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Examining the Acceptance of E-Learning Systems During the Pandemic: The Role of Compatibility, Enjoyment and Anxiety

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SUMMARY

Increasing the quality of education with the use of technology has been one of the main goals of education for many years. In this direction, e-learning systems have attracted great interest from higher education institutions and large-scale investments have been made in these systems. The transition to online education worldwide with the effect of the Covid-19 pandemic has made e-learning systems much more critical. At this point, students' e-learning systems acceptance have assumed a vital role for the success of online education. Thus, the purpose of this study is to determine the factors that affect the intention of university students to use e-learning systems, to examine the relationships between factors and to verify an extended technology acceptance model for higher education. The data were collected from 1709 university students studying online. The data of the study, in which the structural equation modeling method was adopted, was analyzed with PLS-SEM technique. According to the analysis results, the developed model explains 76.2% of the intention, 67.9% of the perceived usefulness and 62.9% of the perceived ease of use. In addition, 11 of the 12 proposed hypotheses were supported. The only relationship that is not significant belongs to perceived usefulness, which is a very important determinant in the context of technology adoption. Compatibility had the greatest effect on intention, and all relationships related to the emotion based constructs were found to be significant. The findings of the study are valuable in terms of better understanding the e-learning system use of university students during the pandemic.

Keywords: E-learning, technology acceptance, higher education, university students, TAM, PLS-SEM

INTRODUCTION

The COVID-19 pandemic, which has had a significant impact worldwide, has deeply shaken every part of daily life. Education has been one of the fields where the most prominent effects are observed. Higher education, which has not experienced such an impact since the beginning of the use of technology in education to the present day, has faced considerable problems and had to take many measures to prevent the spread of the pandemic (Liguori & Winkler, 2020). In line with this, large-scale efforts to benefit from technology in order to support distance education and online learning have emerged and developed rapidly (Ali, 2020). Traditional higher education has been paused worldwide, and the online education method has been adopted (Daniel, 2020). The pandemic that has led to a a digital evolution (Kapasia et al., 2020) and this rapid transformation into online learning have created significant impacts on students (Burgess & Sievertsen, 2020).

In the context of online learning, e-learning systems have become an area of investment for many years due to their high potential. E-learning, which takes the form of a basic application for today's education world (Islam, 2016), enables access to information without any restrictions (Althunibat, 2015), improves learning (Salloum et al., 2019), provides an efficient education setting (Al-Busaidi, 2012), and offers flexible education combining motivation, communication, and technology (Tarhini et al., 2017). Considering these characteristics, the potential and the significant contribution that e-learning systems can provide for today's education, which tries to adapt to living with the pandemic, become apparent. However, it is not possible to take full advantage of this potential of e-learning only with investments. The literature emphasizes adopting and using these systems by students as a prerequisite for them to use these systems effectively (Abdullah & Ward, 2016). Additionally, the determination of factors such as social, individual, and institutional factors that may affect the acceptance of these technologies to increase the quality of the education is stated as a need (Salloum et al., 2019; Tarhini et al., 2016). Accordingly, it is of great importance to determine variables that affect students' intention to use e-learning systems in order to provide successful online education both during and after the pandemic.

Upon reviewing studies on technology acceptance, the Technology Acceptance Model (TAM) comes to the fore among those that are frequently used and widely accepted. TAM, which has been selected as a basis for many studies in the field of education due to to its simple structure allowing to expand the model to be tested without making it complicated (Al-Emran et al., 2018; Teo et al., 2008), is also considered a powerful, reliable, and effective model (Davis, 1989). TAM, which has been verified in many studies carried out with students (e.g. Al-Azawei et al., 2017; Cheung & Vogel, 2013; Chang et al., 2017; Salloum et al., 2019; Tarhini et al., 2014), preservice teachers (e.g. Joo et al., 2018; Sánchez-Prieto et al., 2019a; Sánchez-Prieto et al., 2019b; Teo et al., 2019; Ursavaş et al., 2019), teachers (e.g. Nikou & Economides, 2019; Sánchez-Mena et al., 2017; Ursavaş et al., 2019), and instructors (e.g. Fathema et al., 2015; Schoonenboom, 2014; Şahin et al., 2021; Wang & Wang, 2009) in the field of education, was preferred as a model that would form the basic framework of this study. In this context, this study's goal is to determine factors that influence the intention of university students to use e-learning systems and to verify the TAM by expanding it with the variables selected within the scope of the study. In line with these purposes, answers to the following research questions were sought.

