Journal of Education and e-Learning Research
Vol. 12, No. 1, 104-114, 2025
ISSN(E) 2410-9991 / ISSN(P) 2518-0169
DOI: 10.20448/jeelr.v12i1.6449

Acceptance and use of technology in online learning in higher education: A student perspective

Miftah Arifin[1] ✉
Anas Ma'ruf Annizar[2]
Moh. Khusnuridlo[3]
Abd. Halim Soebahar[4]
Agus Yudiawan[5]


(✉ *Corresponding Author)*

[1,2,3,4]*UIN Kiai Haji Achmad Siddiq Jember, Indonesia.*
[1]*Email: miftaharifin@uinkhas.ac.id*
[2]*Email: anasannizar28@gmail.com*
[3]*Email: ridlostainjbr@gmail.com*
[4]*Email: ahalims1961@gmail.com*
[5]*Institut Agama Islam Negeri Sorong, Indonesia.*
[5]*Email: agusyudiawan@iainsorong.ac.id*

Abstract

This study examines a level and model for technology acceptability and use in online learning inside universities. The unified theory of UTAUT is used as an analysis tool. An associative quantitative method is used with a sample of 392 students. Data were collected by distributing questionnaires through a specially designed Google Form. The data obtained were then analyzed using variance-based SEM-PLS. The study findings show the adoption and utilization of technology in online education for university students are excellent. In addition, the structural analysis shows that all hypotheses developed in the model have a solid and significant direct and indirect correlation. Four predictors tested as a model, namely performance expectancy, effort expectancy, social influence, and facilitating conditions can predict behavioral intentions. Furthermore, behavioral intentions influence usage behavior positively and significantly. The conclusion of this study makes it clear that the UTAUT model can predict the acceptance and use of technology in online learning for university students. This study provides practical implications for university managers and policymakers to build students' trust in the technology offered by providing easy access and facilities according to their needs and expectations. Facilitating conditions including performance, adequate internet network access and compatible technology need to be considered by all parties so that the use of technology can be carried out smoothly.

Keywords: Acceptance technology, Online learning, Use of technology.

Citation | Arifin, M., Annizar, A. M., Khusnuridlo, M., Soebahar, A. H., & Yudiawan, A. (2025). Acceptance and use of technology in online learning in higher education: A student perspective. *Journal of Education and E-Learning Research, 12*(1), 104–114. 10.20448/jeelr.v12i1.6449
History:
Received: 30 May 2024
Revised: 23 January 2025
Accepted: 6 February 2025
Published: 25 February 2025

Publisher: Asian Online Journal Publishing Group

Funding: This study received no specific financial support.
Institutional Review Board Statement: The Ethical Committee of the Universitas Islam Negeri Kiai Haji Achmad Siddiq Jember, Indonesia, has granted approval for this study on 13 September 2023 (Ref. No. B-PPS.2143/In.20/PP.00.9/9/2023).
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

Contents

Contribution of this paper to the literature
This study enhances the current literature regarding the acceptability and use of technological equipment by students in online learning. This study emphasizes the necessity of including student perspectives to evaluate the efficacy of technology utilization in universities thoroughly. This study's UTAUT model can forecast the effective and efficient acceptance and use of technology in online learning.

1. Introduction

The COVID-19 pandemic has induced substantial transformations throughout all facets of life, particularly within the education sector. Education, which used to be managed manually has now transformed into a digital one (Mhlanga, 2022). Learning that used to be in-person has now turned into online learning (El-Soussi, 2022). Changes in the learning model towards online have been carried out at all levels of education (Churiyah, Sholikhan, Filianti, & Sakdiyyah, 2020). Interestingly, the online learning methodology continues to be utilized today despite the conclusion of the COVID-19 pandemic (Daniel, 2020).

Online learning is an educational modality that incorporates information technology as its primary component (Adedoyin & Soykan, 2023). The integration of technology in education is evidenced by the multitude of universities employing diverse digital platforms (Habib, Jamal, Khalil, & Khan, 2021). Zoom and Google Meetings' digital platforms and learning management systems continue to be used by multiple parties to carry out learning (Kansal, Gautam, Chintalapudi, Jain, & Battineni, 2021). Interestingly, there are still parties (both lecturers and students) who are reluctant and forced to use the platform provided by the university. Instead, they choose traditional learning (Mpungose, 2020) because digital platforms are still complicated for people to accept and use with the advancement of information technology and digitalization.

Various studies have positioned information technology in online learning as two sides of the coin. On the one hand, many parties encourage learning transformation using multiple media and digital platforms while some still refuse (Balaman & Baş, 2023). Agreeers reasoned that "online learning should be done because of its ease of access, flexibility, and the fact that there is no need to go to campus" (Muthuprasad, Aiswarya, Aditya, & Jha, 2021). Online learning can reduce disparities in the quality of higher education. Meanwhile, those who disagree think that online learning is quite tricky. Online learning prevents them from interacting directly with their friends and lecturers in class (Famularsih, 2020). In addition, many methods, media, and platforms lecturers use to teach students are quite troublesome (Febrianto, Mas'udah, & Megasari, 2020). Furthermore, the internet infrastructure, which is the fundamental component of technological utilization constitutes the primary challenge in online learning (Ferri, Grifoni, & Guzzo, 2020; Sartika, Ritonga, Lahmi, Rasyid, & Febriani, 2021).

Despite various literatures that state that online learning is effectively used as a learning method, it seems that quite a lot of students are reluctant to accept it. The problem is simple. Sometimes, university information technology devices do not follow student expectations (Ashour, 2020). This will have far-reaching implications. Learning technology is unsuitable for acceptance and will impacts the effectiveness of online learning itself (Isaac, Aldholay, Abdullah, & Ramayah, 2019). Acceptance here is defined as a person's desire to use a particular technology for its intended purpose and implicates the actual use of that technology (Davis, 1993). It would be interesting to see if the university prepares all forms of technology platforms in advance to know the acceptance rate. In addition, if the technological device has been accepted, are students willing and able to use it or not? This phenomenon is undoubtedly fascinating to seek an explanation for.

The latest study was successfully developed by Venkatesh, Morris, Davis, and Davis (2003) is enough to provide a new perspective on how the acceptance of technology is formed. In his study, Venkatesh et al. (2003) provided a model that could predict how a person could receive and use information technology to benefit him. The model found is called UTAUT (Unified Theory of Acceptance and Use of Technology). The UTAUT model has been used and validated in various fields and activities including economics, training etc. However, this study provides recommendations so that the UTAUT model can be tested on other organizations to reinforce its findings including in the education sector.

