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Students' behavior and intention to use e-learning during the COVID-19 pandemic: A case of TAM through SEM analysis in Albania

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Abstract

Higher education institutions in developing countries encountered several challenges and barriers when attempting to transition to e-learning during the COVID-19 pandemic. The objective of this study is to ascertain the perspectives of students regarding e-learning by examining the many aspects that impact their inclination to adopt e-learning in the Albanian setting during the COVID-19 pandemic. The researchers chose to utilize the Technology Acceptance Model (TAM) to examine the behavioural intentions of a total of 482 students who were currently enrolled at "Fan S. Noli" University. The utilization of Structural Equation Modelling (SEM) has been employed for the purpose of data elaboration. The research discovered that the variable "Attitude towards Use" had a direct influence on students' Behavioural Intention towards e-learning during the COVID-19 epidemic. The variable "Perceived Usefulness" did not have a statistically significant impact on the students' Behaviour Intention. Additionally, the results showed that the students have adapted quickly to the online platform, which has led to a wide acceptance of its usefulness, and this was reflected in a favorable attitude towards its use. The conclusions of this research are important indicators for the enhancement and perspective of the e-learning process in Albanian high education institutions, as they emphasize the importance of identifying and comprehending various factors related to e-learning in Albania. The findings of this study have the potential to provide universities and policymakers with useful insights into the e-learning process, particularly in developing contexts.

Keywords: Behavior intention, COVID-19, Education, e-Learning, Structural equation modeling, Technology acceptance model.

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Contents

Contribution of this paper to the literature

The implementation of e-learning during the COVID-19 pandemic was a mandatory measure in Albania, as well as in other countries. Consequently, it is imperative to do more research to examine the many elements that influence students' attitudes and behaviours towards the adoption of e-learning. This is a quantitative study that uses the TAM model to investigate how Albanian university students adopted and used e-learning during this period.

1. Introduction

The dependency on the Internet and online uses in education has witnessed a significant increase as a result of improvements in Information and Communication Technologies (ICTs). This trend has given rise to a new concept: the e-learning process, which allows students to access learning materials online. The e-learning process is described as "technology-based learning in which learning materials are delivered electronically to remote learners via a computer network" (Zhang, Zhao, Zhou, & Nunamaker Jr, 2004). Muhammad, Ghalib, Ahmad, Naveed, and Shah (2016) defined e-learning as an internet-based learning activity that disseminates information through network courses. It enables the worldwide sharing and distribution of learning resources, creates a virtual study environment, and is a flexible method of learning that can be undertaken anytime, anywhere.

Global chaos was brought on by the COVID-19 pandemic, which first appeared in late December 2019. To stop the virus's spread, all everyday activities—including education—were suspended. Higher education institutions all around the world, including Albania, have converted from traditional learning courses to online classes as the sole means to continue their students' education. This is because of global isolation and distancing policies. As a result, Albania's public and private educational institutions were compelled to implement the e-learning method.

The switch from traditional to online classes was quite abrupt. Before the COVID-19 pandemic, e-learning courses were not officially implemented in Albanian public or private universities. Therefore, Albanian students and Higher Education Institutions (HEI) were unprepared, inexperienced, and not equipped with adequate knowledge, experience, and infrastructure to properly adapt to the e-learning process. Even though all universities across Albania were forced to incorporate e-learning systems, the effectiveness of their implementation hinges on a thorough comprehension of the end-user acceptance process. According to Baber (2021), as the situation during the pandemic has been very severe and the e-learning process has been an imposition, not a choice, students' acceptance of e-learning should be further explored. The student's behavioral intention to adapt to e-learning needs to be investigated.

Various qualitative and quantitative studies have been conducted related to the e-learning process during the pandemic closedown, both in developed and developing countries (Balogun, Adeleke, Abdulrahaman, Shehu, & Adedoyin, 2023; Dehghan, Esmaeili, Paridokht, Javadzade, & Jalali, 2022; Stecuła & Wolniak, 2022; Wagiran, Suharjana, Nurtanto, & Mutohhari, 2022). All these studies have confirmed the challenges of e-learning faced by university students worldwide. In the Albanian context, we could find few descriptive studies oriented towards explaining the situation and challenges of the e-learning process during pandemic conditions (Dhimitri, Pepkolaj, & Avdia, 2021; Hoti, Dragusha, & Ndou, 2022; Xhelili, Ibrahimi, Rruci, & Sheme, 2021). There is a dearth of research investigating how Albanian university students adopted and used e-learning during this period. Only Dibra, Gerdoçi, Sula, and Kurti (2022) conducted quantitative research in predicting the behavioral intention among graduate students in emergency remote teaching. Therefore, more research is required on the variables that influence students' behavioral intentions to utilize e-learning during COVID-19 in the Albanian context. The main purpose of this study is to explore these variables among students at the University 'Fan S. Noli', Korçë (Albania), an institution that attempted to successfully adopt the e-learning process. In this study, we built a conceptual model based on the Technology Acceptance Model (TAM) to identify what variables have influenced students' willingness to embrace e-learning during the COVID-19 pandemic in the Albanian context. The TAM model, which Davis (1986) first suggested, has been extensively used by researchers to examine students' behavioral intention to use e-learning (Fathema, Shannon, & Ross, 2015; Fathema & Sutton, 2013; Ibrahim et al., 2017; Mailizar, Burg, & Maulina, 2021; Masrom, 2007; Park, 2009; Salloum, Alhamad, Al-Emran, Monem, & Shaalan, 2019; Setiyani, Effendy, & Slamet, 2021). The objective of this study is to examine the correlation between three core variables (perceived ease of use, perceived usefulness, and attitude towards using e-learning) and four external variables (subjective norms, self-efficacy, facilitating conditions, and system quality) in relation to their impact on the dependent variable (students' behavioural intention to use e-learning). This research encompassed the examination of a total of 13 possibilities.