1. What are the variables that influence the intentions of university students to use e-learning systems?

2. What is the relationship between variables that influence the intention to use e-learning systems?

3. Is the model to be developed by extending the technology acceptance model an applicable model for higher education in Turkey?

LITERATURE

Technology Acceptance Model

The technology acceptance model, which has been used in many areas to better understand the use of technology and the intention to use technology, is among the leading models of the education field. TAM, which is widely accepted and among the most frequently used models, comes to the forefront among the most popular and dominant models (King & He, 2006; Marangunic & Granic, 2015). TAM consists of five basic constructs: perceived ease of use (PEU), perceived usefulness (PU), attitude (A), intention (INTN), and actual use (AU) (Davis, 1989). When the literature is reviewed, it is observed that these constructs are included in models in ways varying according to the field and characteristics of studies. In line with this, the most commonly used TAM constructs emerge as perceived ease of use, perceived usefulness, and intention.

Based on the fact that variables affecting the intention to use e-learning systems were examined in this study, the actual use as an output variable and the attitude, for the model to exhibit a simple structure, were not included among the core TAM constructs. Accordingly, PEU, PU, and INTN formed the core TAM constructs of the model proposal. PEU is defined as the degree of an individual's perception of how little effort is required to utilize a technology. PU is expressed as an individual's perception of the degree of benefit to be obtained using a technology. INTN is explained as the intention of an individual to use a technology (Davis, 1989). In the field of education, there are many studies reporting findings indicating that these constructs are closely associated (e.g. Al-Azawei et al., 2017; Baydaş, 2015; Baydaş & Göktaş, 2017; Chang et al., 2017; Tarhini et al., 2014; Ursavaş, 2014). Accordingly, the following hypotheses were proposed.

H1. PEU has a significant effect on PU.

H2. PEU has a significant effect on INTN.

H3. PU has a significant effect on INTN.

Perceived Enjoyment

The effect of the enjoyment factor (PEN) in the context of technology acceptance has been extensively studied in the research in the field of education. Enjoyment based on intrinsic motivation (Ryan & Deci, 2000) is expressed as the degree to which the used technology is perceived as enjoyable regardless of any performance-related outcome (Davis et al., 1992). The enjoyment construct (Rafiee & Abbasian-Naghneh, 2019), which is examined in terms of the contribution of intrinsic factors to technology acceptance, is among the factors with the most intensive use in the acceptance studies conducted in the domain of e-learning (Abdullah & Ward, 2016). Upon reviewing previous studies, there are various studies concluding that the enjoyment is related to PEU, PU, and INT (e.g. Al-Rahmi et al., 2019; Sánchez-Prieto et al., 2019; Teo & Noyes, 2011; Teo et al., 2019; Ursavaş, 2014). Accordingly, the following hypotheses were proposed.

H4. PEN has a significant effect on PEU.

H5. PEN has a significant effect on PU.

H6. PEN has a significant effect on INTN.

Anxiety

Anxiety (ANX), which is among the significant obstacles in terms of technology acceptance (Rahimi & Yadollahi, 2010), is expressed as an individual's tendency to feel uncomfortable, anxious, and fearful about the current or future use of information technologies (computers, etc.) (Igbaria & Parasuraman, 1989). Anxiety that has been expressed to affect various technology acceptance in the context of the use of information technologies in the field of education (Abdullah & Ward, 2016; Baydaş, 2015; Baydaş & Göktaş, 2017: Sánchez-Prieto et al., 2017; Şahin, 2016; Ursavaş, 2014) is emphasized as a factor with effects that may hinder the adoption of e-learning or reduce usage (Agudo-Peregrina et al., 2014; Park et al., 2012). In line with this, it is stated that users who are anxious about technology will tend to avoid using e-learning systems (Al-alak & Alnawas, 2011). Based on this, the following hypotheses were proposed.