Therefore, this research aims to continue previous studies and at the same time, answer challenges in the education sector where the use of online learning technology is still found to be complex. The UTAUT model will be used as an analysis tool to determine students' level and model of technology acceptance. This study will address a minimum of two research issues. What is the acceptance rate of information technology and its utilization by students? What is the predictive model for student acceptance and utilization of technology in online learning? The premise is evident. Understanding the degree and framework of acceptance and utilization of technology in online education can enhance the efficacy of online learning. Furthermore, the university administration can formulate appropriate policies to enhance the utilization of technology on their campuses to facilitate digital learning informed by the findings of this research.

2. Literature Review

2.1. Use of Technology in Online Learning

Digital transformation in various organizations and institutions is being carried out intensively, including in education (Castro & Tumibay, 2021; Rof, Bikfalvi, & Marques, 2022). In education, digitalization is carried out in institutional governance and, more broadly, in learning. Both at the elementary education level and in higher education all have switched to online modes of learning. Learning that used to be done conventionally has now changed to online learning (He & Wei, 2021). Educational institutions compete to use online modes to integrate high-quality and modern knowledge and technology (Gurban & Almogren, 2022). Online education employs technology and social media to deliver comprehensive learning experiences (Aljawarneh, 2020). Online learning allows unlimited interaction by space and time for teachers, students and content in learning optimization (Alzahrani, 2022). In their study, Moore, Dickson-Deane, and Galyen (2011) explained that "online learning allows information technology innovation to improve the effective learning process". Online learning in practice requires an internet network and computers to obtain various pedagogical content studied with lecturers and students

(Ferri et al., 2020; Sridharan, Deng, & Corbitt, 2010). Finally, this positive change in learning also increases flexibility and removes geographical barriers (Veletsianos, Kimmons, Larsen, & Rogers, 2021).

Apart from various literatures that mention the advantages and effectiveness of online learning and the incessant transformation of universities, many students are reluctant to accept it. The information technology devices provided by the university sometimes do not match the expectations of students (Ashour, 2020). This will have far-reaching implications. Technological devices that are less accepted by students will have an impact on the effectiveness of the learning process itself (Isaac et al., 2019). Acceptance is described as an individual's inclination to utilize a specific technology for its intended purpose and the consequences of its actual use (Davis, 1993). Consequently, students' adoption and utilization of technology must be actively sought in the continuous influx of technological advancements in education. Universities must find a suitable model to predict and ensure that all parties can accept the technological devices offered in bold learning.

2.2. UTAUT Model: Prediction of the Acceptance and Use of Technology in Online Learning

Researchers have long studied models of use and acceptance of technology in various activities. The Technology Acceptance Model (TAM) is the most frequently studied and used in building a technology acceptance model (Han & Sa, 2022; Park, Nam, & Cha, 2012). TAM can still not accurately validate the acceptance of the technology despite its advantages as a prediction model (Ahmad, 2018). It still has limitations because it has not considered social influence in using new technology (Malhotra & Galletta, 1999). This is a severe concern for researchers trying to determine the ideal model for predicting technology acceptance.

Recently, the TAM model has been further developed by Venkatesh et al. (2003) into the Unified Theory of Acceptance and Utilization of Technology (UTAUT) model. UTAUT is built from various models of acceptance and use of pre-existing technology, namely TAM, TRA, MPCU, MM, TPB, IDT, SCT, and TAM-TPB (Venkatesh et al., 2003). The contributions of these eight technological acceptance models have been extensively utilized across several scientific domains including information systems, economics, management, and government (Gurban & Almogren, 2022). UTAUT has demonstrated superiority over its eight previous theories and remains a robust and validated model today (Venkatesh et al., 2003). The UTAUT model has four predictors that determine a person's ability to receive and use information technology.

The first predictor in the UTAUT model is performance expectancy defined as an individual's belief that using technology will increase their effectiveness (Venkatesh et al., 2003). One must be convinced that the technological devices can meet their needs. If not, then how sophisticated the technological devices offered will be in vain. An individual's intention to utilize technology is significantly affected by their performance expectations (Chen & Hwang, 2019; Rabaa'i, Abu ALmaati, & Zhu, 2021). Moreover, Alam, Mahmud, Hoque, Akter, and Rana (2022) mentioned that job expectations are the main factor in predicting a person's chances of using technology. Next is the second predictor, namely effort expectancy which is the belief that individuals will find it inconvenient to use technological devices in their activities (Venkatesh et al., 2003). This predictor explained that the technology developing and offered today should provide ease of use. It can be assured that it will not be used if it is difficult because the principle of technology should provide convenience for its users. Therefore, effort expectancy significantly determines behavioural intentions using technology (Chen & Hwang, 2019; Zhang, Zhang, & Kim, 2021).

The third predictor is social impact defined as a societal incentive to adopt new technology equipment (Venkatesh et al., 2003). This prediction demonstrates that support from friends, family, and organizations increases an individual propensity to adopt and employ technology (Tewari, Singh, Mathur, & Pande, 2023). Research demonstrates that social circumstances affect individuals' tendencies to engage in online learning (Khechine, Raymond, & Augier, 2020). The enabling condition is an individual's trust in the infrastructure supporting technology use (Venkatesh et al., 2003). This study analyzes the condition of the university's facilities and infrastructure that support technological accessibility. Prior research demonstrates a positive relationship between facilitating conditions, and behavioral intentions for technology utilization (Chen & Hwang, 2019; Tewari et al., 2023). When individuals have the necessary knowledge and resources, their inclination to employ technology rises due to its alignment with established systems (Almaiah, Alamri, & Al-Rahmi, 2019; Zhang et al., 2021).

The UTAUT model was chosen for its extensive capacity to measure and forecast the adoption of information technology, marketing, and training (Venkatesh et al., 2003). This model integrates diverse aspects of prior technology usage behavior (Chao, 2019). Consequently, four predictors are employed to ascertain the adoption and utilization of information technology in online education. This study will empirically assess the relevance of the predictor model. Figure 1 illustrates the relationship among the four predictors regarding the information technology acceptance serving as the conceptual underpinning for this study.

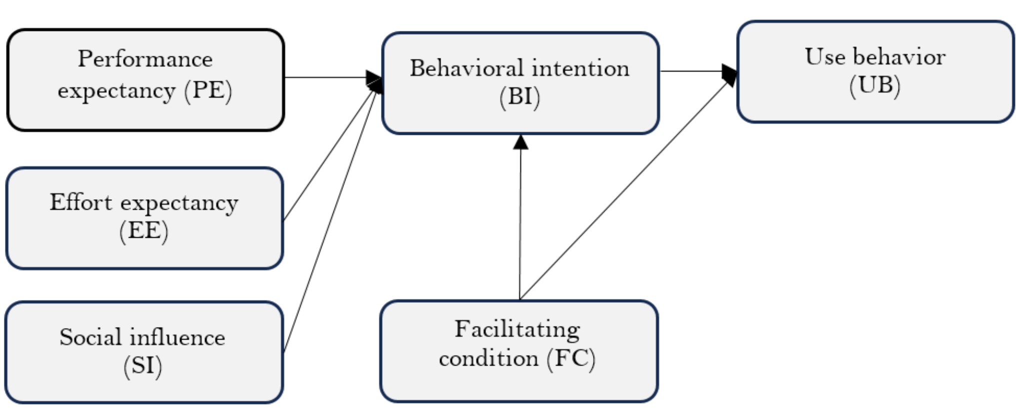

Figure 1. Conceptual framework, an adaptation of the UTAUT model.

