Perceived Usefulness, Ease of Use, and Usage of Distance Education Systems: Evidence from Turkey

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Abstract
Distance education and e-learning have become pivotal during the COVID-19 pandemic, offering a solution to maintain education continuity amidst restrictions. This study delves into the application of the Technology Acceptance Model (TAM) to assess the acceptance and utilization of e-learning among university students, with a particular focus on Turkey. This geographical context presents an opportunity to investigate the multifaceted factors influencing the effectiveness of e-learning, which have received limited exploration thus far. A survey-based quantitative approach employs Structural Equation Modeling (SEM) to understand student attitudes toward distance education and investigate the relationships among various dimensions such as learning, usage, and barriers. The study, conducted among 1040 undergraduate students enrolled in Turkish distance education programs, reveals significant positive relationships between learning and usage dimensions, while negative relationships exist between learning and barriers and usage and barriers. The findings underscore the importance of enhancing the ease of use of distance education platforms and addressing encountered barriers to foster effective utilization. Recommendations include establishing robust support mechanisms, improving training programs, and facilitating better communication channels between students and educators. The study contributes to the understanding of e-learning acceptance and usage among university students, providing insights for designing more effective educational interventions and enhancing higher education systems, especially in the case of Turkey.
Keywords: Distance Education, E-Learning, Higher Education; Student Attitudes; Structural Equation Modeling, and Technology Acceptance Model

Introduction

Distance education and e-learning can be defined as a learning model that delivers knowledge and skills to students through the Internet or other digital technologies. In this educational model, students receive their lessons via online platforms instead of traditional classroom settings. E-learning methods utilize tools such as content in various formats, interactive materials, video conferences, live sessions, and learning management systems (Bates, 2011). This allows students to receive education independently of spatial and temporal constraints. The global education landscape has been significantly impacted by the COVID-19 pandemic, emphasizing the importance of distance education and e-learning. During this period, with the closure of traditional classroom environments, educational institutions and students rapidly turned to digital platforms. Amid the pandemic, face-to-face education became impossible due to the necessity of maintaining physical distance, reducing contact, and quarantine requirements, highlighting the prominence of distance education and e-learning alternatives. Notably, during measures taken to control the spread of COVID-19, e-learning and distance education have offered a solution to minimize health risks (Dhawan, 2020 & Liguori, 2020). Students have been able to receive education from their homes or in a safe environment, thus supporting efforts to prevent the spread of the pandemic.

Additionally, distance education and e-learning can enhance educational equity by overcoming geographical barriers and providing access to individuals living in remote areas or with physical disabilities, thereby expanding the reach of educational services and creating an equitable learning environment. A study by Alsobhi et al. (2021) emphasizes that the COVID-19 pandemic has accelerated the digital transformation in education and increased the significance of e-learning. Throughout the pandemic, distance education and e-learning have demonstrated the resilience and adaptability of educational systems and enhanced their capacity to cope with similar emergencies in

the future. Therefore, distance education and e-learning have played a significant role in education during and after the pandemic.

TAM is widely used in information systems and technology to understand how users accept a technology developed by Davis et al. (1985, 1989, 1993). The TAM encompasses a set of variables that influence the process of users accepting a technology. These variables include perceived ease of use, perceived usefulness, social interaction, attitude toward technology, experience, and demographic factors. Essentially, the decision of users to accept a technology is determined by the balance between perceived usefulness and perceived ease of use. In this research, the TAM, one of the most widely utilized models in information systems research, has been predominantly utilized to assess its influence on the adoption of e-learning as a platform (Venkatesh, 2000). This study investigated perceptions of ease of use, usefulness, usage expectations, satisfaction, and demographic characteristics of university students towards the distance education system within the scope of technology adoption theory (Venkatesh et al., 1996, 2003). E-learning has become a mandatory and increasingly popular learning approach in higher education institutions during COVID-19, with many universities integrating e-learning services into their programs. At the same time, some have built their distance education systems.

The purpose of distance education is not to replace the traditional classroom environment but to provide new opportunities for interaction and communication between students and instructors. This study aims to investigate the acceptance levels of e-learning at universities as a practical learning tool by individual users and to develop an e-learning usage model based on students' perceptions, attitudes, expectations, and satisfaction with the e-learning system.

However, despite the extensive adoption of e-learning, there exists a research gap concerning the nuanced factors influencing its acceptance and efficacy among university students in the case of Turkey. Understanding the determinants of e-learning acceptance and usage can inform the design of more effective educational interventions and contribute to enhancing higher educational systems based on the case of Turkey. Thus, this study aims to investigate the acceptance levels of university e-learning as a practical learning tool by individual users. Specifically, it seeks to develop an e-learning usage model grounded in students' perceptions, attitudes, expectations, and satisfaction with the e-learning system.