H7. ANX has a significant effect on PEU.

H8. ANX has a significant effect on INTN.

Compatibility

Compatibility (CMPY) is expressed as the degree of compliance with the task performed by a technology that is used or will be used by an individual (Venkatesh & Davis, 2000). In the field of education, CMPY, which focuses on the compatibility between the technology used and the learning and teaching style of an individual, is among the significant obstacles towards integration processes (Sánchez-Prieto et al., 2019). In the literature, it is emphasized that if users find the technologies they use compatible with their methods, they will find the technology more useful and tend to use it (Rogers, 1995). Furthermore, studies report that CMPY is associated with the core TAM constructs, such as ease of use, usefulness, attitude, and intention (Chen, 2002; Sánchez-Prieto et al., 2019; Şahin et al., 2021; Ursavaş, 2014). In this context, the following hypotheses were proposed.

H9. CMPY has a significant effect on PEU.

H10. CMPY has a significant effect on PU.

H11. CMPY has a significant effect on INTN.

METHOD

Participant Group

The study participants consisted of 1709 university students studying at a state university through e-learning systems and distance education platforms. Through these systems, providing access to live lectures, course records, summary videos, and various educational materials, university students studying in the fall semester of 2020 were reached by an online method. The information on the participating students is presented in the Table 1.

Table 1. Profile of the participants

Participants		*f*	%
Course Year	**1**	1098	64.2
	2	251	14.7
	3	218	12.8
	4	142	8.3
Department Type	**Associate degree**	904	52.9
	Bachelor's degree	805	47.1
Gender	**Female**	780	45.6
	Male	929	54.4

Data Collection

The study data were collected online using the data collection tool consisting of two parts. The first part of the data collection tool consists of questions about the participants' demographic information, whereas the second part consists of items for variables. The items in the second part, consisting of 6 factors and 20 items (5-point Likert-type, 1= I strongly disagree, 5= I strongly agree), were adapted from the studies compatible with the theoretical foundations of the study and participant characteristics. The items of the perceived ease of use and perceived usefulness factors were adapted from the study performed by Teo, Ursavaş and Bahçekapılı (2012), while the items of perceived enjoyment, anxiety, compatibility, and intention factors were adapted from the study conducted by Ursavaş (2014).

Data Analysis

For the analysis in the study, the SmartPLS software was used, and structural equation modeling were carried out with the PLS-SEM (Partial Least Squares Structural Equation Modeling) technique. The complex structure of the model proposed in the study and the effectiveness of the PLS-SEM technique for explanatory models have been decisive in the preference of this method (Hair et al., 2011; Hair et al., 2017). For the analyses conducted in two stages, primarily, the convergent and discriminant validities were tested by evaluating the measurement model. At the next stage, the structural model was examined, and which hypotheses were supported and which were not supported and the explanation rates of the dependent variables of the model were determined.

RESULTS

Measurement Model

Convergent validity, which is one of the sub-stages of the construct validity tests, was evaluated over Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE) values. It was determined that all Cronbach's alpha (α) and composite reliability (CR) values were above 0.7 and AVE values were higher than .50. Convergent validity was established based on the values obtained (Hair et al., 2017). At the stage of discriminant validity, the HTMT ratio and the Fornell-Larcker criterion were examined. When the table related to the HTMT ratio was examined, it was observed that all index values were below .90. For the evaluation of the Fornell-Larcker criterion, it was determined that the square root values of the average variance extracted (AVE) values were higher than the correlation coefficients between the constructs (Fornell & Larcker, 1981; Hair et al., 2017). Accordingly, discriminant validity was established. The convergent and discriminant validity tests are summarized in Table 2, Table 3, and Table 4.

