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Original Article

Acceptance of Online Education by Undergraduate Students During the Covid-19 Pandemic: A Case Study from Kerman, Iran

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Abstract

Background: Online education has become more vastly recognized as a powerful educational tool after the Covid-19 pandemic. It provides educational opportunities that were not previously possible because of time or place restrictions.

Objectives: This study investigated the factors influencing students' acceptance of online learning systems during the Covid-19 pandemic.

Methods: The study sample comprised 435 students from Kerman University of Medical Sciences. We used the external technology acceptance model (TAM) to determine the acceptance of online education systems by undergraduate students during the Covid-19 pandemic. Partial least square structural equation modeling (PLS-SEM) was used to check the model hypotheses. P-values less than 0.05 were considered statistically significant.

Results: In this study, 65% of the participants were men. The mean score for the items in the questionnaire was 53.1±19.3. The constructs of perceived ease of use and perceived usefulness had a significant effect on students' attitudes, and students' attitudes and perceived usefulness strongly influenced their behavior in using the online education system.

Conclusion: The results of this study show that the perceived ease of use and perceived usefulness of the online education system indirectly affect students' behavior in using online education. Thus, educational policymakers at universities can emphasize the ease of learning and especially the easy use of mobile phones when choosing an online education system. In addition, the creation and expansion of the necessary infrastructure can facilitate student use of online education.

Keywords: Technology Acceptance Model (TAM), Covid-19, Online Education, Iran

Background

The Covid-19 pandemic provoked massive changes in the lives of people around the world. Medical restrictions at the peak of the pandemic and economic problems caused by the imposed restrictions, and direct and indirect deaths due to Covid-19 compelled people of the world to experience critical conditions (1, 2). Governments and organizations had to accept the new conditions and change their policies in line with them. These changes also affected the quality of education at universities and schools (1).

The suspension of public education and university courses had a tremendous impact on students, teachers, and educational institutions in different parts of the world (3). Like other countries, Iran adopted online education as one of the first policies to combat and control the Covid-19 outbreak and break the chain of Covid-19 transmission (3). Students were deprived

access to facilities such as libraries and sports halls and were unable to accompany their friends or receive help from them in classrooms and laboratories (3). The change in students' behavior towards online learning during the pandemic was sudden and unplanned. These issues caused many learning problems related to the use of technology for curriculum design and internet skills (1, 4). In addition, online education exposed professors and teachers to many difficulties in conveying course knowledge to students. Students also struggled to learn course material effectively (5, 6). These problems were especially evident at universities in developing countries with little experience in conducting online courses (7).

Students' unpreparedness to accept online learning and learning in unfavorable environmental conditions with inadequate communication equipment and facilities can affect their enthusiasm for learning (8). Moreover, the immediate adoption of an online learning system, especially in universities with less experience in using online education systems, may negatively affect students' learning process.

Before the pandemic, online education was not well-established in most Iranian universities. Some undergraduate students lacked experience in using online education systems. Thus, examining the factors affecting students' acceptance and use of online education systems can contribute to the effective use of these systems. Exploring these factors will also help policymakers manage and possibly remove obstacles that impact the successful acceptance of online educational systems and help teachers and educational institutions take advantage of these systems.

The Technology Acceptance Model (TAM) developed by Davis in 1986 is one of the most widely used and best technological acceptance models. It has been employed in various studies and is the most well-known model addressing technology acceptance (1, 4, 8). Compared to other theoretical methods, TAM is a highly effective model (9).

Experts have developed no clear criteria for the adoption of online educational systems, especially during the Covid-19 pandemic (10). Different countries have used different extended models of TAM based on the level of technological advancement and previous experience in using online education (1, 4, 8). Iran has one of the largest numbers of students among the universities of the MENA region (11).