The structure of the paper is outlined as follows: firstly, the TAM is reviewed in the present section, which serves as the theoretical framework for understanding technology adoption. Following that, the methodology section delineates the research design, data collection procedures, and analysis techniques, incorporating Structural Equation Modeling (SEM), confirmatory factor analysis, and internal consistency analysis (Jöreskog & Sörbom, 1982; Schumacker & Lomax, 2010). Ultimately, the paper wraps up with discussions regarding the implications of the findings and potential directions for future research.

Data Collection and Measurement

This research aims to understand student attitudes toward distance education and examine the relationships between these attitudes. The study employs a quantitative research design, generally adopting a relational and descriptive approach. Data is collected through a survey that gathers numerical data, which is then evaluated through statistical analysis to reach quantitative results. This study embraces both relational and descriptive research approaches. The relational approach focuses on understanding and assessing the relationships between student attitudes, while the descriptive approach aims to describe and explain student attitudes comprehensively.

This study adopts a descriptive research design and employs a survey model for data collection. SEM is employed as the analysis method to evaluate the relationships between dimensions of student attitudes. Additionally, a descriptive approach is adopted in the research. The descriptive approach aims to detail and describe student attitudes comprehensively. Descriptive statistics help define essential variables such as demographic characteristics of the sample and scores on the attitude scale towards distance education, among others.

The study population comprises students enrolled in undergraduate-level distance education programs in Turkey. A convenient sampling method is used in the research, involving selecting participants that are easily accessible to researchers. The study sample consists of 1040 undergraduate students enrolled in distance education programs. Many of the included students reside in metropolitan areas. Among the participants, 904 students live in metropolitan areas, 25 in non-metropolitan cities, 90 in districts, 3 in towns, and 18 in rural areas. Regarding gender distribution, the sample consists of 273 male and 767 female students.

The data collection tool used in the research is a survey form consisting of three main sections:

Attitude Towards Distance Education: This scale measures students' attitudes toward distance education. It comprises twenty items in three dimensions: learning, usage, and barriers.

Situational Feature Questions: Special situational feature questions are included to understand students' experiences and usage of distance education.

Demographic Questions: Fundamental questions such as gender, department, class, and place of residence are included to understand participants' demographic characteristics.

Statistical Methods

In this study, SEM is used for data analysis. SEM is a statistical technique that models and analyzes causal relationships between variables (Hoe, 2008). This modeling approach is commonly used to examine and understand complex structures across various disciplines, especially in social sciences such as business management, psychology, education, health, and marketing, to analyze models that include latent variables (variables that cannot be directly measured or observed) along with observed variables (variables that researchers can directly measure or observe) such as those observed in this research. This model allows researchers to test causal relationships between variables within a specific theoretical framework and match observational data with these relationships (Loehlin and Beaujean, 2016).

The discriminant and convergent validity of the study is supported by confirmatory factor analysis (Fornel, 1981). Confirmatory factor analysis is a commonly used method to test these types of validity, during which researchers evaluate the degree of accuracy underlying the factors beneath the scales while assessing discriminant and convergent validity (Kline, 2013). Discriminant validity confirms that each scale represents different conceptual factors, whereas convergent validity confirms that each factor demonstrates consistency among measured variables (Cable and DeRue, 2002). These two types of validity are used together to ensure the reliability and accuracy of measurements. Internal consistency analysis assesses whether the measurement tool is internally consistent by examining correlations among different scale items or elements (Hajjar, 2018). It measures how well the scale items agree, indicating whether they measure the same concept. Internal consistency analysis uses statistical criteria such as Cronbach's Alpha. Cronbach's Alpha is a reliability coefficient that measures the internal consistency of all scale items within a measurement tool (Taber, 2018). Values usually range from 0 to 1, where a Cronbach's Alpha value of 0.70 or higher indicates an acceptable level of internal consistency (Spiliotopoulou, 2009). Internal consistency analysis provides assurance that the measurement tool is reliable and stable, yielding consistent results. The reliability of this study is also supported by internal consistency analysis.

The dataset acquired for the study underwent exploratory factor analysis using the IBM SPSS Statistics Standard Concurrent User V 26 (IBM Corp., Armonk, New York, USA) statistical package program. In exploratory factor analysis, factors are derived as linear combinations of observed variables. These factors represent hypothetical variables constructed from the observed variables. Before conducting factor analysis, it is crucial to evaluate the suitability of the data by examining the correlation matrix. If a substantial portion of the coefficients in the correlation matrix is below 0.30, employing factor analysis may not be suitable. Bartlett’s sphericity test is used statistically to test the correlation between variables in the data matrices. Bartlett’s test of sphericity tests whether the created matrix between questions is an identity matrix.