Table 2. Convergent validity

Constructs	Item	Loading	α	CR	AVE
Intention	INTN1	0.895	.928	.949	.822
	INTN4	0.896			
	INTN3	0.925			
	INTN4	0.911			
Perceived Usefulness	PU1	0.929	.930	.955	.877
	PU2	0.949			
	PU3	0.931			
Perceived Ease of Use	PEU1	0.921	.911	.944	.849
	PEU2	0.928			
	PEU3	0.914			
Perceived Enjoyment	PEN1	0.901	.937	.955	.842
	PEN2	0.945			
	PEN3	0.907			
	PEN4	0.916			
Compatibility	CMPY1	0.851	.880	.926	.807
	CMPY2	0.920			
	CMPY3	0.923			
Anxiety	ANX1	0.906	.892	.932	.819
	ANX2	0.885			
	ANX3	0.924			

α: Cronbach's alpha, CR: Composite reliability, AVE: Average variance extracted

After convergent and discriminant validity was established, the variance inflation factor (VIF) values were examined to determine whether there were any multicollinearity problems.

Table 3. Discriminant validity (Fornell-Larcker)

Constructs	ANX	CMPY	INTN	PEN	PEU	PU
ANX	**0.905**					
CMPY	-0.033	**0.899**				
INTN	-0.112	0.836	**0.907**			
PEN	-0.105	0.745	0.761	**0.917**		
PEU	-0.214	0.684	0.736	0.759	**0.921**	
PU	-0.150	0.660	0.683	0.763	0.775	**0.936**

Values in bold represent the square root of the AVE (average variance extracted)

As a result of the examination, it was revealed that all VIF values for predictor variables were less than 5, and there was no problem in terms of linearity. Within the scope of the model fit, it was observed that the SRMR (standardized root mean square residual) value was 0.042 and accordingly, the model fit was good.

Table 4. Discriminant validity (HTMT ratio)

Constructs	ANX	CMPY	INTN	PEN	PEU	PU
ANX						
CMPY	0.080					
INTN	0.113	0.892				
PEN	0.110	0.818	0.812			
PEU	0.232	0.763	0.799	0.818		
PU	0.161	0.729	0.733	0.817	0.841	

Structural Model

The model tested by structural equation modeling explains 62.9% of perceived ease of use, 67.9% of perceived usefulness, and 76.2% of intention. According to these values, it can be stated that the model proposal has high explanation power. Moreover, almost all of the hypotheses (10 hypotheses were accepted, 1 hypothesis was rejected) proposed were supported. The results demonstrated that ANX, CMPY, PEN, and PEU were effective on INTN. The single construct not affecting INTN is PU. PU->INTN is also the only insignificant relationship in the model proposal, and all the relationships related to ANX, CMPY, PEN, and PEU were significant. The effect sizes of the significant relationships are large for CMPY->INT, medium for PEN->PEU and PEU->PU, and small for others. The hypothesis test results are summarized in Table 5. The visual of the structural model is shown in Figure 1.