Evaluation of the determinants influencing the adoption of online education by students in Iran and the adoption of effective educational policies can affect the education of a large number of students. However, despite the importance of online education, few studies have addressed the factors affecting its acceptance by students, especially students of medical sciences in Iran during the COVID-19 pandemic. A study was conducted to analyze the determinants that affect the behavioral intentions of university students majoring in agriculture using the developed Technology Acceptance Model (TAM) model during and after the COVID-19 pandemic (12). The findings showed that attitudes and perceived self-efficacy have a direct relationship with behavioral intention to use online education. Providing education for students of medical universities in charge of training an effective workforce for healthcare systems is of special importance. Some of the courses in medical programs are practical. Before the Covid-19 pandemic, universities had no experience in conducting practical courses online, nor was it possible for Iran to use conventional global platforms for medical sciences universities. Each university, especially at the beginning of the pandemic, used customized online educational systems to offer their courses. Furthermore, some students were initially less familiar with how to use online education and had limited access to it. Thus, an innovative aspect of the current study is its focus on CSE and PA dimensions in the use of online education systems by students at medical universities. Examining the factors that influence the adoption of online learning, the acceptance of online education by medical students, and reflecting on their experiences can help professors more effectively conduct online education courses and assist educational policymakers in removing possible obstacles to contributing to continuing online education programs after the Covid-19 crisis.

To this end, the current study purposed to analyze factors affecting the acceptance of online learning systems during the Covid-19 crisis in Iran using the TAM model and to determine online education policies after Covid-19.

Research Framework and Hypotheses: TAM provides a short but useful theoretical framework for examining how perceived usefulness and ease of use of a new technology or service affect its adoption by users (1). According to this theory, people's attitudes toward using technology are influenced by external factors. A number of studies have considered various variables as external factors, depending on whether they were conducted in developed or developing countries (1, 7). The current study considered the two variables of computer self-

efficacy (CSE) and perceived accessibility (PA) as external factors affecting the acceptance of online education. Attitude is a vital factor accounting for technology use behavior. According to TAM, perceived usefulness and ease of use lead to positive attitudes toward technology acceptance. Many features of technology affect its acceptance and use by users (13). Thus, technology acceptance behavior was taken as a dependent variable in this study. Based on a review of previous TAM-related studies, various hypotheses according to internal and external factors were developed (Figure 1).

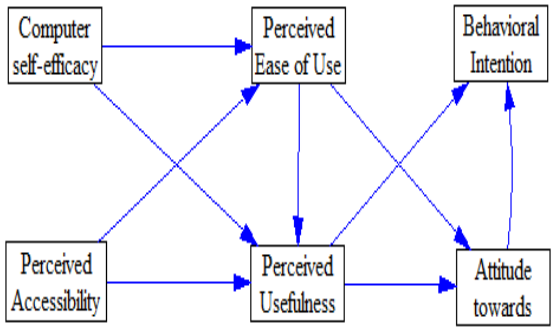

Figure 1. Research Model
TAM: Technology Acceptance Model

Computer Self-Efficacy (CSE): Computer self-efficacy (CSE) is one of the external factors most commonly used in TAM. Self-efficacy is defined as "an individual's belief in his or her capacity to execute behaviors necessary to face future situations" (14). In this study, self-efficacy is operationalized as users' confidence in their ability to use an online education system. Various research studies have indicated that computer self-efficacy plays a crucial role in determining the perceived usefulness and perceived ease of use of online education systems (7, 15).

Perceived Accessibility (PA): Perceived accessibility (PA) of a system refers to how easily users can access and utilize information from the online educational platform (16). Different studies have indicated that perceived accessibility significantly affects the users' perceived ease of use and the perceived usefulness of the online education system (17, 18). The more access to the online education system increases, the higher its perceived ease and usefulness will be (18). Perceived accessibility (PA) was taken as another external factor in TAM.

Perceived Ease of Use (PEU): received ease of use (PEU) of a system refers to the degree to which a person perceives that the use of a particular technology (e.g., learning through an online education system) is not complicated and does not require much effort (7, 13). Studies have shown that perceived ease significantly affects perceived usefulness and strongly predicts the attitude toward the use of online learning (19, 20).