3. Methodology

3.1. Research Design

This study is designed using an associative quantitative approach. This approach was chosen because this study is intended to test the strength of relationships in the model of technology acceptance in online learning in universities. The UTAUT model found in the literature is considered suitable for development. Six predictors in the UTAUT model were adapted as a reference in the preparation of the questionnaire. Partial Least Squares Structural Equation Modeling (PLS-SEM) analyzed the data collected through the survey using three stages of measurement to verify the completeness and clarity of the model of the acceptance technology structure for variables and categories. This research's design flow can be seen in Figure 2.

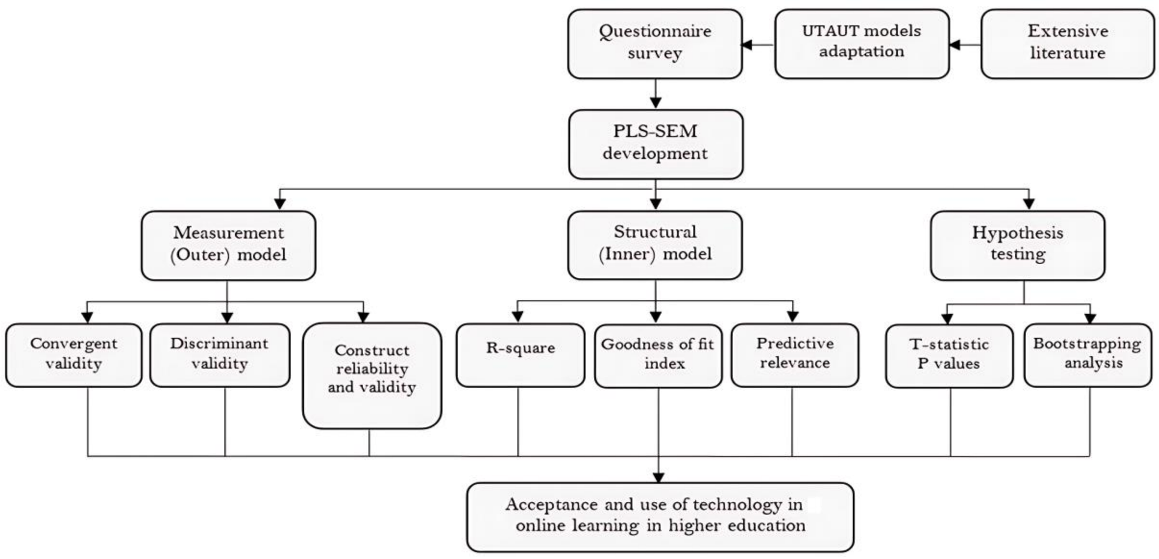

Figure 2. Research design.

3.2. Population and Sample

This research was carried out from June to December 2023 and took place at UIN Kiai Haji Achmad Siddiq and Jember. This university was chosen because it has used technology in online learning since the COVID-19 pandemic until now. All 18,871 students constitute the research population. The sample size is calculated using the Slovin formula at a 5% margin of error. Once the sample size is established, the sample is identified utilizing a stratified random sampling method. This technique is chosen so that each faculty, study program, and semester has a proportionally representative sample. The number of samples is calculated in detail in Table 1.

Table 1. Sample calculation with the Slovin formula.

Population	Margin of error	Slovin formula	Sample acquisition
18,871	5%	$\frac{18871}{18871\ x\ (0.05)^2 + 1}$	392

3.3. Research Instruments

Closed questionnaires are used as a data collection tool. According to the questions provided, respondents only provide answers. This questionnaire is intended to measure respondents' acceptance of information technology in online learning. The questionnaire uses a rating scale with ten alternative answers (1-10) (Wright & Masters, 1982). The indicators used in the questionnaire are given in Table 2.

Table 2. Research questionnaire indicators.

Aspect	Description	Indicator	Symbol
Performance expectancy (PE)	A person's expectation to get high performance if using technology in their activities.	Speed up performance.	PE.1
		Improve quality.	PE.2
		Increase productivity.	PE.3
Effort expectancy (EE)	One's expectation that convenience will be obtained when using technology.	Clear and easy to understand.	EE.1
		Easy to use.	EE.2
		Widely used.	EE.3
		Easily accessible.	EE.4
Social influence (SI)	Social influences that can influence others who can change their behavior to use technology.	Family influence.	SI.1
		Influence of friends.	SI.2
		Group influence.	SI.3
		Influence of lecturers and management.	SI.4
Facilitating conditions (SC)	A person is convinced that the technological and organizational environment is established to facilitate the utilization of technology.	Availability of compatible resources.	FC.1
		Access and network availability.	FC.2
		User skills.	FC.3
		Support if issues are found.	FC.4
Behavioral intention (BI)	A person's desire to use a particular technology with its expected purpose.	The desire to wear it shortly.	BI.1
		Intend to use it in the future.	BI.2
		Plan to use continuously.	BI.3
		Plan to recommend to the other party.	BI.4
Use behavior (UB)	A person's actual use of a technology.	High intensity of use.	UB.1
		Willing to use long-term.	UB.2
		Don't mind providing a fee.	UB.3
		Don't mind making time.	UB.4
		Recommend to others.	UB.5

The rating scale questionnaire with ten alternative answers (1-10) was previously tested for validity and was given to 392 students who use technology in learning. Survey work was conducted during July 2023 excluding feedback collection time.

3.4. Validity and Reliability

All utilized questionnaires have undergone validity and reliability assessments. The assessment was conducted by examining Cronbach's alpha values. According to the literature, an effective questionnaire possesses a Cronbach's alpha score exceeding 0.7 (Hair, Hult, Ringle, & arstedt, 2022). The test findings yielded a Cronbach's alpha score of 0.981 indicating the questionnaire's appropriateness as a research tool. The outcomes of the instrument assessment are presented in Table 3.

Table 3. Instrument testing results.

Cronbach's alpha	Cronbach's alpha based on standardized item	No. of items
0.981	0.982	24

3.5. Data Collection Techniques

This study investigates the extent and framework of technology acceptance and utilization in online learning among higher-education students with data gathered through survey methods. A questionnaire whose validity had been tested was used to conduct a survey on 392 students at UIN Kiai Haji Achmad Siddiq Jember. The current questionnaire was disseminated online through Google Forms. Google Forms was chosen because of the ease of access and validity of the data collected. Furthermore, to ensure that those who filled out the questionnaire matched the specified sample, the respondents were confirmed directly through telephone or WhatsApp. The collected survey response data was subsequently analyzed to delineate the demographics of the respondents. Data tabulation and formatting were also carried out correctly for further statistical analysis using Smart-PLS software.