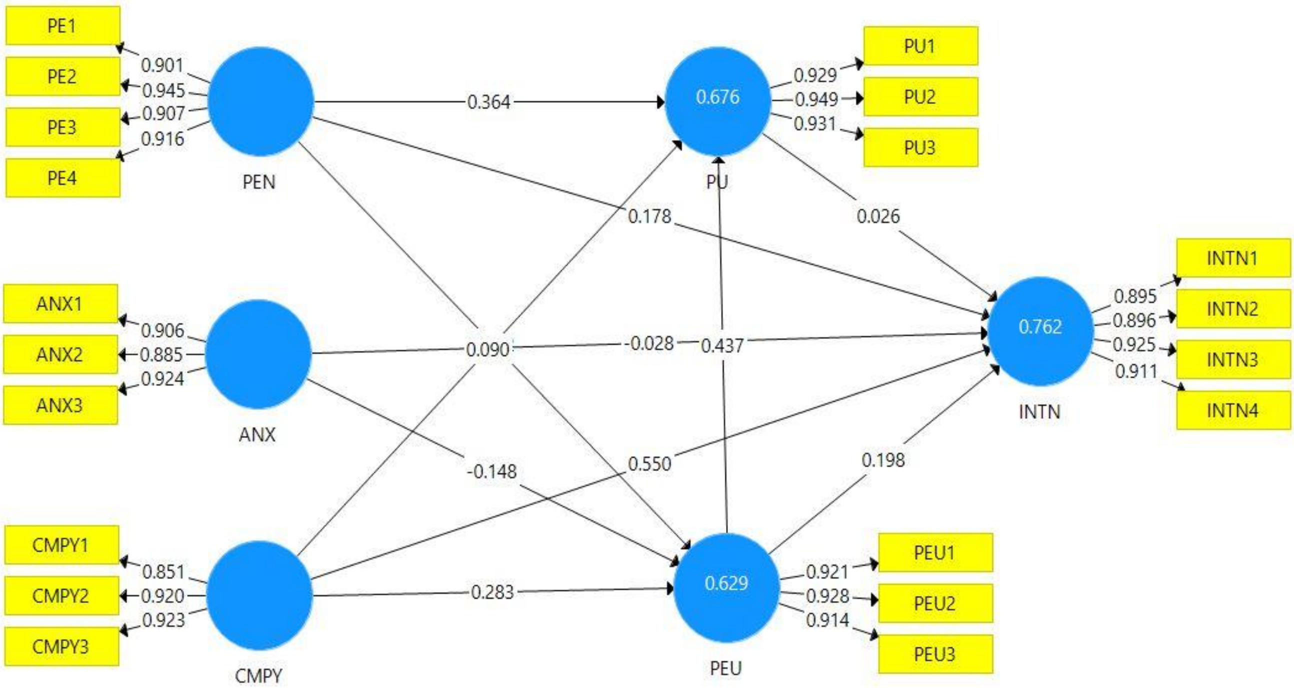

Figure 1. Structural Model

DISCUSSION

Factors affecting the intention of university students to use e-learning systems were examined in this study. An extended TAM was tested and verified in the context of higher education in Turkey. It can be stated that this version of TAM, developed in the study, is an applicable model for higher education, and the model contributes to the effectiveness and power of TAM with its high explanatory power. In line with this, R2 values for the dependent variables and supporting 11 of the 12 proposed hypotheses indicate that the developed model works effectively. The fact that the model created is an effective tool that can be used in future technology acceptance studies to be carried out in the field of education and that it provides information that can contribute to a better understanding of the e-learning system use of university students can be shown among the significant contributions of the study.

The results regarding PEU, PU, and INTN demonstrated that PEU->INTN relationship was significant and PU->INTN relationship was not significant. PEU->INTN result, which largely overlaps with the literature (Al-Azawei et al., 2017; Chang et al., 2017; Tarhini et al., 2014), suggests that the easy use of e-learning systems is regarded as a priority for university students. Accordingly, it can be stated that university students will tend to use an e-learning system that provides ease of use. PU->INTN relationship, which was found to be insignificant contrary to expectations, largely contradicts previous studies (e.g. Agudo-Peregrina et al., 2014; Al-Azawei et al., 2017; Al-Rahmi et al., 2019; Rafiee & Abbasian-Naghneh, 2019; Salloum et al., 2019). It is a critical finding that PU, which can be expressed as the strongest determinant in terms of affecting user intentions (Venkatesh and Davis, 2000), and providing motivation in the context of technology acceptance (Şahin et al., 2021), did not have a significant effect on university students' intention to use e-learning systems.