Perceived Usefulness (PU): Perceived usefulness (PU) refers to the degree to which individuals believe that the use of new technology (e.g., learning through an online education system) can improve their job performance (achieving educational and learning goals) (13, 21). Many studies have suggested that PU significantly affects the behavioral intention to accept online learning and students' attitudes toward its use (22, 23).

Attitude Towards (AT): An individual's attitude towards using online education systems refers to the "degree to which a person has a positive or negative feeling towards electronic education systems" (24). Studies have indicated that attitude directly and significantly affects students' behavioral intention to use online education. In other words, students' intention to use online education is strongly influenced by their attitudes (13, 25).

Behavioral Intention (BI): The behavioral intention to use online learning refers to students' desire to use online learning (13, 26). Studies have shown that BI is strongly correlated with system acceptance and, as a result, its use. Therefore, it is one of the most important variables affecting the success of a system (13). In the present study BI was considered the main construct in the research model and also the response variable.

Study Context: The focus group of this research was undergraduate students studying at Kerman University of Medical Sciences. This university is one of the largest of its kind in Iran with over 6000 students in more than 150 fields of study and more than 50 years of educational experience. The students used two platforms, Adobe Connect and a national platform called Sky room, to take online courses.

Objectives

This study investigated the factors influencing students' acceptance of online learning systems during the Covid-19 pandemic.

Methods

Instruments: This cross-sectional, descriptive-analytical study was conducted using a quantitative approach. The data in this study were collected using a research-made questionnaire which consisted of two sections. The first section assessed the students' demographic characteristics (gender, grade of

education, major), and the second section contained 24 items to measure the research variables on a 5-point Likert scale ranging from strongly agree (score 5) to strongly disagree (score 1). The total score on the scale varied between 24 and 120. Questionnaire constructs included computer self-efficacy (CSE), perceived accessibility (PA), perceived ease of use (PEU), perceived usefulness (PU), attitude towards (AT), and behavioral intention (BI).

The items in the questionnaire were developed using sources based on a review of the literature. The items were translated and back-translated from English to Farsi by an English translator. After the initial item bank was collected, ten subject-matter experts, who were active in this field and had deep insights into the online education system, checked the items to assess the face and content validity of the questionnaire. The content validity index (CVI) was greater than 0.8, confirming the content validity of the questionnaire. After making the necessary revisions, the questionnaire was piloted on a sample of 30 students to assess its reliability. The reliability of the whole questionnaire was confirmed with Cronbach's alpha coefficient of 0.93. The final version of the questionnaire contained 24 items and 6 components.

Sample Size and Sampling: We recruited 450 students randomly from both genders and different study fields. As our theoretical model had 24 items, we chose at least ten subjects per item according to the "rule of 10 times," which is the most widely used method of estimating sample size in PLS-SEM (6). The data were collected in the fall semester. Fifteen students who provided incomplete responses to the items were excluded from the study. Thus, the final sample consisted of 435 students.

Measurement Model Evaluation and Statistical Analysis: The questionnaire was evaluated using convergent validity, internal consistency, and discriminant validity. Convergent validity was assessed using averaged variance extracted (AVE), and the internal consistency was checked using Cronbach's alpha (CA) and composite reliability (CR) (27).

The Fornell-Larcker (FL) criterion and the heterotrait-monotrait ratio of correlations (HTMT) were used to assess discriminant validity in this study. According to the Fornell-Larcker (FL) criterion, the square root of AVE by a construct should be greater than the correlation between that construct and any other (28). The HTMT ratio is an index developed based on the Monte Carlo simulation and used to check divergent validity. Studies have recommended the value of this coefficient be less than 0.9 to establish divergent validity (26).

The results are presented as mean ± standard deviation (SD) for the quantitative variables and frequency and percentage for the qualitative variables.