3.6. Data Analysis Techniques

The collected data is then organized and examined using variant-based SEM-PLS. The structural analysis is performed in the following three stages: the outer model, inner model, and hypothesis testing (Hair et al., 2022). Outer model analysis is employed to examine the link between indicators and latent variables. The external model is assessed by the results of convergent and discriminant validity evaluations (Hair et al., 2022). Subsequently, proceed to the inner model step. The internal model was examined to validate the accuracy and robustness of the structural model developed. The internal model was evaluated using the coefficient of determination, goodness of fit index, and predictive relevance (Sarstedt, Ringle, & Hair, 2022). The concluding stage of structural analysis is hypothesis testing. The hypothesis test was evaluated using the t-statistic and significant values obtained from the SEM-PLS bootstrapping results. The hypothesis is considered acceptable if the t-statistic surpasses 1.96 or the p-value falls below 0.05 (Hair et al., 2022). Figure 3 illustrates the phases of study for this structural model.

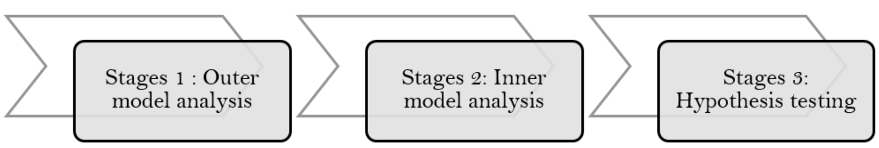

Figure 3. Data analysis steps.

4. Result

4.1. Respondent Demographics

Table 4 presents the demographics of the sample. The majority of respondents identified as female comprising 55.1% while males accounted for 44.1%. 8.5% of respondents were under 18 years old, 78.1% fell within the 18 to 22 age range, 14.5% were aged 23 to 27, 2.6% were between 28 and 32, 1.3% were students aged 33 to 35, and only 0.5% of respondents were above 35 years old. Furthermore, this research also assessed the respondents' education level. Findings showed that most participants had educational qualifications at the bachelor's level (n=344; 87.8%) followed by those who had master's qualifications (n=36; 9.2%). Meanwhile, it was n=12; 3.1% for the doctoral level. Finally, respondents' experiences using technology in online learning were revealed in this research. The results show that 4.6% have used technology in online learning for less than one year, 19.4% have used it for 1 to 2 years, 43.9% have used it between 3 and 4 years and 32.1% have used technology in learning online for more than five years.

Table 4. Respondent demographics.

Demographic	Category	Frequency (n=392)	Percentage (%)
Gender	Male	173	44.1
	Female	219	55.9
Age	<18 years	12	3.1
	18-22 years	306	78.1
	23-27 years	57	14.5
	28-32 years	10	2.6
	33-35 years	5	1.3
	> 35 years	2	0.5
Educational (Level)	Bachelor	344	87.8
	Masters	36	9.2
	Doctoral	12	3.1
Experience using technology in online learning	< 1 years	18	4.6
	1-2 years	76	19.4
	3-4 years	172	43.9
	> 5 years	126	32.1

4.2. Acceptance Rate and Use of Technology in Online Learning

The level of acceptability and the use of technology determined by calculating the average score from the questionnaire administered to students. The average score obtained is then compared with the acceptance rate criterion on a scale 10. The criteria in question are as follows: 0-2 is not good, 2-4 is less good, 4-6 is good, 6-8 is very good, and 8-10 is good (Azman, Ahamad, Majid, Yahaya, & Hanafi, 2013; Flynn, Sakakibara, Schroeder, Bates, & Flynn, 1990). The findings from a descriptive analysis regarding the acceptance of technology in the learning process for students at UIN Kiai Haji Achmad Siddiq Jember are presented in Table 5.

Table 5. Level of acceptance and use of technology in online learning.

Aspect	Mean	Criteria
Performance expectancy (PE)	7.349	Very good
Effort expectancy (EE)	7.404	Very good
Social influence (SI)	7.936	Very good
Facilitating conditions (FC)	7.750	Very good
Behavioral intention (BI)	7.619	Very good
Use behavior (UB)	7.634	Very good

Table 5 illustrates how students' accept technology in their learning processes. The results showed that the average scores and criteria on aspects of performance expectancy (7.349/ very good), effort expectancy (7.404/ very good), social influence (7.936/ very good), facilitating conditions (7.750/ very good), behavioral intention (7.619/ very good), and use behavior (7.634/ very good). The research findings show a high level of acceptance for using technology in online learning for students at UIN Kiai Haji Achmad Siddiq Jember. In other words, the technological devices provided by the university are very responsive to being accepted and used by students in online learning.

4.3 Model of Acceptance and Use of Technology in Online Learning

The examination of structural model data is conducted in three stages as detailed in the methodology. The stages under consideration include outer model measurement, inner model measurement and hypothesis testing. The outcomes of the measurement phases of the structural model are elaborated below.

4.3.1. Stages 1: Outer Model Measurement

The outer model pertains to evaluating the exterior aspect of the model. The outer model is assessed to investigate the correlation between indicators and latent variables. The external model is assessed via convergent and discriminant validity (Monecke & Leisch, 2012). In PLS, the assessment of convergent validity relies on the loading factor's value associated with its latent variable. When the loading factor value exceeds 0.7, it is considered acceptable. A loading factor ranging from 0.5 to 0.7 is also deemed acceptable while any loading factor below 0.5 should be discarded or removed from the model (Hair et al., 2022). Table 6 presents the measurement of the loading factor.

Table 6. Outer loading measurement.

Indicators	Behavioral intention	Effort expectancy	Facilitating conditions	Performance expectancy	Social influence	Use behavior
BI.1	0.911					
BI.2	0.931					
BI.3	0.944					
BI.4	0.912					
EE.1		0.855				
EE.2		0.891				
EE.3		0.900				
EE.4		0.893				
FC.1			0.889			
FC.2			0.897			
FC.3			0.801			
FC.4			0.899			
PE.1				0.910		
PE.2				0.927		
PE.3				0.900		
SI.1					0.875	
SI.2					0.897	
SI.3					0.888	
SI.4					0.900	
UB.1						0.931
UB.2						0.951
UB.3						0.952
UB.4						0.893
UB.5						0.931

According to the data presented in Table 6, the UB.3 indicator exhibits the highest loading factor value at 0.952, while the FC.3 indicator shows the lowest value at 0.801. All indicators are deemed valid and accepted since every indicator in the construct variable exhibits a loading factor exceeding 0.5. Subsequently, measurements for discriminant validity are conducted. Testing for discriminant validity is conducted to confirm that each concept or indicator suggested by each latent model is distinct from other variables. The team is evaluating discriminant validity by examining the output of the Fornell-Larcker Criterion. Table 7 presents the results of the discriminant validity testing.