Identifying and understanding these factors will help both public and private universities in Albania get some feedback about the e-learning process in emerging conditions. Furthermore, because e-learning is not a legally recognized process of learning in Albania, the results of this study could be considered by decision-makers when designing the future of the HEIs.

2. Literature Review

Albanian students were forced to transition to e-learning during the COVID-19 pandemic. To ensure that e-learning becomes a successful instrument for instruction and learning in education, it is essential to identify what impacts students' acceptance of this new mode of learning (Sharma & Chandel, 2013). The literature review suggests various theories on technology acceptance: "Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Task Technology Fit (TTF), Unified Theory of Acceptance and Use of Technology (UTAUT), and Technology Acceptance Model (TAM)". "Among these theories, TAM has resulted in being the most common ground theory in e-learning acceptance literature" (Alsharida, Hammood, & Al-Emran, 2021; Assegaff, 2015; Šumak, Heričko, & Pušnik, 2011).

The acceptability and usage of information systems and technology, especially e-learning, have been extensively studied using TAM (Pan, Gunter, Sivo, & Cornell, 2005). It is a well-known model that has undergone extensive testing and validation, making it a reliable tool for predicting the success or failure of information system projects (Binyamin, Rutter, & Smith, 2019; Mailizar et al., 2021; Surendran, 2012). The popularity of TAM increased in the meta-analyses of Scherer, Siddiq, and Tondeur (2019), which found that TAM is a widely used approach used for evaluating technology usage. Despite being developed in 1989, more and more researchers are referring to it, increasing its credibility (Alsharida et al., 2021). Therefore, TAM was chosen to study the elements influencing students' acceptance and intention towards e-learning at the University "Fan S. Noli", Korçë, Albania.

2.1. Theoretical Framework

Davis (1986), in his Ph.D. thesis, introduced TAM as an adaptation of the Theory of Reasoned Action (TRA) proposed by Ajzen and Fishbein (1980). When examining consumers' attitudes and intentions to embrace technology, many researchers turned to the TAM model, which has now become a fundamental innovation adoption paradigm. Davis (1989) proposed that the temporal relationship among perception, attitudes, intention, and conduct might aid in anticipating the application of new technology. The TAM model claims that perceived usefulness (PU) and perceived ease of use (PEU) have the most effects on how people feel about using technology. The individual's behavioral intention (BI) to utilize the technology is influenced by both PU and PEU. The attitude towards usage (AU), which is controlled both directly and indirectly by perceived usefulness (PU) and perceived ease of use (PEU), also has an impact on this behavioral intention. In the end, a person's behavioral intention (BI) directly affects how they utilize technology (AU). Perceived usefulness (PU) and perceived ease of use (PEU), which are human opinions, are subject to external influences. Figure 1 depicts the initial TAM Davis suggested in 1989.

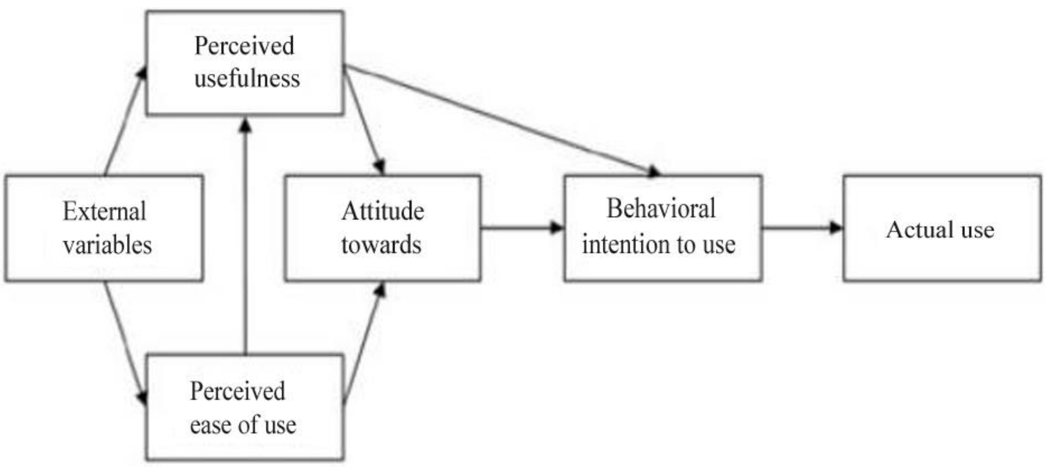

Figure 1. Original technology acceptance model (TAM).

TAM includes three core variables (PEU, PU, and AT) and two outcome variables (BI and AU). PEU and PU are the main factors that determine the outcomes. They are influenced by external factors, too (Davis, 1989).

