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E-Learning acceptance among university students in Iran during the Covid-19 pandemic

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Abstract: Evaluating e-learning acceptance at the universities in Iran during the Covid-19 pandemic was conducted to discover the challenges and students' preferences. During the lockdown, virtual classes run in Iran by using online platforms based on universities' facilities. The importance of online education led to form the framework of this quantitative study based on the Technology Acceptance Model (TAM) and external factors including perceived resources, subjective norms, and Covid-19 stress. The Partial Least Squares (PLS) was used to analyze data. To generate a consistent model and reliable results, 136 students were the sample size which was identified based on the exact calculations for PLS sampling. The questionnaire which was prepared in Google Drive was distributed through the online universities' groups. The results disclosed that perceived ease of use was a strong predictor of perceived usefulness. Both perceived usefulness and perceived ease of use displayed a significant role as a predictor of attitude. Behavioral intention to use was influenced meaningfully by attitude and subjective norms. The effect of behavioral intention on online system usage was proved, on the contrary, the influence of COVID-19 stress on online system usage was not confirmed. It is hoped that a standard scale would be introduced by future psychological studies to fill the lack of information about COVID-19's mental facets. This study confirmed the significant effects of e-learning challenges on students' behavior toward using online systems. Future research might explore each university platform separately in order to offer suitable solutions based on each university's needs.

Keywords: Online learning, E-learning, Technology acceptance model, Covid-19 pandemic, online educational challenges

Highlights

What is already known about this topic:

- The Covid-19 pandemic led to the collapse of face-to-face learning-teaching method of education.
- The lack of studies that have explored the acceptance of online learning during the Covid-19 pandemic is obvious.
- TAM model was used widely to examine the acceptance of new technology in Iran.

This paper contributes:

- The Covid-19 stress does not influence the system usage among Iranian students.
- Perceived ease of use is a strong predictor of perceived usefulness.
- E-learning challenges affect students' behavior toward using the online platform.

Implications for theory, practice and/or policy:

- The students in Iran, in the first place, gave precedence to an easy-to-use online platform, on the second place, they referred to its usefulness.
- The online technical support and the infrastructure affect the smooth use of online- learning.
- Applying the PLSpredict procedures in Smart PLS 3.3.2 increases the out-of-sample prediction power of the model of this study.

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Introduction

Human communication methods change in the 21st century by improving technology. The Internet penetration rate can be evidence of the important role of the Internet and linked technologies (Bishop & Verleger, 2013). The educational system is one of the important parts that has been influenced by these new technologies, as a result, it needs some reforms in order to satisfy young generations. During the COVID-19 pandemic, which has spread rapidly since December 2019 and led to severe outbreaks (WHO,2020), the necessity of online education became clear more than ever. Based on the United Nations (UN) announcement, around 1.6 billion students left schools to break the virus cycle (UN,2020). While governments around the world have locked down all activities, education appeared to be the only sector that cannot be stopped, therefore, online education was an alternative to physical classes and it connected lecturers and students in this turbulent time. In terms of online education, quality is a critical issue, moreover, the acceptance of remote classes among students needs more assessments. This research has explored the acceptance of online education among Iranian students during the COVID-19 pandemic because Iran was among the first countries which suffered severely from coronavirus and closed educational services (Chabook,2020). Although there were virtual universities in Iran, most popular and famous universities did not conduct online learning as a core method of education. Therefore, this issue and its related dilemma are completely new in Iran.

The main purpose of this study is to find students' acceptance and preferences of online learning in Iran during the turbulent time of the coronavirus pandemic by conducting the TAM. Based on the above explanation, the research question can be developed as below: What are students' preferences to accept the e-learning method during the COVID-19 pandemic in Iran? This study examines the acceptance of e-learning among Iranian students by considering the effect of the COVID-19 pandemic which is the pioneer aspect of the present study as an external factor in accepting a new educational method.

Despite the problems concerning e-learning including infrastructural problems, ineffective learning design, lack of technical support, students' inability to use the online method, control challenges, and emotional support of learners which lead to low satisfaction in online education (Mystakidis, 2020), it is strongly believed that by ending this pandemic, the educational systems should continue their online services to create innovative and attractive methods of teaching in order to motivate the young generation to show their hidden aspects of creativity. It is obvious that, nowadays, the Internet and smart devices play an important role in young students' life (Guri-Rosenblit,2005). Mentioned explanations have arranged the structure of this study which is presented in the following sections.

Literature

Based on the UN's Sustainable Development Goals (SDGs), education, which is the fourth goal, is a key factor to lead societies to a better and more sustainable future by rising socioeconomic movement and reducing poverty (UN, 2020). With the spread of the Covid-19 pandemic in early 2020, nearly 1.6 billion students were out of schools and universities to prevent the spread of the virus. It is the first time that these amounts of youth break learning at the physical schools (UN,2020). To gain solving-problem ability in the information era, it is necessary to educate flexible students who will be able to cope with difficulties in critical times, therefore, one solution to solve the aforementioned problem is online learning (Illeris, 2004).

E-learning

E-learning refers to delivering learning materials electronically by using computer networks (Tsai & Machado, 2002; Zhang et al., 2004; Guri-Rosenblit, 2005; Moore et al., 2011). Moreover, online classrooms can be a full replacement for face-to-face classrooms (Zhang et al., 2004; Guri-Rosenblit,2005). In order to make more investigation into e-learning, Zhang et al. (2004) offered Virtual Mentor (VM) idea with this definition "a multimedia-based e-learning environment that enables wellstructured, synchronized, and interactive multimedia instructions" (p.76). VM was proposed with six dimensions including multimedia integration, just-in-time knowledge acquisition, interactivity, self-directivity, flexibility, and intelligence. For implementing the VM idea, Learning By Asking (LBA) system with mentioned dimensions was developed (Zhang et al.,2004). Although applying interactive E-classroom of LBA showed better performance than the traditional classroom, more investigation should be applied to different aspects of e-learning such as trust, authorization, confidentiality, and individual responsibility (Zhang et al., 2004).

The present study has applied "e-learning" equal to "online learning" based on Guri-Rosenblit's study (2005) which used e-learning terms for all online learning/teaching activities through the information and communication technology (ICT), furthermore, the concepts and structure of Zhang et al.'s study (2004) are applied.