Furthermore, the KMO measure, derived from correlation and partial correlation coefficients, serves as a crucial criterion for assessing the data's suitability for factor analysis. In this study, the principal component method was employed to extract factors. The selection of an appropriate number of factors was guided by the criterion of retaining factors with eigenvalues greater than one (Ruscio and Roche, 2012). Additionally, factor rotation was conducted to elucidate the variables contributing to each common factor, utilizing the varimax method (Mvududu and Sink, 2013). Confirmatory factor analysis was also employed to assess the alignment of the factors derived from exploratory factor analysis with theoretical or hypothetical factor structures. Exploratory factor analysis typically precedes scale development and the evaluation of structural validity. Conversely, confirmatory factor analysis validates the structure obtained from exploratory factor analysis or a predetermined theoretical factor structure. While exploratory factor analysis determines the optimal number of factors based on the data matrix, the number of factors is predetermined in confirmatory factor analysis. For this study, confirmatory factor analysis was conducted using the Amos (Version 24.0) statistical package program.

Findings

The KMO test evaluates the adequacy of the distribution for factor analysis, with values exceeding 0.80 indicating excellent suitability. In this study, the KMO value attains an excellent level. The Bartlett test yielded a statistic of 11,957.741 ($p<0.05$), indicating the multivariate nature of the variable being measured in the population parameter.

No constraints were imposed on the number of factors in this research, and factors with eigenvalues surpassing 1.50 were incorporated into the scale. Eigenvalues of 1 or higher are deemed significant in factor analysis. Additionally, the variance ratios obtained in this study, falling within the 40% to 60% range, are considered satisfactory.

Table 1: Common Factor Variances and Factor Loadings for Attitudes Towards Distance Education Scale

Scale Items	Factor Loadings		
	Learning	Usage	Barriers
The lessons given by the distance education system are more memorable.	0.858		
I understand the relationships between concepts better in the lessons given with the distance education system.	0.822		
The distance education system makes the lessons more understandable than traditional methods.	0.808		
The use of the distance education system in lessons increases my motivation.	0.798		
Following the lesson with the distance education system is easier than traditional methods.	0.791		
Using the distance education system in lessons develops my researcher spirit.	0.768		
The distance education system helped me to use my time more efficiently.	0.753		
The courses taken with the distance education system contribute to my personal development.	0.695		
I take notes more easily in the distance education system courses than in the classroom.	0.640		
I started using internet resources related to my field more effectively during the distance education system process.	0.538		
The distance education system and its applications are easy to use.		0.766	
The distance education system unit provides sufficient support when I need it.		0.758	
The distance education system unit of the university provides sufficient training at the beginning of each academic year.		0.693	
I have the necessary knowledge and skills to use the distance education system.		0.617	
Recording the lectures and providing the opportunity to watch them again is beneficial for my learning.		0.525	
I do not have problems preparing homework for the courses taught with the distance education system.		0.419	
I have technical problems in using the distance education system.			0.745
I have difficulty in using the distance education system.			0.679
Using the distance education system makes it difficult for me to communicate with the lecturer.			0.607
The courses taught with the distance education system bring me an additional workload.			0.567
Eigenvalue	6.399	3.461	2.023
Variance explained (%)	31.997	19.307	10.113
Croncbachs'Alpha (α)	0.939	0.782	0.68
Total variance explained (%)		59.417	
Kaiser Meyer Olkin (KMO)		0.939	
Bartlett's test		11,957.74**	
Croncbach's Alpha (α)		0.829	

*Note. *p<0.05; **p<0.01*

As seen in Table 1, the factor loadings of the questions in the first dimension (Learning) range from 0.538 to 0.858, those in the second dimension (Usage) range from 0.419 to 0.766, and those in the third dimension (Barriers) range from 0.567 to 0.745. It is considered sufficient since Cronbach's Alpha (α) is above 0.70. Therefore, it can be said that the three dimensions of the Attitude Towards Distance Education Scale measure different characteristics. According to these results, the developed survey is a reliable measurement tool. The model obtained for the Attitude Towards Distance Education Scale consists of three dimensions ($\chi 2$= 704.578, df= 154). Fit indices related to this model have shown that the model is acceptably compatible (Table 2).

Table 2: Fit Indices of the SEM

Indices	Good Fit	Acceptable Fit	Fit Index of the Model
χ^2/df	≤ 3	≤ 4-5	4.575*
RMSEA	≤ 0.05	0.06-0.08	0.059**
IFI	≥ 0.95	0.94-0.90	0.954**
CFI	≥ 0.97	≥ 0.90	0.954*
GFI	≥ 0.90	0.89-0.85	0.935**
TLI	≥ 0.95	0.94-0.90	0.943*

*Note. *Acceptable fit; **Good fit*

Based on the fit indices evaluated in Table 2, it is evident that the model exhibits excellent fit characteristics. The model under examination is depicted in Figure 1.