PU->INTN relationship, which has been widely reported as significant in studies in the field of education and represents one of the strongest relationships in models in general, indicates that the finding obtained in the study reveals an extraordinary situation. This relationship, which was not found to be significant, suggests that university students' perceptions of the benefit and potential performance increase they can obtain using e-learning systems do not affect their intention to use these technologies. It can be indicated that university students do not prioritize the benefits of these systems, which represent one of the foundations of online education, especially in today's world. As a possible explanation for this unexpected result, it can be shown that education has experienced a very rapid and radical transformation due to the pandemic (livari et al., 2020), this transformation has created significant effects on students (Abidah, 2020), and under the effect of these, learning with technology has ceased to be an option for students and turned into an obligation. Accordingly, PU->INTN relationship, which was not found to be significant, suggests that the motivational effect of the performance increase that the e-learning system can provide on students can be weakened in cases of compulsory use. The effect of the sudden digital transformation in education and the fact that online education has become a necessity are thought to cause the factor of usefulness that can be obtained from e-learning systems to become distinct of the intention to use these technologies.

Table 5. Hypotheses testing

Path	Coef.	t-Value	p-Value	f^2	VIF	Results
ANX -> INTN	-0.028	2.200*	0.028	0.003^c	1.076	Supported
ANX -> PEU	-0.148	9.159***	0.000	0.059^c	1.016	Supported
CMPY -> INTN	0.551	19.000***	0.000	0.508^a	2.498	Supported
CMPY -> PEU	0.283	9.733***	0.000	0.096^c	2.255	Supported
CMPY -> PU	0.090	2.951**	0.003	0.010^c	2.427	Supported
PEN -> INTN	0.177	5.875***	0.000	0.039^c	3.272	Supported
PEN -> PEU	0.532	18.954***	0.000	0.335^b	2.278	Supported
PEN -> PU	0.364	10.919***	0.000	0.135^b	3.040	Supported
PEU -> INTN	0.199	6.796***	0.000	0.050^c	0.050	Supported
PEU -> PU	0.437	12.881***	0.000	0.232^b	2.548	Supported
PU -> INTN	0.024	$0.921^{(ns)}$	0.358	0.001^c	3.091	Not Supported

p: ns ≥ 0.05; * < 0.05; ** < 0.01; *** < 0.001. a Large effect size, b Medium effect size, c Small effect size.

All relationships related to ANX and PEN, which are emotional variables added to TAM, were found to be significant in the study. These results for the emotional variables indicate that emotions may play a critical role in technology acceptance (Şahin et al., 2021). When the literature is reviewed in ANX->PEU and ANX->INTN context, it is observed that the results obtained coincide with previous studies on information technologies in the field of education (Baydaş & Göktaş, 2017; Chang et al., 2017; Ursavaş, 2014). ANX->PEU relationship suggests that university students' anxiety and concerns about using e-learning systems affect their perception of the level of effort required to use these technologies effectively. Accordingly, it can be stated that students who have anxiety about using e-learning systems find it more difficult to use these technologies and perceive the effort required for effective use as higher than it is. Furthermore, the results suggest that students with low anxiety levels can regard e-learning systems as more user-friendly. The significant ANX->INTN relationship demonstrated that students' anxiety about these technologies adversely affected their intention to use them. Previous study findings indicating that students who are anxious about technology may give up or be unwilling to use it support the results of the study (Abdullah & Ward, 2016; Al-alak & Alnawas, 2011).

The results demonstrated that PEN was associated with all basic constructs of TAM. When studies in the field of education examining the relationships of the enjoyment factor based on intrinsic motivation (Ryan & Deci, 2000) with PU, PEU, and INTN are reviewed, it is observed that the study findings are generally in line with the literature (e.g. Al-Rahmi et al., 2019; Rafiee & Abbasian-Naghneh, 2019; Sánchez-Prieto et al., 2019). The study results indicate that university students will tend to use e-learning systems if they find it enjoyable to use them (Cheng, 2012). Moreover, the fact that university students perceive e-learning systems as enjoyable affects students' perceptions of the degree of effort required to use these technologies and their thoughts on the benefits they can obtain from these technologies. Accordingly, it can be stated that university students who find e-learning systems enjoyable may perceive the use of these systems as easier, tend to think that they can improve their performance by learning through these technologies, and as a result, they may be more willing to learn using e-learning systems.