During the early years of spreading the high-speed Internet, researchers found different factors related to online learning. E-learning advantages were explored in different studies which had used diverse electronic tools as part of the e-learning process. Babu and Vishal (2007) employed Course Management System (CMS) such as the Blackboard tool among students with sensory problems such as vision or hearing weaknesses. Means et al. (2010) conducted three online methods to deliver educational content and interaction between students and teachers including asynchronous communication tools (e-mails), synchronous technologies (desktop audio/video technology), and the combination of them. The findings of these studies showed Increasing satisfaction with accessibility among students with sensory problems, flexible access to educational documents without the time and place limitations, growing evidence for the effectiveness of e-learning in comparison with the traditional face-to-face instruction, moreover, exploring students' academic outputs disclosed the appropriate effect of online learning on students' performance (Makkar et al.,2016). Although these researchers observed effective facets of online learning among students, Farahat's study (2012) disclosed that the Egyptian students had a negative attitude toward using e-learning.

As online education is spreading across the world, Massive Open Online Courses (MOOCs) has been introduced as a new feature of online learning by engaging the Internet technology and many universities used it as a pioneering method of e-learning (Jordan,2014). Although The popularity of this type of courses were increasing, Hew and Wing (2014) identified some key challenges of MOOCs such as students' assignments assessments and students' absence which may affect teachers' communication skills. Deep and meaningful learning in the online environment was another concept that was explored by Mystakidis (2020) to show more effective classroom-based instruction; consequently, not only is the quality of improvement of e-learning a meaningful way to meet UN's educational goals, but also it is a powerful tool to achieve economic, social, and healthcare goals of the UN (Mystakidis 2020).

TAM and E-learning

Technology Acceptance Model (TAM) which was developed by Davis (1989) is one of the extensions of Ajzen's Theory of Reasoned Action (TRA) (1991) that has been widely used to predict user acceptance of new technology. It concluded that behavioral intention to use technology is predicted by perceived usefulness and perceived ease of use. According to Davis (1986), perceived usefulness is related to productivity, but perceived ease-of-use is related to effort, moreover, intentions influence the decision of applying actual technology. The noteworthy results of Davis' study (1986) were the strong relationship between usefulness and usage of new technology. It means difficulties have negative effects on acceptance of a useful system, furthermore, ease of use cannot save a useful system that does not perform well. Conducting word processing program among the university students showed perceived usefulness was a significant predictor of behavioral intention to use the computer program, besides, their usage of computer was predictable by their intentions, additionally, perceived ease of use was a major determinant of people's intentions to use computers (Davis et al.,1989). By using the Blackboard tool as an educational online technology, Landry et al. (2006) applied TAM in order to conduct a study about students' Web-Enhanced Instruction (WEI) acceptance. The results unveiled that TAM was an appropriate structure to measure students' reaction toward Blackboard, also the usefulness of the Blackboard tool and the use of technological tools in universities were not deniable. In contrast with Landry et al.'s findings (2006), Masrom (2007) concluded that TAM did not provide analytical skills for drawbacks in technology, on the contrary, it can just help to assess and forecast technology acceptability. One more study which is related to the acceptance of the online platforms was done by Arteaga and Duarte (2010) to expand the knowledge of accepting Moodle as a Web-based platform by applying TAM and two additional constructs, technical support and perceived self-efficacy. The findings of their study confirmed the important role of technical support as an external resource to impact the perceived ease of use and perceived usefulness, additionally, the usage of Moodle was affected by perceived ease of use and attitude.

Cheung and Vogel (2013) conducted their research by blending the original TAM structure and Theory of Planned Behavior (TPB) to examine perceptions and acceptance of collaborative technologies including Google Applications to solve students' group learning challenges; in addition to applying theories, they used different constructs including compatibility from Corrocher's study (2011), that is the degree to which applying Google Applications for team-working's goal is perceived in line with students' skills and necessities. The perceived resource was applied from Ngai et al.'s study (2007) that refers to the online learning supporting including perceived technical support which is a vital factor that influences ease of use and usefulness of online learning system. Self-efficacy from TPB, sharing based on Wasko and Faraj (2005), which refers to the sharing information, documents, and taking part in online debates. In addition to the traditional TAM structure, Cheung and Vogel (2013) inserted subjective norm to the study based on the TPB (Ajzen, 1991) as a factor that influences behavior intention that affects individual behavior in applying a new technology. TPB is an extended structure of TRA with an additional construct which is perceived behavioral control (Fishbein & Ajzen, 1975). Based on the TPB, perceived behavioral control and behavioral intention to use technology can be used to forecast behavioral accomplishment (Ajzen, 1991). Ajzen (1991) believed that TPB gives a strong theoretical framework to discover human social behavior and defines thoughts to forecast and recognize the specific behavior in particular frameworks, therefore, he proposed a framework to predict behavioral intentions of individuals with two factors: subjective norms and attitudes toward behavior (Ajzen,1991). Ajzen (1991) believed three kinds of salient beliefs, that guide people's intentions and behaviors, are identified including behavioral beliefs, normative beliefs, and control beliefs. Normative beliefs form the main factors of subjective norms which are used in different studies such as Cheung and Vogel (2013) who claimed their study found significant relationships between mentioned variables and users' acceptance and gave a better understanding of user's acceptance behavior.

Covid-19 pandemic effects

One important feature of this study is discovering the effect of the Covid-19 pandemic on student behavior to accept e-learning. In the last month of 2019, the world faced the biggest pandemic in history and the educational system was closed around the world including Iran (Chabook, 2020). Researchers tried to disclose the psychological effects of this phenomenon on the general public including medical staff and older adults (Yang et al., 2020; Cao et al., 2020; Chen et al., 2020). Examining the impact of the Covid-19 pandemic on the students in China was done by Cao et al. (2020) and it was found near 25 per cent of college students who took part in the survey were distressed with anxiety which may come from future unemployment, social distancing, and study postpone because of the coronavirus outbreak. Prior to Yang et al. (2020) and Cao et al. (2020), Saade and Kira (2009) found the strong effect of anxiety on the ease-of-use construct of using the computer in online learning. In an attempt to understand the COVID-19 psychopathological signs, Taylor et al. (2020) proved their designed scale with different dimensions including danger, fears about economic consequences, xenophobia, checking, and traumatic factor. Among Taylor et al.'s (2020) scale, the traumatic factor is near to Hoan's study (2015) which explored higher education stress inventory. Both mentioned studies found that mental factors affect students' learning process likewise Davis (1989), Fishbein and Ajzen (1975), and Igbaria et al.(1995) proved the effect of external factors on the usage of the system.