Table 7. Discriminant validity measurement.

Aspects	Behavioral intention	Effort expectancy	Facilitating conditions	Performance expectancy	Social influence	Use behavior
Behavioral intention	0.924					
Effort expectancy	0.719	0.885				
Facilitating conditions	0.742	0.726	0.873			
Performance expectancy	0.672	0.838	0.641	0.913		
Social influence	0.762	0.707	0.834	0.624	0.890	
Use behavior	0.872	0.756	0.813	0.668	0.792	0.932

Table 7 indicates that the AVE value's square root exceeds the preceding construct's correlation. The square root value of AVE is presented with a bold notation. This shows that the discriminant validity value requirements have been met and can be accepted.

Finally, construct reliability and validity checks are also carried out in the outer model measurement stage. Construct reliability testing is performed to ensure that there are no measurement problems. This assessment utilized composite reliability and Cronbach's alpha metrics. When the composite reliability values or Cronbach's alpha exceed 0.6 for all constructs, it indicates that the model demonstrates reliability (Hair et al., 2022). The analysis results presented in Table 8 indicate that all composite reliability values or Cronbach's alpha exceed 0.6. This indicates that the model demonstrates reliability.

Table 8. Construct reliability and validity measurement.

Aspects	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
Behavioral intention	0.943	0.944	0.959	0.855
Effort expectancy	0.908	0.908	0.935	0.783
Facilitating conditions	0.895	0.901	0.927	0.761
Performance expectancy	0.900	0.901	0.937	0.833
Social influence	0.913	0.913	0.938	0.792
Use behavior	0.962	0.962	0.971	0.868

4.3.2. Stages 2: Inner Model Measurement

The inner model often called the structural model plays a crucial role in understanding the underlying relationships within the framework. A structural model establishes connections among latent variables. The evaluation of the inner model in the PLS-SEM structure is assessed through the R-Square (R2) value, the Goodness of Fit (GoF), and the predictive relevance (Q2). R-Square has the following four categories: R-square values 0-0.19 (weak), 0.20-0.33 (moderate), 0.34-0.67 (substantial), and 0.68-1 (robust) (Chin, Peterson, & Brown, 2008). Table 9 presents the outcomes of the R-square test.

Table 9. R-square measurement.

Aspects	R square	R square adjusted
Behavioral intention	0.667	0.663
Use behavior	0.822	0.821

Table 9 clearly shows that the R-square values are 0.667 and 0.822. This means the research model is substantial and robust in explaining the relationship between variables.

The GoF is carried out to test both outer and inner models thoroughly. This test is intended to see the match of the observed value with the expected value in the model. The GoF value is derived from the root calculation of the average AVE value multiplied by the mean square value of R-Square (Tenenhaus, Amato, & Esposito Vinzi, 2004). GoF value spans between 0 to 1 with interpretations of values 0 – 0.24 (small), 0.25 – 0.37 (moderate), and 0.38 - 1 (high). The result of the GoF test is displayed in Table 10. The GoF value presented in Table 8 is 0.695 indicating that the model fit is categorized as high.

Table 10. Goodness of fit index (GoF) measurement.

Aspects	R square	$(R\ square)^2$	AVE	GoF
Behavioral intention	0.667	0.445	0.855	0.695
Use behavior	0.822	0.676	0.868	
Mean	0.745	0.560	0.862	

Furthermore, predictive relevance (Q^2) testing was carried out. This test aimed to examine the impact of structural models on observational measurements concerning latent dependent variables (endogenous latent variables) (Garson, 2016). Q^2 values greater than 0 suggest that the observed values have been accurately reconstructed indicating that the model possesses predictive relevance. Values of Q2 less than 0 signify a lack of predictive relevance (Hair et al., 2022). The Q^2 test results in Table 11 indicate Q^2 values above 0 and approaching 1. This indicates the model possesses significant predictive value.

Table 11. Predictive relevance (Q2) measurement.

Aspects	R square	1- R square	$(1\text{- }R\ square)^2$	Predictive relevance (Q^2)
Behavioral intention	0.667	0.445	0.855	0.742
Use behavior	0.822	0.676	0.868	

4.3.3. Stages 3: Hypothesis Testing

T- statistics in the inner model test help test the significance of hypotheses. Hypothesis testing can be seen from the bootstrapping output. The following bootstrapping output test results are displayed in Figure 4.