2.2. Perceived Ease of Use (PEU)

PEU "is the degree to which a person believes that using a particular system would be free from effort" (Davis, 1989). PEU is crucial in influencing students' perceptions regarding e-learning as a cutting-edge teaching strategy. Students will benefit from this novel learning strategy when they believe it to be user-friendly and comfortable (Lazim, Ismail, & Tazilah, 2021). PEU has a significant impact on both PU and AT, according to the TAM model (Davis, 1986). Studies by Al-Adwan and Smedley (2013), Binyamin et al. (2019), Fathema et al. (2015), Findik-Coşkunçay, Alkiş, and Özkan-Yildirim (2018), Lee, Cheung, and Chen (2005), and Mailizar et al. (2021) all show that this relationship has been supported by several other researchers. Considering these studies, two hypotheses were examined:

H_1: PEU significantly and positively affects PU.

H_2: PEU significantly and positively affects AT.

2.3. Perceived Usefulness (PU)

PU is "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). Hence, it is an important factor that may significantly affect students' acceptance of e-learning platforms (Lazim et al., 2021). If they perceive these platforms as beneficial, they are more likely to have the desire to adopt them, and this can influence them to accept e-learning. Earlier research has confirmed the supposed influence of PU in AT and BI (Akman & Turhan, 2017; Al-Adwan & Smedley, 2013; Alharbi & Drew, 2014; Cheng, 2011; Johari, Mustaffha, Ripain, Zulkifli, & Ahmad, 2015; Mahmodi, 2017; Salloum et al., 2019). Considering these studies, the following hypotheses were examined:

H_3: PU significantly and positively affects AT.

H_4: PU significantly and positively affects BI.

2.4. Attitude towards using (AT)

Davis (1986) defines Attitude (AT) as "the degree to which a person has a positive or negative feeling towards e-learning systems". Previous studies on e-learning have confirmed AT as an important factor of influence on BI (Cheng, 2011; Fathema et al., 2015; Mailizar et al., 2021; Salloum et al., 2019). Based on the above studies, the following hypothesis was examined:

H_5: AT significantly and positively affects BI.

2.5. Behavioral Intention (BI)

Behavior Intention (BI) is defined by Davis (1989) as "an individual performing a conscious act, such as deciding to accept (or use) a technology". BI is the most important factor that influences the performance of a process or system (Mailizar et al., 2021). According to the original TAM model proposed by Davis (1986), AT and PU are the main factors that influence the users' BI to use the technology.

2.6. External Variables

The original TAM model indicates that the most important factors (PEU and PU) are influenced by external factors, which explain technology adoption behavior Figure 1. Different studies have tested many external factors (Abdullah & Ward, 2016; Baydas & Goktas, 2017; Mailizar et al., 2021; Park, 2009; Park, Nam, & Cha, 2012). After deep research, we chose SN, SE, FC, and SQ as the most influencing factors that can help enhance the predictability of the TAM model related to student acceptance as well as the use of e-learning in University "Fan S. Noli", Korçë, Albania. Considering the chosen external variables, the following hypotheses were examined:

Facilitating Condition (FC) is "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of a system" (Venkatesh, Morris, Davis, & Davis, 2003). The availability of technical support, access to reliable internet infrastructure, appropriate hardware and software, training, and online help are crucial in determining individuals' beliefs about their ability to effectively use new learning platforms (Fathema et al., 2015). FC is expected to positively impact PEU and PU (Abdullah & Ward, 2016; Baydas & Goktas, 2017; Ngai, Poon, & Chan, 2007; Park, 2009; Scherer et al., 2019).

H_6: FC significantly and positively affects PU.

H_7: FC significantly and positively affects PEU.

Self-efficacy (SE) "refers to an individual's belief in their ability to perform a specific task using technology" (Bandura, 1988). When talking about e-learning, self-efficacy is an important factor that can influence one's attitude towards e-learning platforms (Compeau & Higgins, 1995). Earlier studies have supported the beneficial effects of self-efficacy on both PEU and PU (Abdullah, Ward, & Ahmed, 2016; Alsharida et al., 2021; Keikhosrokiani, 2020; Park, 2009).

H_8: SE significantly and positively affects PU.

H_9: SE significantly and positively affects PEU.

Subjective Norms (SN) "refer to the perceived social pressure to perform or not perform a certain behavior" (Fishbein & Ajzen, 1975). When students perceive social pressure to use e-learning systems, they tend to perceive them as practical and simple and are thus more likely to accept and use them (Abdullah & Ward, 2016). According to earlier research, SN and the core variables (PEU and PU) have significant correlations (Abdullah & Ward, 2016; Baydas & Goktas, 2017; Park, 2009; Scherer et al., 2019).

H_{10}: SN significantly and positively affects PU.

H_{11}: SN significantly and positively affects PEU.

System Quality (SQ) refers to the perceived quality of the e-learning platforms, which includes various dimensions like "ease-of-use, functionality, reliability, flexibility, data quality, portability, and integration" (Delone & Mclean, 2003). Many studies have confirmed that SQ positively affects the core variables (PU and PEOU) of the e-learning system (Fathema et al., 2015; Mailizar et al., 2021; Park et al., 2012; Salloum et al., 2019).

H_{12}: SQ significantly and positively affects PU.

H_{13}: SQ significantly and positively affects PEU.

2.7. Conceptual Model

This research aims to investigate factors predicting students' acceptance and behavioral intention of e-learning at "Fan S. Noli" University, referring to an extended TAM-based framework. The conceptual model, composed of thirteen Hypotheses, is demonstrated in Figure 2.

A questionnaire based on previous extended TAM model studies was developed and disseminated to gather students' opinions about the core, outcome, and external variables. A Likert scale (1-totally disagree to 5- agree) was used to measure the variables.