Present research may be a pioneer study to add the stress construct as an external factor to TAM in order to find the effect of the COVID-19 pandemic on student acceptance of e-learning among Iranian students. By considering all points and discussions about e-learning, TAM, and COVID-19 stress, the designed framework is presented in Figure 1.

Theoretical Background

According to the purpose of the study and based on the previous studies which are explored in the literature review, the framework is defined in Figure 1.

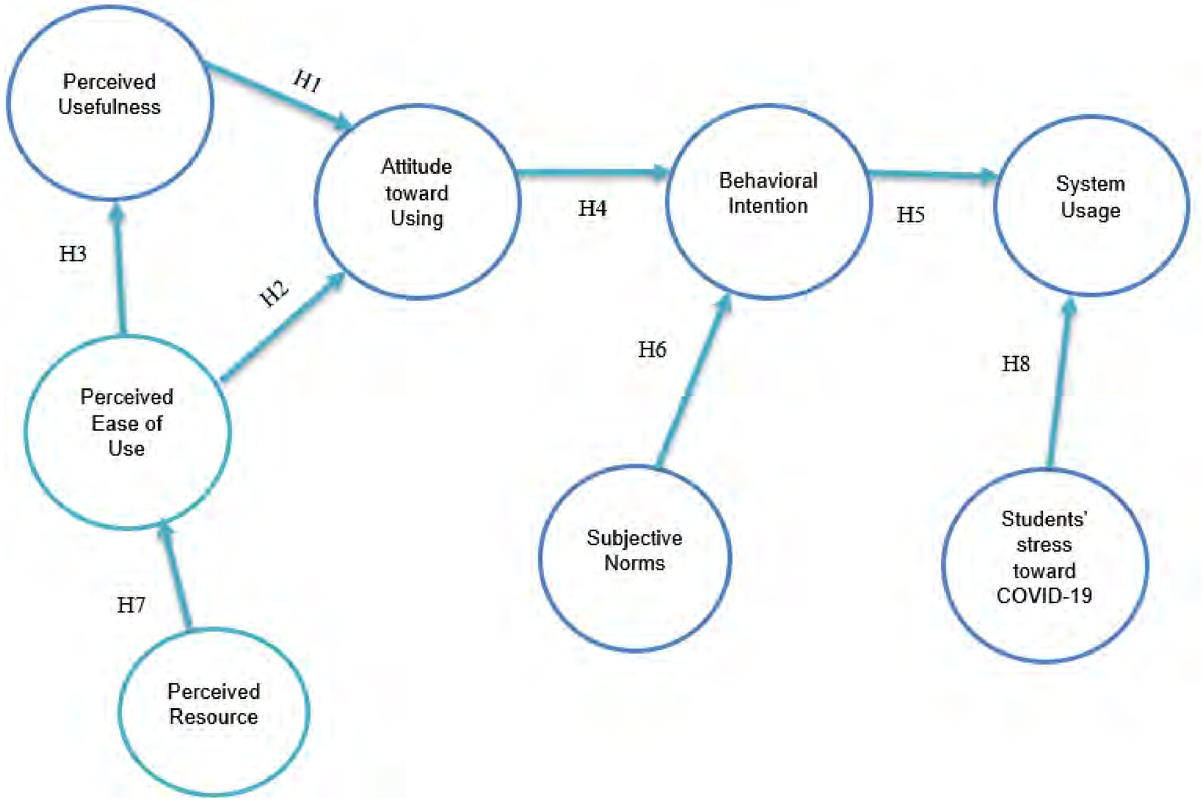

Figure1: Research Framework

Perceived usefulness can be defined based on the direct citation from Davis (1989) who explained perceived usefulness as refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" (P.320). Perceived ease of use is another construct that is used in this study based on Davis (1989) definition: "the degree to which a person believes that using a particular system would be free of effort" (P. 320). According to Cheung and Vogel's study (2013), TAM theorized that perceived usefulness and perceived ease of use influence the attitude to use technology directly, additionally, ease of use influences usefulness positively. Therefore, to address the research question, the following hypotheses were defined:

- H1: There is a significant effect of usefulness on attitude toward using e-learning among Iranian students.

- H2: There is a significant effect of perceived ease of use on attitude toward using e-learning among Iranian students.
- H3: There is a significant effect of perceived ease of use on perceived usefulness among Iranian students.

Fishbein and Ajzen (1975) defined “Attitude is theorized as the degree to which a user is interested to use a system” (As cited in Davis et al.,1989, p. 984). This attitude will define the behavioral intention that finally causes the actual usage (Davis, 1989); consequently, the hypotheses were defined as follow:

- H4: Attitudes have a significant influence on intention to use the e-learning
- H5: Intention to use e-learning has a significant influence on system usage.

Based on Fishbein and Ajzen (1975), a Subjective norm refers to following the family members or important friends’ recommendations in life. "It refers to the perceived social pressure to perform or not to perform the behavior” (Ajzen,1975, p.188). The next hypothesis is derived from Fishbein and Ajzen (1975) and Cheung and Vogel (2013) who applied this construct in their studies and found a strong effect of subjective norms on behavioral intentions.

- H6: Subjective norm has a significant effect on behavioral intention to use e-learning.

The perceived resource is a construct that refers to the resources that individuals and organizations need in order to use a system (Mathieson, 1991). Davis (1989) believed ease of use and usefulness are influenced by certain technology as an external variable, therefore, it should be involved in TAM to measure certain technology acceptance. Cheung and Vogel (2013) proved the important and vital effect of external variables on the determinant of ease of use in e-learning; thus, the following hypothesis was developed:

- H7: perceived resource has a significant effect on ease-of-use construct in online learning.