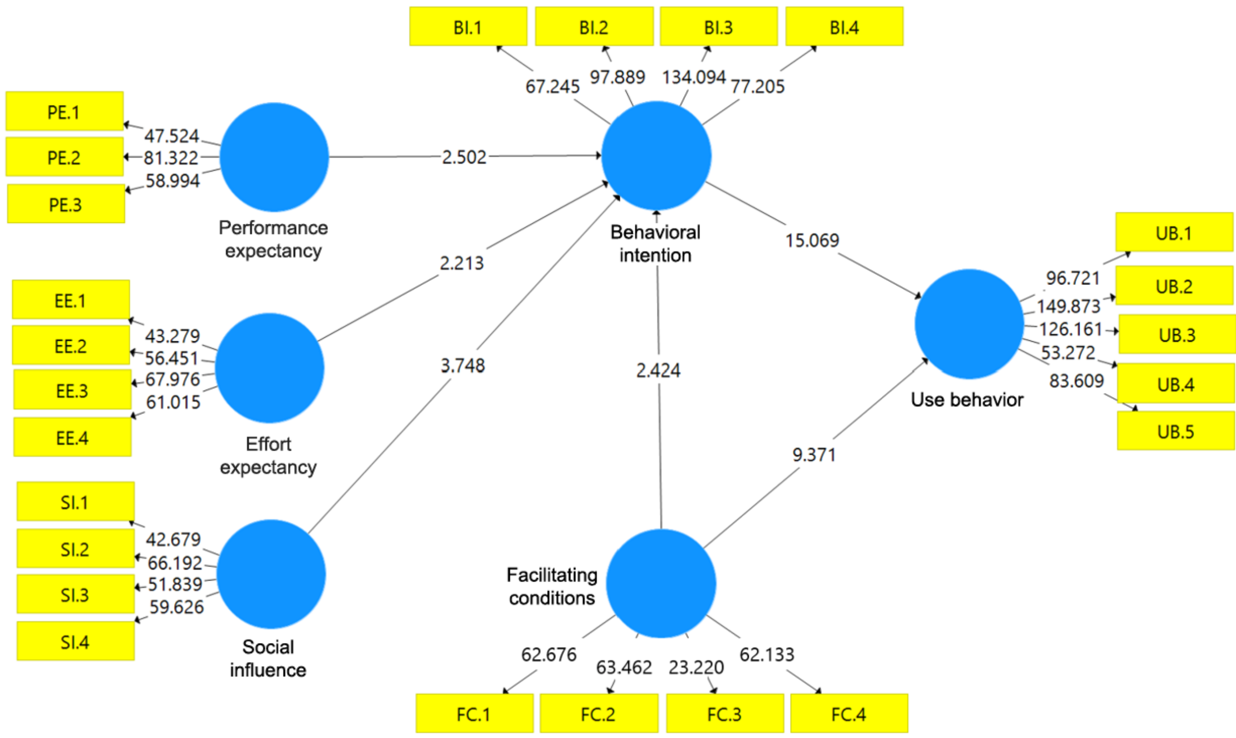

Figure 4. Bootstrapping result

In the hypothesis test, if an alpha level of 5% is used, the critical value in t-statistics is 1.96. The hypothesis is acceptable when the p-value is less than 0.05 or the t-statistic exceeds 1.96 (Hair et al., 2022). The outcomes of the hypothesis test are presented in Table 12.

Table 12. Hypothesis testing results.

Hypotheses relationships	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P-values	Significant
Direct effect						
BI -> UB	0.599	0.598	0.040	15.069	0.000	Yes
EE -> BI	0.169	0.168	0.076	2.213	0.027	Yes
FC -> BI	0.205	0.204	0.085	2.424	0.016	Yes
FC -> UB	0.369	0.370	0.039	9.371	0.000	Yes
PE -> BI	0.171	0.175	0.068	2.502	0.013	Yes
SI -> BI	0.365	0.364	0.097	3.748	0.000	Yes
Indirect effects						
EE -> BI -> UB	0.101	0.101	0.048	2.114	0.035	Yes
FC -> BI -> UB	0.123	0.121	0.050	2.432	0.015	Yes
PE -> BI -> UB	0.102	0.104	0.041	2.480	0.013	Yes
SI -> BI -> UB	0.219	0.217	0.060	3.659	0.000	Yes

The test results presented in Table 12 show that all hypotheses have p-values below 0.05. In addition, the t-statistic values produced are all greater than 1.96. This means that all hypotheses tested directly and indirectly can be accepted and are significant. These results indicate that all predictors tested can be accepted as a model of acceptance of technology in brave learning for students.

5. Discussion

The findings descriptively explain that students' acceptance and utilization of technology in online learning is excellent. This condition clarifies that the university can meet student expectations for the technology provided. Students will use technology for learning if it meets their expectations (Raes & Depaepe, 2020). In addition, the university's support of the facilities also impacts the acceptance of the technology. Facilities include an adequate internet network and support from various parties in using technology (Salloum, Alhamad, Al-Emran, Monem, & Shaalan, 2019). Social support is positive in increasing acceptance and utilization of technology (Benoit-Dube et al., 2023). Finally, increasing acceptance and utilization of various learning technology platforms can be determined by user expectations, supporting facilities and social support. Managerial parties must meet user expectations and provide various supporting facilities to use technology appropriately.

Furthermore, there is a strong correlation between the direct and indirect predictors from the technology acceptance and utilization model perspective. The predictors of facilitating conditions, social influence, effort expectancy, performance expectancy strongly and significantly boost behavioral intention. This behavioral intention has implications for students' use of learning technology developed in the model that the predictors have a strong and significant correlation, both directly and indirectly.

This research has succeeded in proving that the UTAUT model reliably capable of forecasting the adoption and use of technology in online learning by university students. This study reinforces previous findings that user adoption of technology can be explained by the UTAUT model (Momani, 2020; Ye, Zheng, & Yi, 2020) This acceptance is manifested in the form of massive use of technology (Marikyan & Papagiannidis, 2023). Users can use technological devices to meet expectations (Ashour, 2020; Venkatesh et al., 2003). Users will first see how the technology performs and eases before use (Davis, 1993). Family, friends, and the social conditions of society also influence technology acceptance (Lee, Lee, & Lee, 2006; Vannoy & Palvia, 2010). The stronger the social support provided, the more expectancy met, and the facilities that support it, the stronger the technology acceptance to be used (Almaiah et al., 2019; Graf-Vlachy, Buhtz, & König, 2018). Students will only be willing to accept and use technology in online learning if expectations are met, they have social support and the university has adequate facilities to support technology performance.

6. Conclusion

This study highlights the extent and structure of technology acceptance and application in active learning within higher education. The study's findings indicate that accepting technology in bold learning among higher education students is exceptional. The structural analysis indicates that all assumptions formulated in the model exhibit robust and substantial direct and indirect relationships. The UTAUT model can effectively forecast technology utilization in online learning within higher education enhancing student efficiency. Four determinants, including facilitating conditions, social impact, performance expectancy and effort expectancy are essential for effectively utilising technological platforms in online education. Consequently, this model can serve as a reference for online learning organizers to optimize utilization the available technology effectively and efficiently.

7. Implications

As a theoretical implication, this study's findings can explain that job expectations and expectations of technology users can explain the adoption and acceptance of technology in online learning. In addition, social impact and conditions that facilitate participation are also strong determinants of technology acceptance. Conditions conducive to accepting and applying technology in online learning must be fostered through institutional support, regulations, and adequate facilities. This research provides actionable implications for policymakers in higher education. Policymakers and university administrators must foster student confidence in the technology by ensuring that facilities are accessible and adequately meet their needs and expectations. All stakeholders must contemplate enabling aspects including performance, adequate internet connectivity, and appropriate equipment to facilitate significant technology adoption. This study confirms that collaborative efforts among all stakeholders are crucial for establishing performance and effort expectancy, social effect and conducive environments for students which are needed for the acceptance of technology in online learning.

8. Limitations and Future Research Directions

Notwithstanding the merits of this work, there remain limitations that warrant consideration and further investigation by future researchers. This study only emphasizes the technology acceptance in online learning for students at a single university by restricting four predictors within the technology acceptance model. Future studies are anticipated to employ moderators within the UTAUT model to examine the resultant impact thoroughly. A comprehensive examination is required, incorporating the viewpoints of both lecturers and administration as facilitators of online learning. Second, the analysis method in this research uses variance-based SEM (VB-SEM) to develop existing theories. In the future, it is interesting to conduct statistical testing of covariance-based SEM (CB-SEM) in testing existing theories or using mixed methods to find new concepts. The limited population at one university can only be generalized to some higher education in Indonesia. In higher education in Indonesia, difficulties are still found in implementing technology in online learning. Finally, the previously developed UTAUT model predicted the acceptance of technology in online learning for university students.