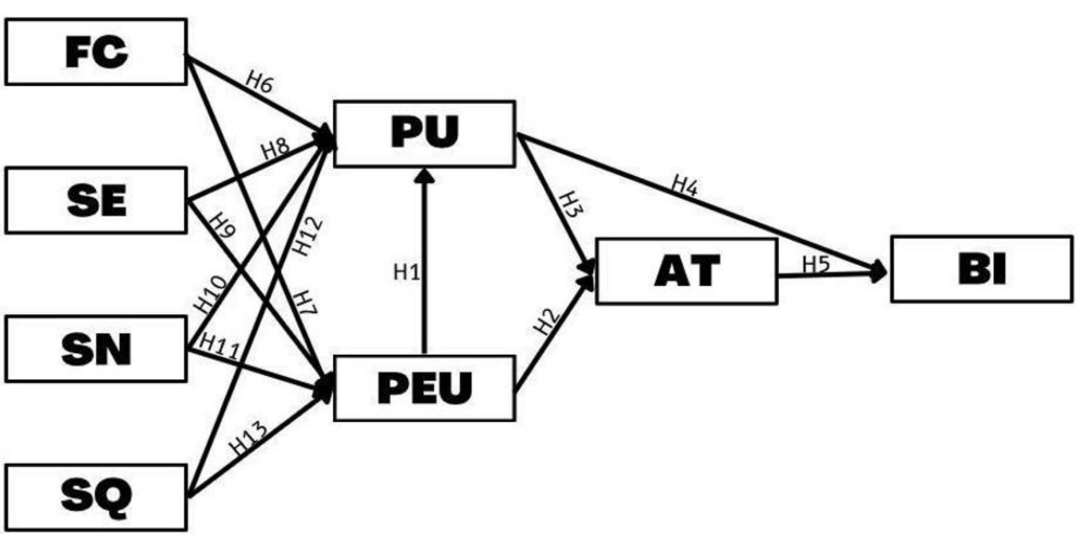

Figure 1. Conceptual model.

3. Methodology

3.1. Pilot Study

In order to assess its internal coherence, the questionnaire underwent a pilot testing process. The survey was sent and afterwards filled out electronically by a total of 38 students during the month of January in the year 2022. One month later, the same questionnaire was sent to the same 38 students to control the consistency of their responses. The Mean and Regression Analyses of the two questionnaires were examined, comparing the responses for each variable. The results showed no differences in the responses to the two questionnaires.

3.2. Data Collection

After piloting, the questionnaire in Google Forms was sent via e-mail to the second- and third-year students of the bachelor programs and the first- and second-year students of master programs enrolled at "Fan S. Noli" University (the first-year students were excluded as they didn't attend e-learning during the academic year 2020-2021). The questionnaires were completed from February 8th to March 20th, 2022. All the questionnaires were valid because all the questions were imposed as mandatory, so there was no missing data. The statistical model used to elaborate the data is PLS-SEM; according to Hair, Hult, Ringle, and Sarstedt (2017), "PLS-SEM works efficiently with small sample sizes and complex models and makes practically no assumptions about the underlying data." The total number of students who received the questionnaire was 2794 in bachelor's and master's programs. We received 482 questionnaires, representing 17.25% of the population.

3.3. Participants of the Study

The analyses of the demographics show that most of the students participating in the study are Females (78.4%), and 21.7% are Males. Most of them are studying in Bachelor's Programs (71.6%). Most of the students (61.8%) confess to having used Smart Phones during e-learning lessons. When asked to describe their Internet and IT skills, the students declared that most of them have very good (34.6%) and good (52.1%) Internet and IT skills, very few of them (12.2%) have moderate skills, and only 5 students (0.8%) claim to have bad or very bad skills. When it comes to attending online lessons, most of the students (76.8%) have attended more than 80% of the online lessons.

3.4. Data Analyses

To investigate the given hypotheses, we have referred to Structural Equation Modeling (SEM). Partial Least Squares SEM (PLS-SEM) is considered the most adequate model for analyzing these data, and it is the common model used in nearly all the TAM studies. Therefore, SMART PLS 3.9 was used for the Confirmatory Factor Analysis (CFA). The model's reliability, validity, and internal consistency were all verified using the same software.

4. Results

For the purpose of this study, nine constructs were identified: core variables (PU, PEU, and AT); outcome variables (BI and AU); and external variables (FC, SE, SN, and SQ). All the variables were subject to factor analysis. Figure 3 shows the R2 values for the endogenous components as well as the path coefficients for the structural model's links.

"The most frequently used metric to assess the structural model is the coefficient of determination (R2 value), and it is used to represent the amount of explained variance of the endogenous constructs in the structural model" (Hair et al., 2017). Therefore, the analyses continue with the examination of the impact of the exogenous constructs on the four endogenous constructs of the study (BI, AT, PU, and PEU). Referring to Hair et al. (2017), "R^2 values of 0.25, 0.50, and 0.75 for target constructs are considered weak, medium, and substantial, respectively."

As shown in Figure 3, R^2 is relatively high (0.753) for BI. PU and AT explain 75.3% of the variation in BI. The results of the inner model (β=0.483, t=2.061) also indicate that AT is a medium predictor of BI. A substantial correlation between AT and BI was also shown by the presence of t-values >1.96 at a level of significance of 5% (α=0.05) in the two-tailed test. Although the relationship between PU and BI shows a moderate prediction (β=0.410, t=1.709), the two-tailed tests indicate that the t-values are less than 1.96 at a significance level of α=5%, suggesting that PU does not have a statistically significant impact on BI.