Normality of data was checked by the Kolmogorov-Smirnov (K-S) test. The Mann–Whitney U test was run to compare the mean scores for the questionnaire constructs with the demographic variables. To address the lateral collinearity issue, the variance inflation factor (VIF) was measured**.** Studies have shown that VIF values less than 10 indicate the absence of worrisome collinearity (29).

The model hypotheses were checked using partial least square structural equation modeling (PLS-SEM). Standardized root means square residual (SRMR), incremental fit index (IFI), R^2 index, and Cohen's f2 effect size were used to check the fit of the structural equation model (30, 31). All analyses were performed in Smart PLS 3.0 software.

The standardized root means square residual (SRMR) and the incremental fit index (IFI) were measured for the model's goodness of fit. Previous studies have indicated that the SRMR index is acceptable when it is less than 0.10, and the model has a good fit index when it is less than 0.05 (32, 33). Moreover, IFI values greater than 0.9 indicate a good fit for the model (34).

Results

Demographic Characteristics: Of the 435 students who completed the questionnaire, 55.6% were female, 54.0% reported using mobile internet, and 46.0% used modems to participate in online courses. The most commonly used devices used to take online courses were computers or laptops (55.8%) followed by mobile phones or tablets (44.2%).

Most of the participants (58.4%) were medicine, dentistry, or pharmacy majors (MDP), and 41.6% of the participants were other undergraduate students (B.S.). Table 1 shows the questionnaire items and the mean, standard deviation, and percentage of the responses to each item (Table 1).

The result of the Kolmogorov-Smirnov test was significant for all instruments of the questionnaire. Thus, the results of the Mann–Whitney U test showed no significant difference between the mean scores of male and female participants in any of the studied constructs.