All hypotheses related to CMPY were supported. The findings obtained revealed that CMPY was associated with all of the core TAM structures. In addition to the fact that all the relationships were found to be significant, CMPY->INT relationship represents the strongest relationship in the model. In line with this, the construct that creates the strongest effect on intention is CMPY. Based on this finding regarding CMPY, which has not been sufficiently investigated in the field of education (Şahin et al., 2021), it can be stated that this construct may play a critical role in the adoption of technology. Statements about the effect of CMPY in the context of motivation (Chen, 2011) and its significance in terms of learning-teaching styles (Ursavaş, 2014) indicate that the study findings are supported. In this context, it can be stated that the expectations of university students in terms of education and the close relationship of e-learning systems and the courses they take affect both their perceptions of usefulness, their thoughts about ease of use, and their intention to use. The study findings suggest that if university students' courses and e-learning systems are compatible and their expectations from online education are met, they will regard e-learning systems as more useful, will perceive the use of systems as easier, and will tend to use e-learning systems.

CONCLUSION AND IMPLICATIONS

The fact that this study, which provides valuable information on the factors that affect the intention of university students to use e-learning systems during the pandemic, helps to better understand the processes of technology adoption is the main contribution of the research. Moreover, the fact that the model with high explanatory power was verified in the context of higher education in Turkey can be expressed as another contribution of the study. Accordingly, it is thought that the model developed within the scope of the study provides a suitable tool for future studies with a similar structure.

For the relationships between PEU, PU, and INTN, PEU->PU and PEU->INTN were supported, but PU->INTN was not supported. Supporting both hypotheses regarding PEU, suggests that university students think they can benefit more from e-learning systems, which they regard as easy to use, and their tendency to use e-learning systems will be higher. PU->INTN result indicates that the perception of performance increase that can be obtained using e-learning systems may not be a direct factor in the context of the tendency to use. In parallel, it is emphasized that second-order barriers and mandatory distance education weaken the influence of core TAM constructs during the pandemic (Şahin et al., 2021). From this critical finding, it can be deduced that some motivational variables that are valid for the traditional education may not be valid for online education during the pandemic. Based on this, examining the potential variables effective in the use of e-learning systems separately for the education during the pandemic can play a vital role in obtaining the desired results from online education.

CMPY->INT, which is the strongest relationship in the model, presents a critical finding regarding the e-learning system preferences of university students. Based on the fact that the strongest determinant of INT is CMPY, it can be deduced that the primary factor for students' tendencies to use e-learning systems is that the e-learning system meets the expectations of students from learning. This finding indicates that the compatibility of the e-learning system with students' lessons and learning styles and its ability to respond to expectations are the dominant factor in e-learning system use. Accordingly, it can be stated that considering CMPY factor, especially by program and system designers, will play a major role in fully utilizing the potential of these technologies and ensuring a higher quality of learning and teaching processes.

All relationships related to ANX and PEN included in the model in the context of emotional variables were found to be significant. These results emphasize the role of emotional factors in the context of the adoption of technologies (Şahin et al., 2021). In line with this, it is important to address emotional factors more comprehensively in technology acceptance studies to be performed for e-learning systems. Furthermore, considering emotional factors for designs to be made in the context of technology use in education may be effective in ensuring more successful adoption processes.

Based on the results obtained, it is predicted that theoretical and practical suggestions for future research can contribute to the field. Model development studies for the acceptance and use of technology are important in terms of ensuring and maintaining the quality of online education during pandemic. At this point, one of the urgent issues can be expressed as university students' continuance intention to use and user experiences regarding online learning environments. In the context of user experience, consideration of facilitating factors such as technical support, troubleshooting, system quality, and compatibility factors such as relevance of technology to educational content, learning styles and teaching-related expectations may play an important role. In addition, focusing on the potential effects of the emotional outcomes of using online teaching-learning technologies can also contribute to the success of technologies such as e-learning systems and distance education platforms. Considering the suggestions for system design, program development and technological applications has a critical role in terms of providing education effectively during the pandemic.

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