The model shows that R2 for AT is 0.819 when AT is considered an endogenous construct, which means that the combination of two exogenous components (PU and PEU) can explain 81.9% of the variance in AT. The analysis of the inner model shows that PEU is a weaker predictor of AT (β=0.267, t=2.923,) while PU is the strongest predictor of AT (β=0.678, t=7.057). The two-tailed test with t-values exceeding 1.96 at a significance level of α=5% provides further evidence of a significant relationship between PU, PEU, and AT, (Hair et al., 2017).

Perceived usefulness (PU) has an R2 value of 0.679, meaning that 67.9% of the variance in PU can be attributed to the five exogenous components SN, FC, SE, SQ, and PEU taken together. Perceived ease of use (PEU) emerges as the most significant predictor of PU inside the inner model (β=0.607, t=6.919), followed by SQ (β=0.288, t=3.100). PEU and SQ both had t-values larger than 1.96, indicating a substantial positive connection with PU. However, the PU is only moderately predicted by the external parameters SN, FC, and SE (β=0.087, 0.039, -0.126, and t=1.142, 0.520, and 1.551, respectively). Their t-values below 1.96 show that there is no significant positive link with PU.

The four exogenous constructs (SN, FC, SE, and SQ) jointly account for 58.6% of the variation in the endogenous construct PEU, which has an R2 value of 0.586. SQ is the strongest predictor of PEU, according to the model, with a coefficient of β=0.300 and a t-value of 3.489. SE is the next strongest predictor, with a coefficient of β=0.250 and a t-value of 3.044, FC is the next strongest predictor, with a coefficient of β=0.190 and a t-value of 2.397, and SN is the least influential. With t-values above 1.96 at a significant positive relationship of α=0.05, the two-tailed test reveals that all of the exogenous constructs have a significant positive connection with PEU.

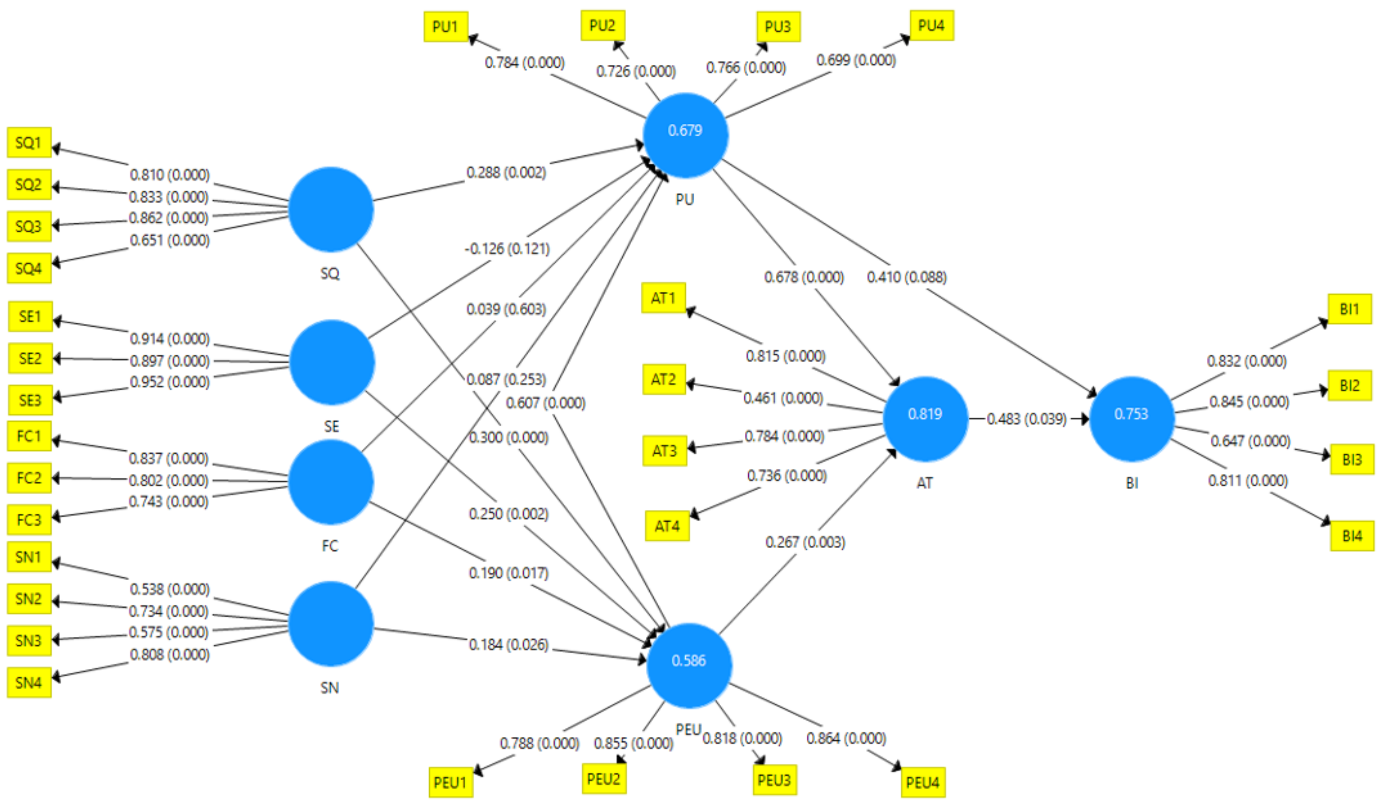

Figure 3. The structural model with path coefficients, standard β, and t-values.