Table 1. Constructs and indicator

Construct	Statements/Items	Strongly Disagree	Disagree	Moderate	Agree	Strongly Agree	Mean (SD)
		n (%)					
AT[1]	I feel positive regarding the utilization of online education.	30 (6.9)	54 (12.4)	110 (25.3)	111 (25.6)	129 (29.7)	2.41 (1.23)
AT	In general, I admire the utilization of online education.	41 (9.4)	74 (17.1)	99 (22.8)	98 (22.6)	122 (28.1)	2.57 (1.31)
AT	Overall, I like using the online education.	34 (7.9)	60 (13.9)	103 (23.8)	106 (24.5)	129 (29.9)	2.45 (1.26)
AT	Online education, provides an attractive learning environment.	75 (17.4)	84 (19.4)	113 (26.2)	58 (13.4)	102 (23.6)	2.93 (1.40)
PU[2]	The use of online education is beneficial for my learning activities during the Covid 19 pandemic.	8 (1.8)	16 (3.7)	64 (14.7)	161 (37.1)	185 (42.6)	1.85 (0.93)
PU	The use of online education during university closure due to the Covid-19 pandemic helps me to access learning resources.	11 (2.5)	48 (11.1)	112 (25.9)	154 (35.6)	108 (24.9)	2.31 (1.04)
PU	Using online education will improve learning performance in distance learning during the Covid-19 pandemic.	6 (1.4)	21 (4.8)	63 (14.5)	175 (40.4)	168 (38.8)	1.90 (0.92)
PU	The use of online education will increase my productivity in distance learning during the Covid-19 pandemic.	5 (1.2)	13 (3.0)	50 (11.5)	177 (40.9)	188 (43.4)	1.78 (0.85)
PEU[3]	It is easy for me to use the university online learning system.	36 (8.3)	66 (15.2)	119 (27.4)	95 (21.9)	118 (27.2)	2.55 (1.26)
PEU	Overall, the university online learning system is easy to use.	23 (5.3)	47 (10.8)	98 (22.5)	135 (31.0)	132 (30.3)	2.30 (1.16)
PEU	It is easy to learn how to use the university online learning system.	38 (8.8)	78 (18.0)	117 (27.0)	83 (19.1)	118 (27.2)	2.62 (1.29)
PEU	It is easy to remember how to use the university online learning system.	60 (13.9)	94 (21.8)	102 (23.7)	78 (18.1)	97 (22.5)	2.86 (1.36)
BI[4]	I will recommend using an online learning system in the future.	52 (12.0)	64 (14.7)	80 (18.4)	96 (22.1)	143 (32.9)	2.51 (1.39)
BI	I want all courses to be offered via an online learning system during Covid-19 and beyond.	53 (12.2)	68 (15.7)	104 (24.0)	101 (23.3)	107 (24.7)	2.67 (1.33)
BI	I will use online learning system if it is available in the post-Covid-19 pandemic.	38 (8.8)	55 (12.7)	89 (20.6)	122 (28.2)	129 (29.8)	2.42 (1.27)
PA[5]	I access and use the online learning system in the university without any problems.	16 (3.7)	27 (6.2)	96 (22.2)	147 (33.9)	147 (33.9)	2.12 (1.06)
PA	The online learning system can be accessed appropriately by using the chain of communication.	14 (3.2)	23 (5.3)	115 (26.6)	146 (33.7)	135 (31.2)	2.16 (1.03)
PA	The online learning system is accessible according to my own possibilities.	8 (1.8)	15 (3.4)	88 (20.2)	169 (38.9)	155 (35.6)	1.97 (0.93)
PA	The chain of communication is suitable to get access to the online learning tool.	12 (2.8)	18 (4.2)	98 (22.6)	165 (38.1)	140 (32.3)	2.07 (0.98)
CSE[6]	I feel confident in the utilization of online learning system even when no one is there for assistance.	6 (1.4)	13 (3.0)	43 (9.9)	144 (33.2)	228 (52.5)	1.67 (0.87)
CSE	I have sufficient skills to use the online learning system.	4 (0.9)	7 (1.6)	51 (11.8)	149 (34.3)	223 (51.4)	1.66 (0.82)
CSE	I feel confident when using the online learning system features.	5 (1.2)	7 (1.6)	54 (12.50)	173 (40.0)	194 (44.8)	1.74 (0.82)
CSE	I feel confident when using the online learning system even if I have only the online instructions.	12 (2.8)	22 (5.1)	75 (17.3)	152 (35.0)	173 (39.9)	1.96 (1.01)
CSE	I feel confident when using the online learning content in the online learning system.	8 (1.80)	11 (2.50)	65 (15.0)	158 (36.4)	192 (44.2)	1.81 (0.91)

Reference constructs: 1. AT: (Salloum et al., 2019); 2. PU: (Mailizar et al., 2021); 3.PEU: (Alshurafat et al., 2021); 4. BI: (Mailizar et al., 2021); 5. PA: (Salloum et al., 2019); 6. CSE: (Salloum et al., 2019).
SD: Standard deviation

Likewise, there was no significant difference between the mean scores of the investigated constructs and type of internet use (mobile or modem) except CSE. In all studied constructs other than AT, CSE, and PU, students who used mobile phones or tablets for online education courses obtained significantly higher mean scores for the questionnaire constructs. In addition, the mean scores of MDP students in all questionnaire constructs were significantly lower than those of undergraduate students (Table 2).

Model Evaluation: The highest AEU, Cronbach's alpha, and CR values for the investigated constructs were related to the AT area, and the lowest values were related to the PU construct. The AVE values were greater than 0.75 for all constructs. Moreover, Cronbach's alpha for all indices was greater than 0.87, and the CR index was greater than 0.75. The analysis of the measurement model suggested a positive indication of the robustness of the constructs' measures. The lowest FL value for the constructs in question was calculated as 0.85. In addition, all HTMT values were less than 0.86, demonstrating that every construct had adequate discriminant validity. As a result, the constructs had sufficient convergent and discriminant validity (Table 3).