Igbaria et al. (1995) defined three variables as the external factors which influence the computer system usage; furthermore, Cheung and Vogel (2013) used different external factors such as sharing to show the effect of these factors on perceived usefulness and compatibility on perceived ease of use. This study follows Igbaria et al. (1995), Davis (1989), Fishbein and Ajzen (1975) to develop students’ stress construct as an external factor that affects e-learning. Therefore, the last hypothesis of the study was defined based on Igbaria et al. (1995).

- H8: COVID-19 pandemic stress among Iranian students has a significant effect on using e-learning.

Methodology

This study is a quantitative research with a correlational design to investigate the relationship between variables (Sekaran,2003; Creswell,2012). The correlational design gives the ability to predict variables’ effect (Creswell,2012). Furthermore, Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis, which is used in this study, confirms prediction in statical models’ estimation (Hair et al,2019).

Assumptions of research

First Assumption

It was necessary to distribute the questionnaires among undergraduate or postgraduate students who took part in the online class for at least one semester, besides, they had to use their official online systems to upload assignments and took part in the online final exam. This assumption was met by choosing universities with the official online system. The official online system is an official online platform that is developed by universities to continue the learning process and communication between lecturer and students. This system has concepts and dimensions of the LBA system which was conducted by Zhang et al. (2004). It means it facilitates synchronized online communication between lecturer and students; moreover, it has the ability to share multimedia materials, presentation slides, and lecturer notes. Another feature of this system is E-classroom with all characteristics of face-to-face classroom including question and answer, group assignments and presentations. Besides, the system has ability to record all activities in the E-classroom, and students can refer to these records whenever they need (Appendix B). In addition to the official systems, in emergency cases such as system collapse, social messengers were used to communicate. During the COVID-19 pandemic, each university had its customized version of online platforms. For example, the University of Applied Science and Technology used its official system as KODOK (Appendix A). SABA, SAHBA, NAVID, and NIMA were the names of the most common online systems in the popular universities in Iran.

Second Assumption

It was assumed that all students had a sufficient amount of English knowledge to understand questionnaire items by referring to the vital role of the English language in planning, crafting, and executing the higher education programs in Iran. Therefore, the English version of the questionnaire was distributed. In the case of language misunderstanding, an official English teacher at Kish Language Institute helped students in the data collection process.

Third Assumption

Exotic and rare information about Covid-19 effects requires precise considerations alongside the complex aspects of psychological issues. Therefore, a licensed psychologist joined the research to support the students.

Data Collecting

The questionnaire was uploaded to Google Drive (Appendix B) and its link was shared in selected universities' groups which meet the first assumption of this study; afterwards, respondents sent back their answers to Google Drive. Among 150 received questionnaires, 136 completed ones were selected to employ in the analysis process. The students with bachelor, master's, and PhD degrees from the following universities cooperated in this project.

The art faculty of Guilan University, students of engineering at AmirKabir University in Tehran, the finance faculty of the University of Applied Science and Technology in Rasht, Islamic Azad University North Tehran and Rasht branches, business management faculty of Ghadr non-profit higher educational institute.

Sample Size

Roscoe (1975) proposed that the appropriate sample size for most research is greater than 30 and less than 500, moreover, Krejcie and Morgan (1970) provided a table of sample sizes according to the population size. For this study, while the Partial Least Squares (PLS) method is conducted for analyzing data, the techniques of calculating sample size are important. Although it is believed that PLS_SEM is less influenced by a small sample size (Gefen et al., 2000; Rigdon, 2016; Rigdon et al., 2017; Sarstedt et al., 2014), it can be a reason to do insufficient effort to estimate a suitable sample size in a large population (Hair et al., 2019). Prior to this, Hair et al. (2011) introduced "10-times rule" to examine the minimum sample size in PLS-SEM. Following Hair et al.'s definition of "10-times rule" (2011), Kock and Hadaya (2018) stated that "the sample size should be larger than 10 times the maximum number of inner or outer model links pointing at any latent variable in the model" (p.228). Although it is the most used method to estimate sample size, its straightforwardness and inaccurate sample size lead to inexact results (Kock & Hadaya, 2018). Later, Hair et al. (2014) conducted "R-squared method" based on the Cohen's power table (1988,1992) relying on three elements including minimum R-squared based on the latent variable pointing arrows, significant level, and R^2 in the model. In this study the Cohen's power table (1988,1992) and Hair et al.'s R-squared method (2014) were applied, also Krejcie and Morgan's sample size (1970) based on the population size was considered. By applying G* power based on the Cohen table, the minimum sample size was 109, by conducting R-squared method, the sample size was 84, and Krejcie and Morgan's table (1970) proposed 136 samples. Therefore, in order to generate accurate and reliable results, 136 were selected as the sample size for this research.

Procedures

To prevent response bias, negatively worded items in some scales have been revised (Pallant, 2001). A revised process was used for question 5 in the usefulness construct.

Data Analysis

Partial Least Squares (PLS) analysis was used to evaluate the collected data since PLS supports prediction-oriented goals (Hair et al., 2011; Hair et al.,2019). The PLS 3.3.2 software was run to assess both the measurement and the structural model (Ringle et al.2015).

Demographic characteristics of respondents

Based on the descriptive analysis of the questionnaire's part one, 86 female students (63.2%) and 50 male students (36.8%) who belonged to 4 different age groups took part in this study. Most students were in the 18-24 age group with 49% (67 students) and the least students were seen in the 41-50 age group with only 15 students (11%). The majority of them studied at the bachelor sciences level (57.4%) and the minority group were the PhD students with a percentage of 8.8; moreover, the master's degree students were 22.8 % followed by university college students with 11%. Around 60 per cent of these students mentioned that the Internet infrastructures had low quality in their hometown, besides, less than half of them mentioned the Internet had no issue in their places. It can be seen that 38.2% of scholars selected the Islamic Azad universities to study that was followed by applied science universities (25%), public (governmental) universities (16.9%), non-profit higher institutes (13.2%), and Payam Noor centers with the lowest amount of 6.6 per cent. The summary of the demographic part is presented in Appendix C.

