worthwhile conducting a study that examines the transferability of the current study to the hybrid approach.

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