Structural Model: For factor analysis, the six constructs of CSE, PEU, PU, PA, BI, and AT were identified. The structural model and its path coefficients are depicted in Figure 2. R^2 was determined to examine the predictive accuracy of the model. In Figure 2, the numbers inside the circles indicate the coefficient of determination (R^2). R^2 for BI was 0.644. This indicates that the two exogenous constructs (AT and PU) explain 64.4% of the variance in BI. The numbers on the arrow between the circles show the path coefficients, and the numbers on the arrow between the circles and the rectangles are factor loadings. All indicators had factor loading values above 0.5, indicating the validity of the used indicators (27).

The results of the structural model and hypotheses tested are shown in Table 4. VIF values for all variables were less than 5, confirming the absence of worrisome collinearity in this study.

The hypotheses were tested using partial least square structural equation modeling (PLS-SEM). The results indicated that all tested hypotheses were significant except for the effects of computer self-efficacy on PEU, which means CSE did not significantly affect it. CSE, however, had a positive and significant effect on PU; therefore, hypothesis 2 was supported.

PA had a positive and significant effect on PEU and PU, so hypotheses 3 and 4 were supported. PEU had a positive and significant effect on PU and attitude towards using online education systems, indicating that hypothesis 5 and 6 were accepted. PU had a positive and significant effect on the BI of students and their attitude toward using online education systems. Therefore, hypotheses 7 and 8 were supported. Finally, attitude toward using online education systems directly and significantly affected students' BI to use online education; thus, hypothesis 8 was supported. SRMR and IFI were calculated as 0.05 and 0.89, respectively, confirming the good fit for the model. The values of path coefficients for PEU and AT as well as AT and BI variables were higher, indicating the strength of the relationship between these variables.

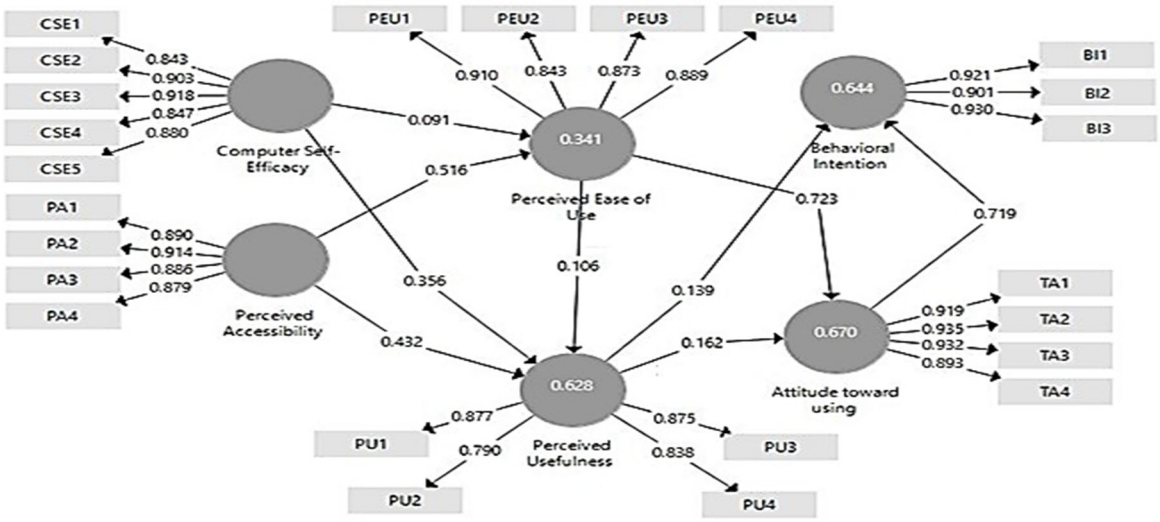

Figure 2. Model layout, factor loadings, coefficients of determination (R2), and model path coefficients