Reflective indicator loadings

To assess the reflective measurement model, the first place is evaluating indicators' loading which is recommended above 0.708 (Hair et al., 2019). One indicator related to the stress construct was omitted to gain internal consistency reliability of item because its factor loading was less than 0.7 (Barclay & Thompson, 1995; Gong et al., 2004; Mohammadi, 2015). Since the Covid-19 is a new phenomenon in its early stage to develop a standard scale, discarding some items is common (Barclay & Thompson,1995; Gong et al.,2004), therefore, one item (Q27) in stress construct was removed. The remaining indicators gained acceptable value (table1). The original questionnaire was presented in Appendix B.

Table1: Factor loading values

Construct	No.of indicators	Item loadings	
usefulness	6	Q1	0.824
		Q2	0.873
		Q3	0.880
		Q4	0.839
		Q5	0.710
		Q6	0.880
Easeofuse	6	Q7	0.840
		Q8	0.889
		Q9	0.871

		Q10	0.838
		Q11	0.707
		Q12	0.817
subjective norms	6	Q13	0.831
		Q14	0.861
		Q15	0.795
		Q16	0.849
		Q17	0.903
		Q18	0.779
Behavioral Intension	3	Q19	0.929
		Q20	0.857
		Q21	0.928
Stress	5	Q22	0.820
		Q23	0.730
		Q24	0.837
		Q25	0.920
		Q26	0.854
Attitude	3	Q28	0.883
		Q29	0.846
		Q30	0.887
System Usage	3	Q31	0.913
		Q32	0.890
		Q33	0.892
Resources	4	Q34	0.785
		Q35	0.809
		Q36	0.779
		Q37	0.736

Internal consistency reliability

To evaluate internal consistency reliability which is the second important step to analyze, in the one side, Hair et al.(2019) suggested applying Jöreskog's composite reliability (1971) because of its liberal nature to weight construct indicators' individual loading, on the other side, they recommended, Cronbach's alpha which presents conservative nature and lower value because of unweighted mechanism, however, both of them produce same thresholds with minimum 0.7 value, while the maximum does not exceed 0.95 because it displays the possibility of undesirable response patterns (Hair et al. (2019), moreover, Dijkstra and Henseler (2015) presented ρ_A , that lies between Cronbach's alpha value and the composite reliability value, to obtain consistent inter-construct correlations to estimate consistent path coefficients. Based on all of the above-mentioned methods, the results of reliability tests confirmed the internal consistency of each construct.

Table 2: Reliability results

	Cronbach's Alpha	rho_A	Composite Reliability
attitude	0.843	0.844	0.905
behavioral Intension	0.889	0.895	0.931
Easeofuse	0.908	0.912	0.929
resources	0.785	0.786	0.859
stress	0.891	0.926	0.919
subjective norm	0.914	0.915	0.933

system usage	0.882	0.897	0.926
Usefulness	0.913	0.922	0.933

Convergent and Discriminant validity

Convergent validity explains the variance of constructs' items, it is the third step to evaluate the model which is measured by average variance extracted (AVE) with the acceptable value of 0.5 or higher. Based on Table 3, the results were higher than the recommended minimum threshold value.

Table 3: Validity results

	Average Variance Extracted (AVE)
attitude	0.761
behavioral Intension	0.819
easeofuse	0.687
resources	0.605
stress	0.696
subjective norm	0.701
system usage	0.807
usefulness	0.700

For the fourth step, discriminant validity, which is an empirical observation to find to what degree a construct is different from another construct in the model, is examined. This study follows Henseler et al. (2015) and Hair et al.'s suggestions (2019) to measure discriminant validity by applying the heterotrait-monotrait (HTMT) ratio of the correlations with an acceptable value lower than 0.9 is very similar conceptual constructs and lower than 0.85 in distinct conceptual constructs. The following results (Table 4) show that there is no discriminant validity problem in this model.

Table 4: discriminant validity (HTMT)

	attitude	behavioral Intension	easeofuse	resources	stress	subjective norm	system usage	usefulness
attitude								
behavioral Intension	0.778							
ease of use	0.665	0.615						
resources	0.757	0.679	0.703					
stress	0.103	0.129	0.154	0.161				
subjective norm	0.729	0.700	0.681	0.717	0.153			
system usage	0.499	0.573	0.578	0.747	0.110	0.478		
usefulness	0.655	0.643	0.822	0.590	0.120	0.644	0.544	

Assessing structural model

To evaluate the structural model, standard assessment criteria including the coefficient of determination (R^2 (, the blindfolding-based cross-validated redundancy measure (Q^2), and the statistical significance and relevance of the path coefficients have to be considered (Hair et al., 2019). Prior to examining mentioned criteria, VIF should be examined because of the collinearity problem. The ideal values for VIF ought to be lower than 3 (Hair et al., 2019; Hair et al., 2017). Through running of PLS algorithm in PLS 3, VIF values were in the acceptable range, therefore, there was no collinearity problem (table 5).

Table 5: VIF values

	attitude	Behavioral intention	Ease of use	resources	stress	Subjective norm	system usage	usefulness
attitude		1.682						
Behavioral intention							1.008	
easeofuse	2.333							1.000
resources			1.000					
stress							1.008	
subjective norm		1.682						
system usage								
usefulness	2.333							

The next step is assessing t-value and its significant level. The 0.05 significance level ($p<0.05$) needs a t-value> 1.657 and the 0.01 significance level ($p < 0.01$) requires a t-value> 2.354 and finally, the t-value >3.152 is significant at $p<0.001$. Table 6 displays t-value and significant level of this study. All t-values were in an acceptable range excluding the stress-system usage path which was H8 with t-value 0.487 and path coefficient 0.050, therefore this hypothesis was rejected. (Figure 2)

Table 6: T-values and significant level

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
attitude -> behavioral intention	0.457	0.454	0.090	5.100	0.000
behavioral intention -> system usage	0.507	0.510	0.063	8.050	0.000
easeofuse -> attitude	0.355	0.349	0.103	3.333	0.001
easeofuse -> usefulness	0.756	0.757	0.042	17.419	0.000
resources -> easeofuse	0.615	0.621	0.051	11.475	0.000
stress -> system usage	0.050	0.055	0.111	0.487	0.627
subjective norm -> behavioral intention	0.346	0.353	0.092	3.912	0.000
usefulness -> attitude	0.313	0.324	0.113	2.723	0.007