"For the evaluation of the quality of the PLS-SEM measurement and structural models, the most important measurement model metrics for PLS-SEM are *internal consistency reliability, convergent validity, and discriminant validity*" (Hair et al., 2017).

The evaluation of internal consistency and reliability is commonly performed using Cronbach's alpha. If it has a score higher than 0.7, the values are regarded as reliable. "Composite Reliability (CR) is another tool used to evaluate the indicators' internal consistency and reliability" (Hair et al., 2017). In terms of consistency and reliability, CR scores above 0.7 are considered acceptable. "The degree to which a measure correlates favorably with different measures of the same construct is known as convergent validity" (Hair et al., 2017). Researchers take into account both the outer loadings of the indicators and the Average Variance Extracted (AVE) to determine convergent validity. Hair et al. (2017) "state that the indicators' outer loadings should be less than 0.708" (pp. 137) and that "the AVE should be more than 0.50" (pg. 144).

Table 1 shows the factor outer loadings, Cronbach's Alpha, CR, and AVE of the indicators. As is obvious, most of the indicators have been accepted as viable because they have outer loading scores higher than 0.708 (Hair et al., 2017). Six indicators have outer loading scores between 0.4 and 0.708. According to Hair et al. (2017), "these indicators should be considered for removal from the scale only when their deletion leads to an increase in the Composite Reliability or the Average Variance Extracted (AVE)". When Table 2 is considered, it is clear that all the indicators have CR > 0.7 and AVE > 0.5 (except SN), which confirms that the constructs satisfy the requirements of reliability and convergent validity according to Hair et al. (2017). When considering SN, which has a score below 0.5 (AVE = 0.453), the authors decided to accept it because, referring to En Ligneformell and Larcker (1981), "if AVE is less than 0.5 but composite reliability is higher than 0.6, the convergent validity of the construct is still adequate." The scores in Table 2 confirm the proposed model's internal coherence and convergent validity.

The following phase consists of evaluating *discriminant validity*, which examines how distinct a concept is from other ones inside the model. The discriminant validity of this model is assessed using two criteria, namely the Heterotrait-Monotrait ratio of correlation (HTMT) and the Cross Loadings.

The initial technique suggests that an indicator's outer loading on the construct to which it corresponds should be greater than any of its cross-loadings (Hair et al., 2017). The findings demonstrated that all of the indicators' loading values are greater than those of the other components. Since discriminant validity has been proven, the first examination of cross-loadings implies that the second approach to assessing the discriminant validity is the Heterotrait-Monotrait ratio of correlation (HTMT), introduced by Henseler, Ringle, and Sarstedt (2015). It aims to demonstrate how the proposed model's constructs vary from one another. The constructs in a route model are conceptually more distinct if their HTMT values < 0.85. The data in Table 2 show that the HTMT values are below 0.85. This result suggests that the notions have appropriate discriminant validity. The aforementioned methodologies provide evidence for the discriminant validity of the constructs proposed in the model.

4.1. Hypothesis Testing

The output of the structural model is shown in Table 3. We started by assessing the correlations between the indicators. Collinearity is measured by the Variance Inflation Factor (VIF). According to Hair et al. (2017), VIF values are preferred above 0.2 and below 5.0. The results of the VIF analyses indicate that all the inner VIF values fall between 0.2 and 5.0, which confirms that the model used in the study does not have any problems related to multicollinearity.

The next steps consist of generating the t-values and p-values for all the paths to test the hypotheses at a significance level of 5%. According to Hair et al. (2017), "when the size of the resulting empirical t-value is above 1.96, it could be maintained that the path coefficient is different from zero at a significance level of α=5%, two-tailed test". As a result, the determined significance level is 5%, meaning that the p-value must be less than 0.05 for the link under investigation to be considered significant. To achieve the above results, the bootstrapping function in SmartPLS 3.9 was utilized.

Table 1. Factor loading, Cronbach alpha, CR, and AVE.

Constructs	Items	Factor loading	Cronbach alpha	CR	AVE
Perceived usefulness (PU)	PU1	0.79	0.833	0.832	0.554
	PU2	0.723			
	PU3	0.765			
	PU4	0.696			
Perceived ease of use (PEU)	PEU1	0.795	0.899	0.9	0.691
	PEU2	0.857			
	PEU3	0.822			
	PEU4	0.851			
Attitude toward using (AT)	AT1	0.798	0.793	0.799	0.507
	AT2	0.487			
	AT2	0.791			
	AT4	0.727			
Behavioral intention (BI)	BI1	0.847	0.866	0.866	0.621
	BI2	0.854			
	BI3	0.632			
	BI4	0.802			
System quality (SQ)	SQ1	0.81	0.865	0.871	0.629
	SQ2	0.833			
	SQ3	0.862			
	SQ4	0.651			
Self-efficacy (SE)	SE1	0.912	0.944	0.944	0.848
	SE2	0.897			
	SE3	0.953			
Facilitating conditions (FC)	FC1	0.828	0.836	0.837	0.631
	FC2	0.799			
	FC3	0.754			
Subjective norms (SN)	SN1	0.538	0.78	0.763	0.453
	SN2	0.734			
	SN3	0.575			
	SN4	0.807			

Table 2. Heterotrait-Monotrait ratio (HTMT).