Table 2. Comparison of mean scores of questionnaires between study variables

Variables	Attitude Toward Using		Behavioral Intention		Computer Self-Efficacy		Perceived Accessibility		Perceived Ease of Use		Perceived Usefulness	
	Mean (SD)	P-value	Mean (SD)	P-value	Mean (SD)	P-value	Mean (SD)	P-value	Mean (SD)	P-value	Mean (SD)	P-value
Gender												
Male	9.95 (4.60)	0.13	7.38 (3.57)	0.26	8.74 (3.68)	0.62	8.42 (3.57)	0.60	10.08 (4.42)	0.27	7.64 (3.00)	0.31
Female	10.70 (4.92)		7.81 (3.73)		8.93 (4.06)		8.22 (3.58)		10.55 (4.50)		7.96 (3.27)	
Device												
PC-Laptop	10.12 (4.69)	0.18	7.31 (3.62)	< 0.05	8.50 (3.60)	0.052	8.00 (3.47)	< 0.05	9.84 (4.30)	< 0.01	7.55 (3.03)	0.06
Mobile-Tablet	10.76 (4.90)		8.06 (3.68)		9.31 (4.21)		8.72 (3.67)		11.04 (4.58)		8.17 (3.26)	
Kind of internet used												
Mobile	10.47 (4.67)	0.83	7.75 (3.58)	0.52	9.15 (4.0)	0.04	8.41 (3.47)	0.35	10.55 (4.43)	0.53	7.93 (3.05)	0.23
Modem	10.43 (4.93)		7.56 (3.76)		8.39 (3.63)		8.21 (3.66)		10.27 ± 4.49		7.65 (3.22)	
Grade												
BS	11.39 (4.92)	< 0.001	8.51 (3.67)	< 0.001	9.68 (4.27)	< 0.001	9.06 (3.82)	< 0.001	10.97 (4.42)	< 0.05	8.46 (3.27)	< 0.001
MDP	9.68 (4.57)		7.02 (3.53)		8.26 (3.50)		7.78 (3.31)		9.90 (4.45)		7.36 (3.00)	
Total score	10.37 (4.79)	-	7.62 (3.66)	-	8.85 (3.89)	-	8.31 (3.58)	-	10.35 (4.47)	-	7.82 (3.15)	-

SD: Standard Deviation

Table 3. Examining convergent and divergent validity Fornell and Larcker (HTMT ratio) and reliability of the model

Variables	Divergent Validity, Fornell and Larcker (HTMT ratio)						Convergent Validity and Reliability of the Model		
	Perceived Usefulness	Perceived Ease of Use	Perceived Accessibility	Computer Self-Efficacy	Behavioral Intention	Attitude Toward Using	Composite Reliability (CR)	Cronbach's Alpha (CA)	Average Variance Extracted (AVE)
Attitude Toward Using	0.920						0.846	0.939	0.956
Behavioral Intention	0.794 (0.86)	0.917					0.842	0.906	0.941
Computer Self-Efficacy	0.450 (0.478)	0.453 (0.491)	0.879				0.772	0.926	0.944
Perceived Accessibility	0.593 (0.639)	0.584 (0.639)	0.704 (0.764)	0.892			0.796	0.915	0.940
Perceived Ease of Use	0.807 (0.875)	0.746 (0.823)	0.453 (0.494)	0.580 (0.638)	0.879		0.773	0.902	0.931
Perceived Usefulness	0.536 (0.591)	0.525 (0.585)	0.708 (0.785)	0.744 (0.830)	0.518 (0.581)	0.846	0.715	0.867	0.909

Table 4. Results of hypothesis testing and lateral collinearity assessment

Hyps	Relationship	VIF	Path Coefficients (P-value)
H1	CSE → PEU	1.980	0.091 (0.062)
H2	CSE → PU	1.992	0.356 (< 0.001)*
H3	PA → PEU	1.980	0.516 (< 0.001)*
H4	PA → PU	2.384	0.432 (< 0.001)*
H5	PEU → AT	1.366	0.723 (< 0.001)*
H6	PEU → PU	1.516	0.106 (< 0.01)*
H7	PU → BI	1.446	0.139 (< 0.01)*
H8	PU → AT	1.366	0.162 (< 0.001)*
H9	AT → BI	3.031	0.719 (< 0.001)*

Discussion

The current study investigated the factors influencing the acceptance of online education by undergraduate students during the Covid-19 pandemic. Investigating these factors, especially in universities in developing countries with relatively little experience in offering online courses, will help policymakers with educational planning. The research hypotheses were tested using TAM with CSE and PA as the external factors.