References

Adedoyin, O. B., & Soykan, E. (2023). Covid-19 pandemic and online learning: The challenges and opportunities. *Interactive Learning Environments*, *31*(2), 863-875. https://doi.org/10.1080/10494820.2020.1813180

Ahmad, M. (2018). Review of the technology acceptance model (TAM) in internet banking and mobile banking. *International Journal of Information Communication Technology and Digital Convergence*, *3*(1), 23-41.

Alam, S., Mahmud, I., Hoque, S. S., Akter, R., & Rana, S. S. (2022). Predicting students' intention to continue business courses on online platforms during the Covid-19: An extended expectation confirmation theory. *The International Journal of Management Education*, *20*(3), 100706. https://doi.org/10.1016/j.ijme.2022.100706

Aljawarneh, S. A. (2020). Reviewing and exploring innovative ubiquitous learning tools in higher education. *Journal of Computing in Higher Education*, *32*(1), 57-73. https://doi.org/10.1007/s12528-019-09207-0

Almaiah, M. A., Alamri, M. M., & Al-Rahmi, W. (2019). Applying the UTAUT model to explain the students' acceptance of mobile learning system in higher education. *IEEE Access*, *7*, 174673-174686.

Alzahrani, M. (2022). Traditional learning compared to online learning during the COVID-19 pandemic: Lessons learned from faculty's perspectives. *Sage Open*, *12*(2), 21582440221091720. https://doi.org/10.1177/21582440221091720

Ashour, S. (2020). How technology has shaped university students' perceptions and expectations around higher education: An exploratory study of the United Arab Emirates. *Studies in Higher Education*, *45*(12), 2513-2525. https://doi.org/10.1080/03075079.2019.1617683

Azman, M. N. A., Ahamad, M. S. S., Majid, T. A., Yahaya, A. S., & Hanafi, M. H. (2013). Statistical evaluation of pre-selection criteria for industrialized building system (IBS). *Journal of Civil Engineering and Management*, *19*(sup1), S131-S140. https://doi.org/10.3846/13923730.2013.801921

Balaman, F., & Baş, M. (2023). Perception of using e-learning platforms in the scope of the technology acceptance model (TAM): A scale development study. *Interactive Learning Environments*, *31*(8), 5395-5419. https://doi.org/10.1080/10494820.2021.2007136

Benoit-Dube, L., Jean, E. K., Aguilar, M. A., Zuniga, A.-M., Bier, N., Couture, M., . . . Belchior, P. (2023). What facilitates the acceptance of technology to promote social participation in later life? A systematic review. *Disability and Rehabilitation: Assistive Technology*, *18*(3), 274-284. https://doi.org/10.1080/17483107.2020.1844320

Castro, M. D. B., & Tumibay, G. M. (2021). A literature review: efficacy of online learning courses for higher education institution using meta-analysis. *Education and Information Technologies*, *26*(2), 1367–1385. https://doi.org/10.1007/s10639-019-10027-z

Chao, C.-M. (2019). Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model. *Frontiers in Psychology*, *10*, 1652. https://doi.org/10.3389/fpsyg.2019.01652

Chen, P.-Y., & Hwang, G.-J. (2019). An empirical examination of the effect of self-regulation and the unified theory of acceptance and use of technology (UTAUT) factors on the online learning behavioural intention of college students. *Asia Pacific Journal of Education, 39*(1), 79-95. https://doi.org/10.1080/02188791.2019.1575184

Chin, W. W., Peterson, R. A., & Brown, S. P. (2008). Structural equation modeling in marketing: Some practical reminders. *Journal of Marketing Theory and Practice, 16*(4), 287-298. https://doi.org/10.2753/MTP1069-6679160402

Churiyah, M., Sholikhan, S., Filianti, F., & Sakdiyyah, D. A. (2020). Indonesia education readiness conducting distance learning in Covid-19 pandemic situation. *International Journal of Multicultural and Multireligious Understanding, 7*(6), 491-507. https://doi.org/10.18415/ijmmu.v7i6.1833

Daniel, S. J. (2020). Education and the COVID-19 pandemic. *Prospects, 49*(1), 91-96. https://doi.org/10.1007/s11125-020-09464-3

Davis, F. D. (1993). User acceptance of information technology: System characteristics, user perceptions and behavioral impacts. *International Journal of Man-Machine Studies, 38*(3), 475-487. https://doi.org/10.1006/imms.1993.1022

El-Soussi, A. (2022). The shift from face-to-face to online teaching due to COVID-19: Its impact on higher education faculty's professional identity. *International Journal of Educational Research Open, 3*, 100139. https://doi.org/10.1016/j.ijedro.2022.100139

Famularsih, S. (2020). Students' experiences in using online learning applications due to COVID-19 in English classroom. *Studies in Learning and Teaching, 1*(2), 112-121. https://doi.org/10.46627/silet.v1i2.40

Febrianto, P. T., Mas'udah, S., & Megasari, L. A. (2020). Implementation of online learning during the covid-19 pandemic on Madura Island, Indonesia. *International Journal of Learning, Teaching and Educational Research, 19*(8), 233-254. https://doi.org/10.26803/ijlter.19.8.13

Ferri, F., Grifoni, P., & Guzzo, T. (2020). Online learning and emergency remote teaching: Opportunities and challenges in emergency situations. *Societies, 10*(4), 86. https://doi.org/10.3390/soc10040086

Flynn, B. B., Sakakibara, S., Schroeder, R. G., Bates, K. A., & Flynn, E. J. (1990). Empirical research methods in operations management. *Journal of Operations Management, 9*(2), 250-284. https://doi.org/10.1016/0272-6963(90)90098-X

Garson, G. D. (2016). Partial least squares: Regression & structural equation models. In (pp. 1–262). Asheboro, NC: Statistical Publishing Associates.

Graf-Vlachy, L., Buhtz, K., & König, A. (2018). Social influence in technology adoption: Taking stock and moving forward. *Management Review Quarterly, 68*, 37-76. https://doi.org/10.1007/s11301-017-0133-3

Gurban, M. A., & Almogren, A. S. (2022). Students' actual use of E-learning in higher education during the COVID-19 pandemic. *Sage Open, 12*(2), 21582440221091250. https://doi.org/10.1177/21582440221091250

Habib, M. N., Jamal, W., Khalil, U., & Khan, Z. (2021). Transforming universities in interactive digital platform: Case of city university of science and information technology. *Education and Information Technologies, 26*(1), 517-541. https://doi.org/10.1007/s10639-020-10237-w

Hair, J. F., Hult, G. T. M., Ringle, C. M., & arstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.): Sage Publishing. https://doi.org/10.1007/978-3-030-80519-7.