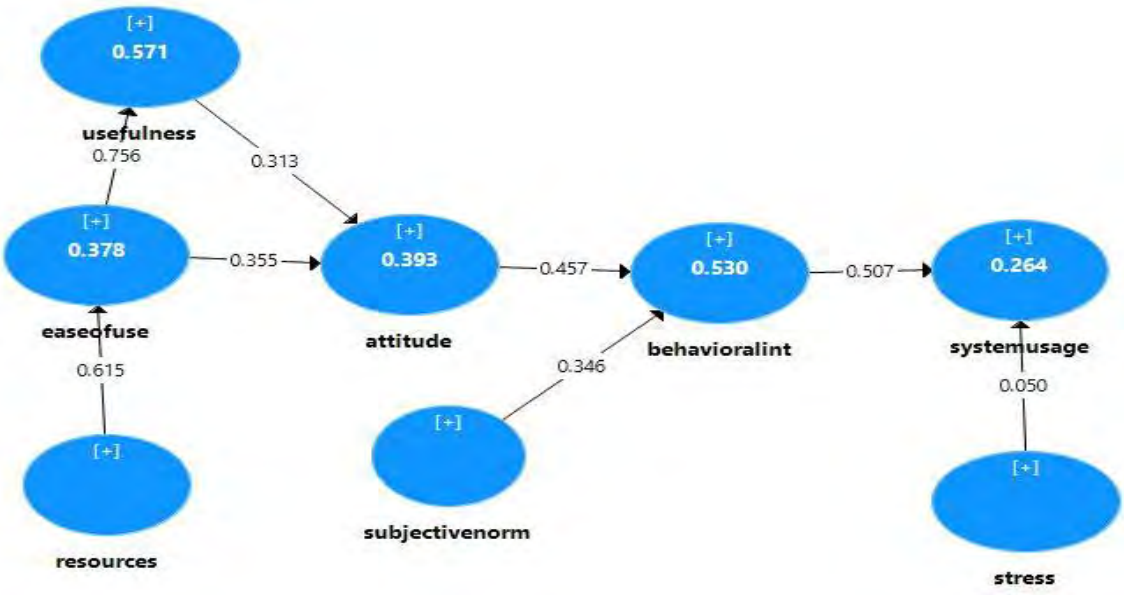

Figure2: hypotheses testing results

Referring to R^2 ,which is explained in each of the dependent constructs (ease of use, usefulness, attitude, behavioral intention, and system usage), Hair et al. (2019) believed that R^2 value should be interpreted according to the context of research, based on similar studies, and model of comparable complication. Three different values for R^2 which were 0.75 as substantial, 0.50 as moderate, and 0.25 as weak were defined (Hair et al.,2019). Moreover Hair et al. (2019) believed R^2 is referred to as in-sample predict power, therefore, by running the PLS algorithm model, R^2 for this study and the hypotheses testing results are presented in Table 7.

Table7: Path Coefficients

Path	β	t-value	Sig.	R^2	Hypotheses supported
attitude -> behavioral intention	0.457	5.100	0.000	0.530	H4: supported
behavioral intention -> system usage	0.507	8.050	0.000	0.264	H5: supported
easeofuse -> attitude	0.355	3.333	0.001	0.393	H2: supported
easeofuse -> usefulness	0.756	17.419	0.000	0.571	H3: supported
resources -> easeofuse	0.615	11.475	0.000	0.378	H7: supported
stress -> system usage	0.050	0.487	0.627	0.264	H8: Rejected
subjective norm -> behavioral intention	0.346	3.912	0.000	0.530	H6: supported
usefulness -> attitude	0.313	2.723	0.007	0.393	H1: supported

The highest R^2 belongs to the usefulness endogenous variable. It shows usefulness with the highest R^2 (0.571) is predicted by the ease of use with the highest path coefficient (0.756). Next R^2 can be explained by attitude and subjective norm in terms of variance in behavioral intention (0.530), while attitude (β=0.45) contributed to behavioral intention more than the subjective norm (β=0.346).The lowest amount of R^2 is observed in the system usage (R^2 =0.264) which is predicted by behavioral intention to use and Covid-19 stress, as mentioned previously, the stress relationship with system usage was rejected (β= 0.05), therefore, the most significant prediction was related to behavioral intention to use the online system (β=0.507).

Hair et al. (2019) mentioned the Q^2 value as another tool to evaluate the PLS model's predictive accuracy which is accessible through running the blindfolding model in PLS with an acceptable value of more than zero (0 is small, 0.25 is medium, and 0.5 is a large predictive accuracy). For the present study, the observed Q^2 values are presented in table 8. Although all values were above zero, system usage Q^2 displays small predictive relevance of the PLS-path model by its related constructs which were behavioral intention and Covid-19's stress.

Table 8: Q^2

	Q^2
attitude_	0.289
Behavioral intention	0.418
easeofuse	0.248
resources	
stress	
subjective norm	
system usage	0.192
usefulness	0.387

In spite of the fact that many prior researchers had interpreted R^2 value as a measure of a model's predicted power, Hair et al. (2019) followed Shmueli et al. (2016) who suggested a set of procedures for out-of-sample prediction which were offered in PLSpredict procedure in smart PLS 3.3.2. In this study, interpreting the PLSpredict model's outputs was formed based on two guidelines. Firstly, Hair et al.'s guidelines (2019) that were designed according to Shmueli et al.'s definition (2019) which was evaluated of $Q^2_{predict}$ statistic to validate if the predictions exceed the maximum naïve scale. Secondly, Danks and Ray's RSME (2018) which was the square root of the average of the squared differences between the predictions and the actual observations. RSME has to compare to the linear regression model (LM) which is produced by the PLSpredict method to generate estimation for the manifest variable through running linear regression of each of the endogenous variables' indicators on the indicators of exogenous latent variables in the PLS path model. The results can be summarized as below:

Table 9: The summary of PLSpredict interpret

			Predictive power of the model
If	All indicators	RMSE(PLS)> RMSE(LM)	Lack of prediction
	Majority of indicators	RMSE(PLS)> RMSE(LM)	Low prediction
	Minority of indicators	RMSE(PLS)> RMSE(LM)	Medium prediction
	All indicators	RMSE(PLS)< RMSE(LM)	High prediction

The results of $Q^2_{predict}$ (table 10) indicated that the model outperforms the most naïve benchmark (Hair et al., 2019).