Constructs	AT	BI	FC	PEU	PU	SE	SN	SQ
AT								
BI	0.841							
FC	0.616	0.593						
PEU	0.811	0.752	0.603					
PU	0.882	0.841	0.558	0.793				
SE	0.712	0.557	0.521	0.654	0.533			
SN	0.556	0.609	0.576	0.568	0.533	0.491		
SQ	0.716	0.667	0.591	0.687	0.692	0.704	0.542	-

Regarding BI, the outcomes concluded that AT significantly affected BI (β=0.483, t-value=2.061, $p<0.05$), and hypothesis H5 is supported, while PU did not affect BI (β=0.410, t-value=1.709, $p>0.05$) and hypotheses H4 is not supported.

The outcomes regarding AT as an endogenous variable concluded that both variables, PEU (β=0.267, t-value=2.923, $p<0.05$) and PU (β=0.678, t-value=7.057, $p<0.05$) significantly affected AT. Therefore, hypotheses 2 and 3 are supported.

When referring to the PU as an endogenous variable, the findings revealed that PEU (β=0.607, t-value=6.919, $p<0.05$) and SQ (β=0.288, t-value=3.1, $p<0.05$) significantly affected PU. Therefore, Hypotheses H1 and H12 were supported. On the other hand, the other variables, FC (β=0.039, t-value=0.520, $p>0.05$); SE (β=-0.125, t-value=1.551, $p>0.05$); and SN (β=0.087, t-value=1.142, $p>0.05$) did not affect PU and the Hypotheses H6, H8, and H10 were not supported.

In respect of PEU, the outcomes demonstrated that all external factors taken into account here consistently affected PEU: FC (β=0.190, t-value=2.397, $p<0.05$); SE (β=0.250, t-value=3.044, $p<0.05$); SN (β=0.184, t-value=2.232, $p<0.05$); and SQ (β=0.300, t-value=3.489, $p>0.05$). Therefore, the following Hypotheses H7, H9, H11, and H13, were supported.

5. Discussions

The unexpected switch from traditional to virtual learning was new to students: they didn't have previous experience in e-learning; they were not trained in using any online platforms; they didn't have the appropriate infrastructure to support the online process; and they faced various other social and psychological challenges. Therefore, it is really important to understand how different factors affected students' intentions to use e-learning during COVID-19. The TAM model, which has been adopted by other similar studies, was used to explore the role of these factors.

The TAM model suggests that PU and AT positively influence BI (H4 and H5). Previous studies have confirmed it (Akman & Turhan, 2017; Fathema et al., 2015; Mahmodi, 2017; Mailizar et al., 2021; Salloum et al., 2019; Sukendro et al., 2020). This study concluded that only AT significantly affected BI. Contrary to the suggestions of the model, PU did not significantly affect BI. Nevertheless, other studies have concluded that PU did not significantly affect: "students' adoption of mobile technology for aiding student-lecturer interactions" (Gan & Balakrishnan, 2018); "students' ability to continue using a cloud-based e-learning software" (Wang, Lew, Lau, & Leow, 2019); "students' BI to use e-learning during COVID-19" (Mailizar et al., 2021). Gan and Balakrishnan (2018) explain "the insignificant influence of PU on students' BI to use e-learning with the swiftness of their mindset and usage of the technology". Mailizar et al. (2021) add the impact of the pandemic situation. Under these circumstances, at a time when technology is widely used among students and during the COVID-19 lockdown, when e-learning was the only way to keep up with the lessons, students' perceived usefulness of e-learning had less impact on their BI to use e-learning.

Table 3. Lateral collinearity assessment and hypothesis testing.

Hypothesis	Relationship	VIF	Std. error	Std. beta	t- value	P- value
H1	PEU -> PU	2.447	0.088	0.607	6.919	0.000
H2	PEU -> AT	2.742	0.091	0.267	2.923	0.003
H3	PU -> AT	2.742	0.096	0.678	7.057	0.000
H4	PU -> BI	4.856	0.240	0.410	1.709	0.088
H5	AT -> BI	4.856	0.234	0.483	2.061	0.039
H6	FC -> PU	1.897	0.075	0.039	0.520	0.603
H7	FC -> PEU	1.809	0.079	0.190	2.397	0.017
H8	SE -> PU	2.236	0.081	-0.125	1.551	0.121
H9	SE -> PEU	2.083	0.082	0.250	3.044	0.002
H10	SN -> PU	1.797	0.076	0.087	1.142	0.253
H11	SN -> PEU	1.714	0.082	0.184	2.232	0.026
H12	SQ -> PU	2.546	0.093	0.288	3.100	0.002
H13	SQ -> PEU	2.326	0.086	0.300	3.489	0.000

Table 4. Results of hypothesis.

Hypothesis	Effects	Path coefficient	Conclusion
H1	PEU -> PU	0.607	Supported
H2	PEU -> AT	0.267	Supported
H3	PU -> AT	0.678	Supported
H4	PU -> BI	0.41	Not supported
H5	AT -> BI	0.483	Supported
H6	FC -> PU	0.039	Not supported
H7	FC -> PEU	0.19	Supported
H8	SE -> PU	-0.125	Not supported
H9	SE -> PEU	0.25	Supported
H10	SN -> PU	0.087	Not supported
H11	SN -> PEU	0.184	Supported
H12	SQ -> PU	0.288	Supported
H13	SQ -> PEU	0.3	Supported

Table 4 presents the results of the 13 hypotheses tested during the analyses. The TAM model proposes that PEU significantly impacts PU (H1) and AT (H2). Additionally, PU significantly affects AT (H3). Several previous studies have supported these impacts (Binyamin et al., 2019; Fathema et al., 2015; Findik-Coşkunçay et al., 2018; Mailizar et al., 2021). The results of this research confirmed these impacts as well. Students have adapted quickly (PEU) to the online platform, which has led to wide acceptance of its usefulness (PU). Indeed, this was reflected in the favorable attitude towards its use (AT). Anyway, PU proved to be the strongest predictor of AT. This result is the same as the ones provided by the study of Mailizar et al. (2021).