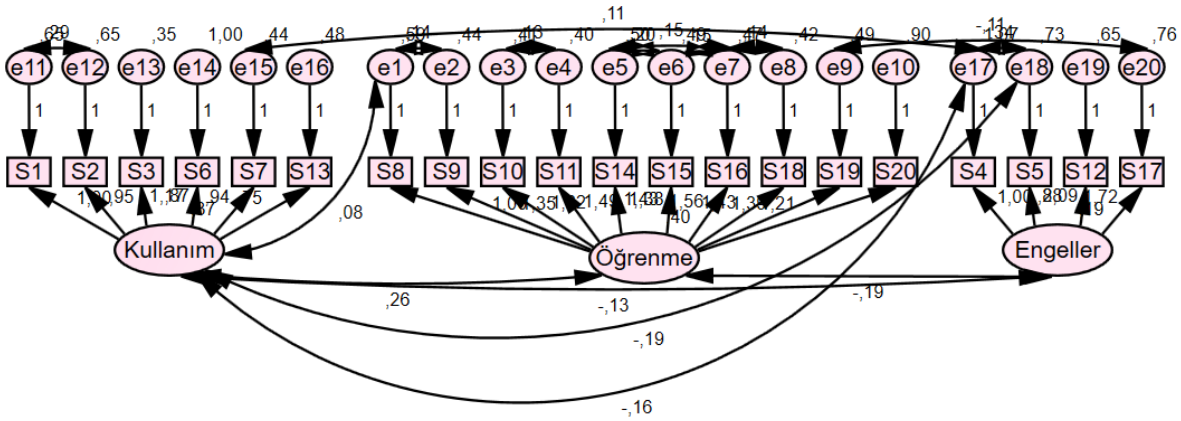

Figure 1: Confirmatory Factor Analysis Model of Attitude Towards Distance Education Scale

After the improvements were obtained, the relationships resulting from the analysis are provided in Table 3. A statistically significant positive relationship was found among the sub-dimensions of the Attitude Scale Towards Distance Education (p <0.05).

Table 3: SEM Regression Weights After Adjustments According to Modification Indices

Path			Standardized Estimate (β)	Estimate (β)	Standard Error	Critical Value	p
Learning	↔	Usage	0.617	0.258	0.023	11.356	0.001**
Learning	↔	Barriers	-0.704	-0.194	0.022	-8.990	0.001**
Usage	↔	Barriers	-0.491	-0.131	0.018	-7.122	0.001**

*Note. *p<0.05; p**<0.01*

Statistically significant relationships were found between the Learning and Usage sub-dimensions (p<0.05). Statistically significant relationships were also observed between the Learning and Barriers sub-dimensions (p<0.05), as well as between the Usage and Barriers sub-dimensions (p<0.05). Overall, when these results are examined, it can be concluded that the survey results for the Attitude Towards Distance Education Scale represent a reliable and valid measurement tool.

Conclusions and Recommendations

This study examines relationships between the dimensions of learning, usage, and barriers using Structural Equation Modeling (SEM). A positive and significant relationship was identified between learning and usage. Additionally, a negative and significant relationship between learning and barriers is found, as well as a negative and significant relationship between usage and barriers. Structural Equation Modeling helps us understand the relationships among the factors of the Attitude Scale for Distance Education. When examining the relationships among students' dimensions of learning, usage, and barriers, a positive connection is found between learning and usage. This result indicates that students perceive distance education as an effective learning tool, and utilizing it more effectively positively impacts learning.

Furthermore, the negative relationship between learning and barriers suggests that while distance education contributes positively to students' learning processes, reducing encountered difficulties is also crucial. Similarly, the negative relationship between usage and barriers indicates that more effective utilization of distance education

can alleviate barriers. Improving the ease of use of distance education systems and applications can help students use this platform more effectively. User-friendly interfaces can enhance students' motivation and attitudes toward Distance Education. Support mechanisms should be established to address barriers encountered in distance education usage. A system should be established to provide technical support and assist students in accessing educational resources more effectively. The quality of training programs related to distance education should be enhanced, especially ensuring that the training offered by distance education Implementation and Research Centers is more comprehensive and tailored to student needs. Findings suggesting that distance education usage complicates student-faculty communication recommend using various communication tools to strengthen communication between educators and students. Regular feedback and interactive learning environments should be established. Social support mechanisms should be created for students to share their experiences with distance education usage. Students who share their experiences can inspire others to use distance education effectively and offer solutions to problems they encounter.

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