Table 10: $Q^2_{predict}$

	Q²_predict (PLS)	Q²_predict (LM)
Q30	0.223	0.201
Q28	0.295	0.359
Q29	0.202	0.279
Q21	0.359	0.389
Q19	0.360	0/372
Q20	0.254	0.281
Q11	0.089	0.215
Q07	0.284	0.341
Q10	0.267	0.379
Q08	0.221	0.294
Q09	0.257	0.244
Q12	0.321	0.545
Q33	0.162	0.287
Q32	0.106	0.140
Q31	0.167	0.202
Q04	0.120	0.093
Q05	0.151	0.128
Q01	0.246	0.209
Q02	0.125	0.176
Q03	0.133	0.159
Q06	0.231	0.447

For this study, based on Table 11, only 5 indicators have higher LM's results than RMSE (PLS). It means the model has a low out-of-sample power of prediction. These 5 indicators were related to attitude (Q30), perceived ease of use (Q09), and perceived usefulness (Q01, Q04, and Q05).

Table 11: RMSE and LM

	RMSE(PLS)	RMSE(LM)
Q30	1.693	1.716
Q28	1.393	1.328
Q29	1.612	1.531
Q21	1.513	1.478
Q19	1.512	1.498
Q20	1.437	1.411
Q11	1.957	1.817
Q07	1.761	1.690
Q10	1.670	1.537
Q08	1.770	1.686
Q09	1.676	1.691
Q12	1.446	1.183
Q33	1.616	1.491
Q32	1.688	1.655
Q31	1.567	1.533
Q04	1.667	1.692
Q05	1.416	1.435
Q01	1.551	1.589
Q02	1.630	1.582
Q03	1.630	1.605
Q06	1.761	1.494

Discussion

This study was conducted during the Covid-19 pandemic in 2020 while education was online around the world. Iran's educational system was forced to use online platforms to continue educational programs with many infrastructures' challenges, therefore, each university selected a method based on its own facilities, besides, social messengers were a supplementary way to help both students and course instructors to communicate. The aim was to find the acceptance of e-learning among Iranian universities' students. The original TAM constructs were applied; additionally, more constructs including perceived resources, subjective norms, and Covid-19 stress were included to enhance the research model qualification. In terms of the effect of ease of use on usefulness (H3) the result was in line with previous research which had proved this relationship (Davis, 1989; Masrom, 2007; Cheung and Vogel, 2013). Based on this result, ease of use is a strong predictor of usefulness which means an easy-to-use device can identify the degree of usefulness of that device. In line with Arteaga and Duarte's findings (2010), both usefulness and ease of use displayed a significant relationship with attitude as the predictors of this construct, although, ease of use had a slightly more effect on attitude (H2) than usefulness (H1). Behavioral intention to use is the next construct that has been influenced significantly by attitude (H4) and subjective norms (H6); although, the attitude had more contribution to behavioral intention to use. These results followed Davis (1989), Ajzen (1991), and Masrom (2007). It is concluded that although the important person in students' life influenced their actions toward their behavioral intention to use a new technology, it was not as strong as attitude construct effect. The significant effect of behavioral intention on system usage (H5) was proved in this research and in prior studies (Davis,1989; Cheung & Vogel, 2013). On the contrary, this significant relation was not confirmed between stress level and system usage (H8). This result occurred because of the unknown nature of Covid-19 psychological aspects. Because it is very soon to reach a universal scale for measuring Covid-19 stress, a localized measurement might display a significant relationship during the years. The perceived resource was the next construct that disclosed a significant relationship with the perceived ease of use (H7) that proved previous research findings such as Arteaga and Duarte (2010). Students confirmed that different kinds of technical supports have a strong influence on the prediction of a technology comfortable using.

Conclusion and suggestions

Due to the significant role of online education in societies, the aim of this type of studies is to discover the important factors as the keys to success in online educational planning, drafting, and executing in order to formulate virtual educational strategies for the young generation. The study shows that the students in Iran, on the first place, gave precedence to easy online platforms, on the second place, they referred to its usefulness; consequently, it is a key to run or reform universities online platforms. Adequate technical support is the next factor in success way for higher educational institutes. The more they assist students, the more scholars discover the easy aspects of these online platforms, accordingly, they break their resistance to use new online educational packages. Based on the first part of the questionnaire, most students believed Iran's Internet infrastructure has no capacity to meet today's online needs, so it is strongly recommended to improve the Internet structure to inspire students to practice online platforms.

Although this research has been evaluating the Covid-19 stress as an external factor in TAM, lack of information about this type of coronavirus and its mental facets were boundaries to gain more reliable results. It is hoped by uncovering more mysterious cognitive sides of this virus, a standard scale would be introduced. The vital role of students' mental situation in the e-learning process is a root to emphasize the accurate measures of this construct. Another important issue is related to IT- system challenges in universities' online platforms. This study confirmed significant effects of these challenges on students' behavior. Future research might explore each university platform separately to explore the students' behaviors and offer suitable solutions based on each university's needs.