The study results showed that students who used mobile phones or tablets to attend online courses had higher mean scores for all questionnaire constructs compared to students who used PCs or laptops. Moreover, the use of mobile internet had higher self-efficacy scores than use of a modem. The cheapness of the mobile phone, its availability, portability, and lightness compared to laptops, and having all the necessary tools including a microphone, webcam, etc., all at once in a small device compared to some desktop computers, made it easier for students to use mobile phones to take online courses. Various studies have also shown that the use of mobile phones can affect the satisfaction of students in taking online courses (35, 36). Other studies have suggested that students were significantly more likely to use laptops and smartphones for online courses and less likely to rely on desktop computers, indicating that the portability of a communication device is particularly important to students (37).

The data from the current study also showed that MDP students obtained significantly lower mean scores than undergraduate students in all the studied constructs. A greater number of practical courses are taken by MDP students than by undergraduate students (38). Studies have shown that it is more difficult to provide practical courses online than theoretical courses (38). A systematic review compared the level of satisfaction of medical and non-medical students with online education during the Covid-19 pandemic in Iran and showed that 58.1% of medical students and 70.1% of non-medical students were satisfied with online education (38).

The results of the structure model showed that only CSE as an external variable did not significantly affect PEU. The findings also indicated that CSE significantly affected PU. Previous studies have shown a positive and significant relationship between CSE and PU (39). CSE as an external variable represents an individual variable. The more a person's individual skills to use online education increase, the more utility they perceive they will receive from the online education system. Contrary to previous studies (7, 15), the data in the current study revealed no significant relationship between PEU and CSE. It is probable that the use of a native platform and the problems of typing in Persian with Adobe-connect software caused even those students with computer skills to find learning through the online education system difficult.

The data in this study indicated that PA had a positive and significant effect on PEU and PU. Other studies have also confirmed this significant relationship (7). The greater the ease of access and use of the online education system by the users, the more likely users will be to perceive the ease of use and usefulness of the online education system (18). Effective and quality access may not have a direct relationship with students, but it can motivate learners to use the online education system more effectively and frequently (18).

The findings of the present study showed that PEU and PU significantly affect students' attitudes toward using the online learning system. Many studies have confirmed these results (40, 41). It can be expected that as the perceived usefulness and ease of use of the online learning system increases, so too will the students' positive attitude towards it. The data in the present study confirmed that students' attitudes and PU strongly influence their behavior in using the online education system. Most previous studies have confirmed the effect of attitudes and perceived usefulness on the intention to use the online education system (7, 26). It is expected that the greater the perceived usefulness and the more positive the students' attitudes towards using the online education system are, the more positive an effect they will have on students' usage behavior.

Limitations: This study had some limitations. First, the students' self-report bias could affect their responses, especially when their skills and performance are questioned. The second limitation was that only CSE and PA were taken as the external variables in the model.

Other factors may also affect students' behavioral intentions, but they were not addressed in this study.

Conclusion

The results of this study suggest that students are more likely to consider online educational systems that are easier to work to be more useful. The ease of use of the online education system will reduce the time spent on learning and, consequently, positively affect students' attitudes. Thus, when choosing an online education system, university officials should focus on the ease of learning and convenient use of mobile phones and pay enough attention to creating the necessary infrastructure for online educational services. Furthermore, professors and students should receive the training necessary to use the online education system. Today, with the experience gained by students and professors, universities can continue using online education even after the Covid-19 crisis.

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