Finally, the impact of different external factors on PEU and PU (H6-H13) was also tested. The proposed model suggests the most important external variables that have the highest impact on PEU and PU: SQ, SE, FC, and SN. The findings of this research confirm the suggested Hypotheses related to the impact of all the external variables on PEU. They confirm the significant impact of SQ, SE, FC, and SN on PEU, as confirmed by earlier research (Abdullah & Ward, 2016; Alsharida et al., 2021; Baydas & Goktas, 2017; Keikhosrokiani, 2020; Park, 2009; Scherer et al., 2019). On the other hand, SQ resulted in being the only external variable that significantly affected the PU of e-learning, while SE, FC, and SN did not affect PU. The results of the study confirmed SQ as the strongest predictor of PEU, followed by SE and FC, and SN has the weakest impact on PEU. The high results for SQ mean that high quality related to the platform's functions, speed, features, and contents has had a positive impact on students' beliefs that using e-learning platforms would be effortless. Similarly, SQ significantly affected students' beliefs that they could be helped by e-learning to complete their academic objectives (PU). *Self-efficacy* was the second-highest predictor of PEU. It means that students have been confident when using the specific options, functions, and contents of the e-learning platform, which has significantly impacted their PEU. On the other hand, the same confidence while using the e-learning platform has not had any effect on their beliefs about the usefulness of the e-learning platform. *Facilitating conditions* was another external variable that significantly affected PEU. This research affirms that the availability of related resources such as technical help, internet infrastructure, and online help to work with e-learning platforms has affected their beliefs about the ease of use of the e-learning platform. These results are supported by previous studies (Sukendro et al., 2020; Wong, 2016). Contrary to expectations, the same factor has not significantly affected students' perceptions about the usefulness of the e-learning platform. Subjective Norms are the external variable that has had a weak impact on PEU but has not significantly affected PU. It means that the opinions of other students, professors, and educational institution policies have influenced students' tendencies to use a certain e-learning platform. Nevertheless, these beliefs have not significantly affected students' perceptions about the usefulness of the e-learning platform in question. The insignificant impact of these external variables on the PU of the e-learning platforms is clarified by the mere fact that during the COVID-19 pandemic, online platforms were the only way to access the learning process.

6. Conclusions

Pandemic COVID-19 has substantially impacted almost all fields of life, and teaching wasn't an exception. Many countries were unprepared for the imposed new conditions of social distancing, as were most sectors. Educational institutions are among the most vulnerable sectors, especially in developing countries like Albania, where the proper infrastructure is very fragmented and the shifting process requires a long time to implement.

This research concluded that all stakeholders must boost the aid allocated in the education sector, and practitioners must advance in technology to ensure the sustainability of education under emerging circumstances. A suggestion stemming from the results is that the availability of proper infrastructure is essential and that the preparation of teachers and students should begin years before they reach university.

Another idea is that government organizations should put more effort into creating technological infrastructure, particularly in suburban regions where there is a wider infrastructure gap and a much higher shortage of funding. To complete the picture, appropriate infrastructure has to be coupled with appropriate capacity building via various trainings on various platforms and applications.

Scholars and practitioners are advised to reconsider how they view the higher education system. Considering that the emphasis is on the internationalization of the institutions of higher education, the fact that e-learning is a stepping stone to this aim and can facilitate distance learning should be taken into consideration. For an institution of higher education to be certified and accredited, it should be kept in mind that this form of learning can assure the same level of knowledge and competence as physical learning. The data set used in this study, the methodological approach, and the findings resulting from the analysis of this study reflect the importance of the quality of both technology and the overall system and can be used by stakeholders as a key factor to improve the higher educational system. Findings are important indicators for the enhancement of the e-learning system and stakeholder integration level for the system's well-functioning in the long term. Additionally, as mentioned before, these findings may provide useful insights for the pre-university educational system and the accreditation of e-learning study programs.

7. Suggestions

This study was conducted on a small sample obtained from only one public university in Albania; therefore, its final results cannot possibly apply to the whole Albanian higher education system. We suggest further studies considering larger populations with different demographics, such as incomes, education, geographical location, and psychological attitudes, from other public and non-public universities in Albania. A highly representative sample enables generalization of the research findings and enables comparative research with public and non-public universities, which would help to get a better picture of how COVID-19 has influenced universities in Albania. Second, the study considers only the opinions of the students. It would help to better understand e-learning acceptance if professors' opinions were also taken into consideration. Therefore, a comparative analysis of students' and professors' perceptions would deepen knowledge of e-learning acceptance and behavior intentions in Albanian universities. Third, this research was developed during Pandemic conditions. Because prior official e-learning courses were absent in Albania, it was not possible to compare the results of this study with previous students' e-learning intentions. The repeating of the study in other different modalities, such as blended learning, is recommended to further validate the conclusions of the study at hand Finally, the study took into account the four most commonly indicated external factors (FC, SE, SN, and SQ), drawing on earlier research. The effect of other suitable factors can be taken into account in future research and situations.

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