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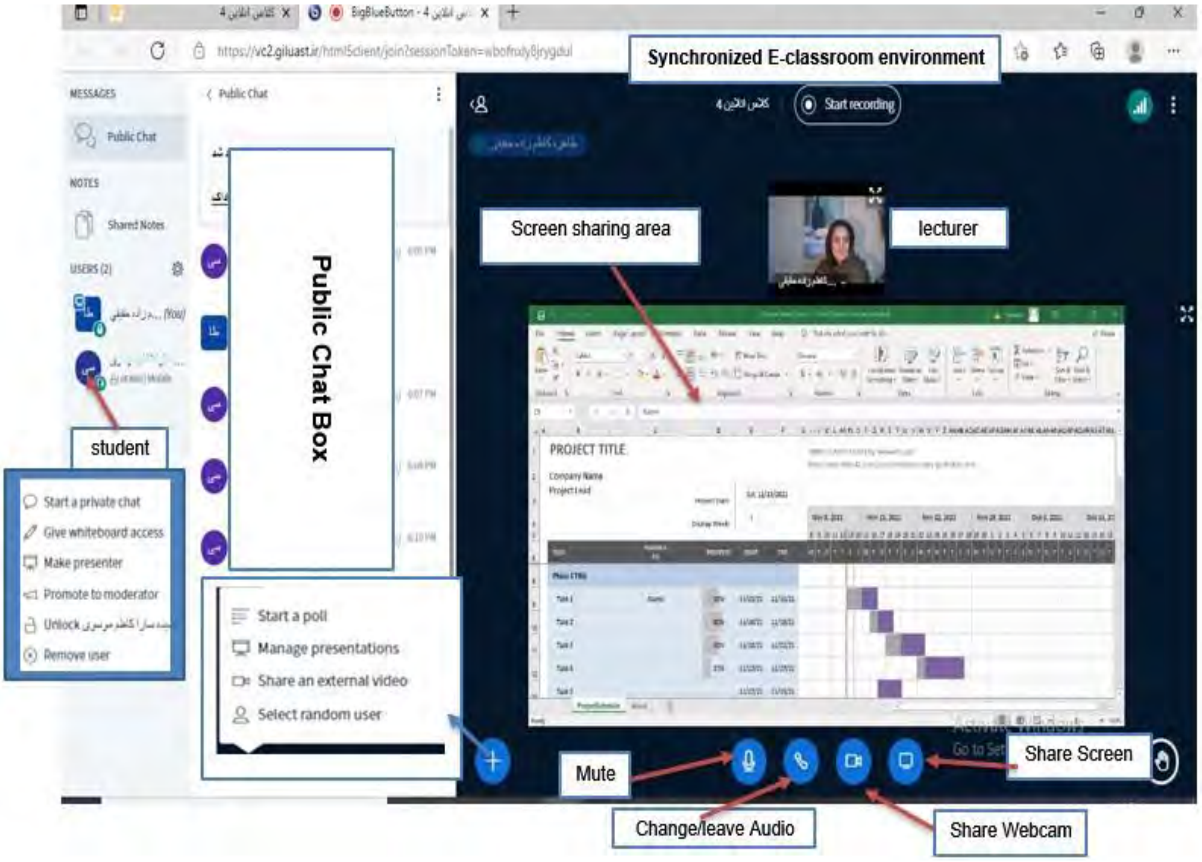
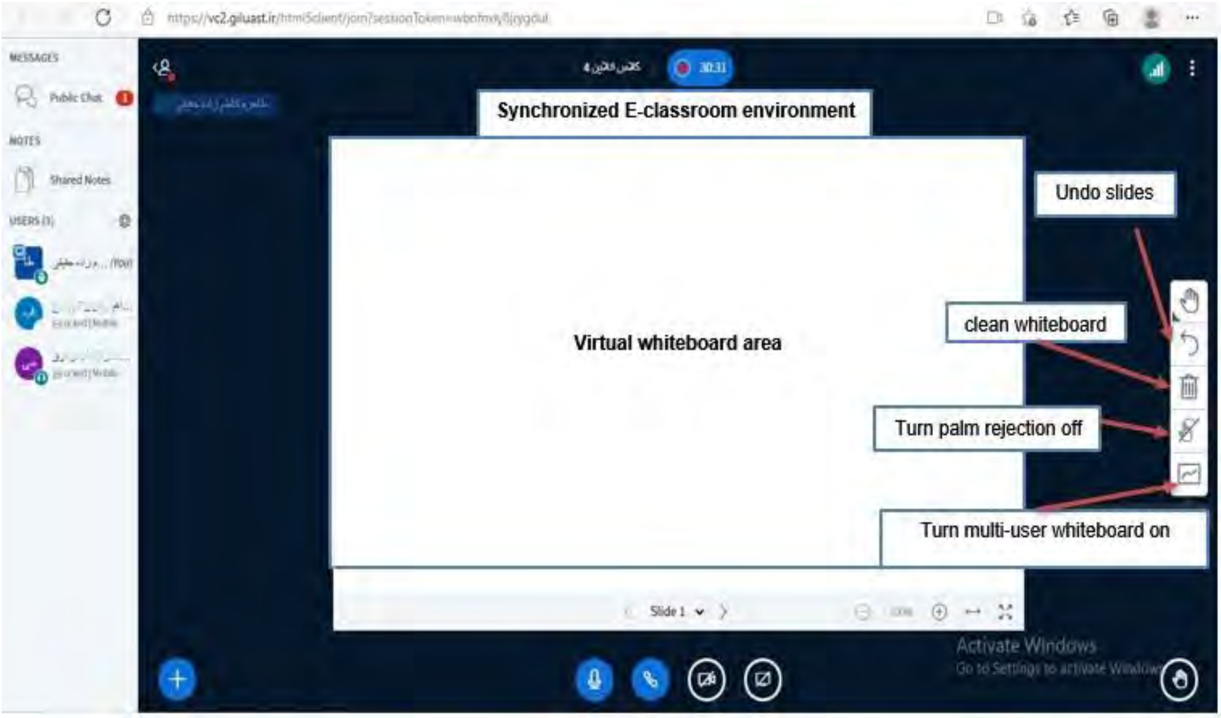
Appendices

Appendix A: Questionnaire of the study
The**e** questionnaire of this study is accessible via: https://forms.gle/GSr3VT3fUzXhuJcVA

Appendix B: The official online system of Applied Science University of Gilan:





Appendix C: demographics summary

sex	Frequency	Percent	age	Frequency	Percent	education	Frequency	Percent
male	50	36.8	18-24	67	49.3	college	11.0	11.0
female	86	63.2	25-32	32	23.5	BS	57.4	68.4
			33-40	22	16.2	Master	22.8	91.2
			41-50	15	11.0	PhD	11.0	11.0
			18-24	67	49.3			

infrastructure			Universities' name		
	Frequency	Percent		Frequency	Percent
bad	81	59.6	Islamic Azad	52	38.2
good	55	40.4	governmental	23	16.9
	Alternative platforms		Payam Noor	9	6.6
Wh	47	34.6	non profit	18	13.2
Tel	28	20.6	Applied science university	34	25.0
both	40	29.4			
other	14	10.3			
no	7	5.1			

Universities' online platforms		
	Frequency	Percentage
SAMA	6	4.4
SAHBA	16	11.8
NIMA	8	5.9
NAVID	23	16.9
OTHER	21	15.4
DAN	30	22.1
KODOK	32	23.5