Han, J.-H., & Sa, H. J. (2022). Acceptance of and satisfaction with online educational classes through the technology acceptance model (TAM): The COVID-19 situation in Korea. *Asia Pacific Education Review, 23*(3), 403-415. https://doi.org/10.1007/s12564-021-09716-7

He, W., & Wei, G. (2021). Higher education in China, a paradigm shift from conventional to online teaching. *Higher Education Studies, 11*(2), 30-41. https://doi.org/10.5539/hes.v11n2p30

Isaac, O., Aldholay, A., Abdullah, Z., & Ramayah, T. (2019). Online learning usage within Yemeni higher education: The role of compatibility and task-technology fit as mediating variables in the IS success model. *Computers & Education, 136*, 113-129. https://doi.org/10.1016/j.compedu.2019.02.012

Kansal, A. K., Gautam, J., Chintalapudi, N., Jain, S., & Battineni, G. (2021). Google trend analysis and paradigm shift of online education platforms during the COVID-19 pandemic. *Infectious Disease Reports, 13*(2), 418-428. https://doi.org/10.3390/idr13020040

Khechine, H., Raymond, B., & Augier, M. (2020). The adoption of a social learning system: Intrinsic value in the UTAUT model. *British Journal of Educational Technology, 51*(6), 2306-2325. https://doi.org/10.1111/bjet.12905

Lee, Y., Lee, J., & Lee, Z. (2006). Social influence on technology acceptance behavior: Self-identity theory perspective. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems, 37*(2-3), 60-75. https://doi.org/10.1145/1161345.1161355

Malhotra, Y., & Galletta, D. F. (1999). *Extending the technology acceptance model to account for social influence: Theoretical bases and empirical validation*. Paper presented at the Proceedings of the 32nd Annual Hawaii International Conference on Systems Sciences. 1999. HICSS-32. Abstracts and CD-ROM of Full Papers, 14-pp. https://www.brint.org/technologyacceptance.pdf.

Marikyan, D., & Papagiannidis, S. (2023). *Unified theory of acceptance and use of technology: A review theoryhub book*. Retrieved from https://open.ncl.ac.uk/theory-library/unified-theory-of-acceptance-and-use-of-technology.pdf

Mhlanga, D. (2022). Digital transformation in education: Relevant paradigms and theories of teaching and learning in the industry 4.0. In Intelligent systems in digital transformation: Theory and applications. In (pp. 453-470). Cham: Springer International Publishing.

Momani, A. M. (2020). The unified theory of acceptance and use of technology: A new approach in technology acceptance. *International Journal of Sociotechnology and Knowledge Development, 12*(3), 79-98. https://doi.org/10.4018/IJSKD.2020070105

Monecke, A., & Leisch, F. (2012). semPLS: Structural equation modeling using partial least squares. *Journal of Statistical Software, 48*, 1-32. https://doi.org/10.18637/jss.v048.i03

Moore, J. L., Dickson-Deane, C., & Galyen, K. (2011). e-Learning, online learning, and distance learning environments: Are they the same? *The Internet and Higher Education, 14*(2), 129-135. https://doi.org/10.1016/j.iheduc.2010.10.001

Mpungose, C. B. (2020). Emergent transition from face-to-face to online learning in a South African University in the context of the Coronavirus pandemic. *Humanities and Social Sciences Communications, 7*(1), 1-9. https://doi.org/10.1057/s41599-020-00603-x

Muthuprasad, T., Aiswarya, S., Aditya, K. S., & Jha, G. K. (2021). Students' perception and preference for online education in India during COVID-19 pandemic. *Social Sciences & Humanities Open, 3*(1), 100101. https://doi.org/10.1016/j.ssaho.2020.100101

Park, S. Y., Nam, M. W., & Cha, S. B. (2012). University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model. *British Journal of Educational Technology, 43*(4), 592-605. https://doi.org/10.1111/j.1467-8535.2011.01229.x

Rabaa'i, A., Abu ALmaati, S., & Zhu, X. (2021). Students' continuance intention to use moodle: An expectation-confirmation model approach. *Interdisciplinary Journal of Information, Knowledge, and Management, 16*, 397–434. https://doi.org/10.28945/4842

Raes, A., & Depaepe, F. (2020). A longitudinal study to understand students' acceptance of technological reform. When experiences exceed expectations. *Education and Information Technologies, 25*(1), 533-552. https://doi.org/10.1007/s10639-019-09975-3

Rof, A., Bikfalvi, A., & Marques, P. (2022). Pandemic-accelerated digital transformation of a born digital higher education institution. *Educational Technology & Society, 25*(1), 124-141.

Salloum, S. A., Alhamad, A. Q. M., Al-Emran, M., Monem, A. A., & Shaalan, K. (2019). Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model. *IEEE Access, 7*, 128445-128462. https://doi.org/10.1109/ACCESS.2019.2939467

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2022). Partial least squares structural equation modeling in handbook of market research. In (pp. 587–632): Springer International Publishing. https://doi.org/10.1007/978-3-319-57413-4_15.

Sartika, F., Ritonga, M., Lahmi, A., Rasyid, A., & Febriani, S. R. (2021). Online learning in the low Internet area, planning, strategies and problems faced by students during the Covid-19 period. *Artificial intelligence for COVID-19*, 413-421. https://doi.org/10.1007/978-3-030-69744-0_23

Sridharan, B., Deng, H., & Corbitt, B. (2010). Critical success factors in e-learning ecosystems: A qualitative study. *Journal of Systems and Information Technology, 12*(4), 263–288. https://doi.org/10.1108/13287261011095798

Tenenhaus, M., Amato, S., & Esposito Vinzi, V. (2004). A global goodness-of-fit index for PLS structural equation modelling. *Proceedings of the XLII SIS Scientific Meeting, 1*(2), 739–742.

Tewari, A., Singh, R., Mathur, S., & Pande, S. (2023). A modified UTAUT framework to predict students' intention to adopt online learning: Moderating role of openness to change. *The International Journal of Information and Learning Technology, 40*(2), 130-147. https://doi.org/10.1108/IJILT-04-2022-0093

Vannoy, S. A., & Palvia, P. (2010). The social influence model of technology adoption. *Communications of the ACM*, *53*(6), 149-153. https://doi.org/10.1145/1743546.1743585

Veletsianos, G., Kimmons, R., Larsen, R., & Rogers, J. (2021). Temporal flexibility, gender, and online learning completion. *Distance Education*, *42*(1), 22-36. https://doi.org/10.1080/01587919.2020.1869523

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Wright, B. D., & Masters, G. N. (1982). *Rating scale analysis*. Chicago: MESA Press.

Ye, J., Zheng, J., & Yi, F. (2020). A study on users' willingness to accept mobility as a service based on UTAUT model. *Technological Forecasting and Social Change*, *157*, 120066. https://doi.org/10.1016/j.techfore.2020.120066

Zhang, Y. B., Zhang, L., & Kim, H. K. (2021). The effect of UTAUT2 on use intention and use behavior in online learning platform. *Journal of Logistics, Informatics and Service Science*, *8*(1), 67-81. https://doi.org/10.33168/liss.2021.0105