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Original Article

Adoption of Online Learning in Indonesian Higher Education during the COVID-19 Pandemic

Wayu Eko Yudiatmaja[1*], Yoserizal Yoserizal[2], Edison Edison[1], Dwi Kristanti[3], Krismena Tovalini[4], Tri Samnuzulsari[1], and Jalaluddin Abdul Malek[5]

Author Affiliation

[1] Assistant Professor, Faculty of Social and Political Sciences, Universitas Maritim Raja Ali Haji, Indonesia.
[2] Associate Professor, Faculty of Social and Political Sciences, Universitas Andalas, Indonesia.
[3] Assistant Professor, Faculty of Law, Social and Political Sciences, Universitas Terbuka, Indonesia
[4] Assistant Professor, STIA Adabiah, Indonesia.
[5] Associate Professor, Faculty of Social Sciences and Humanities, Universiti Kebangsaan Malaysia, Malaysia.

[*]Corresponding author e-mail: wayuguci@umrah.ac.id

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Abstract

This research aims to bridge the gap in the literature by investigating the factors affecting online learning adoption by the academic staff using the unified theory of acceptance and use of technology (UTAUT) model. Data were obtained through a survey of 342 lecturers at public universities in Indonesia from July to August 2021 and analyzed using a structural equation modeling approach. The results showed that social influence ($\beta = .14$, $p = .02$), facilitating conditions ($\beta = .41$, $p < 0.001$), and performance expectancy ($\beta = .30$, $p < 0.01$) related to behavioral intention, and behavioral intention affected lecturers' adoption of online learning while effort expectancy ($\beta = .03$, $p = .58$) had no significant effect on the lecturer's behavioral intention. Moreover, behavioral intention was observed to have mediated the effect of performance expectancy ($\beta = .04$, $p = .02$) and facilitating conditions ($\beta = .06$, $p = .01$) on the adoption of online learning but had no indirect effect on the effort expectancy ($\beta = .01$, $p = .69$) and social influence ($\beta = .02$, $p = .08$). These findings contribute to the behavioral science perspective through the application of the UTAUT model in the case of adopting online learning. Therefore, university administrators need to consider the main results when implementing online learning by focusing on the efforts to increase performance expectancy, effort expectancy, social influence, and facilitating conditions of the educators.

The coronavirus disease (COVID-19) pandemic faced by humankind around the globe transformed human life in several ways due to the restrictions implemented to prevent its spread. For example, the government issued several policies during COVID-19 which include working remotely, schooling from home, and lockdown. Health protocols were also implemented in different places such as wearing a mask, physical distancing, hands washing with soap, social distancing, and limited mobility (World Health Organization, 2020).

In March 2020, Indonesia also officially declared COVID-19 a pandemic in the country, thereby, the Ministry of Health issued a regulation to enforce learning from home in order to address the virus in the educational settings (Megatsari et al., 2020) as contained in *the Ministerial Regulation No. 9 the Year 2020* about large-scale physical restrictions procedures in handling COVID-19. It was noted that 290,650 lecturers out of 9,186,454 in 4,551 universities moved to online teaching and learning after the implementation of the policy (Ministry of Education, Culture, Research and Technology, 2022). In educational literature, this new system is known as digital learning, and it is a form of technology-assisted learning or teaching methodologies that provides effective learning environments. Digital learning includes electronic learning (e-learning) and mobile learning such that the e-learning entails the use of digital electronic tools and media to aid learning and mobile learning refers to electronic learning using technology and wireless transmission (Basak et al., 2018). Several scholars admitted that e-learning is widely similar to online learning (Singh & Thurman, 2019).

The acceptance and use of technology by the teaching staff are crucial in the implementation of online learning. Thongsri et al. (2019) investigated the emergence of a lecturer's ability in the process of imparting knowledge through online platforms and found that academicians have a variety of preferences and capabilities influencing their motivation to use a particular technology. It is important to note that academic staffs play a strategic role in delivering courses to ensure good learning outcomes in an online ecosystem. They need to have the capability and capacity to operate numerous online platforms sufficiently, such as the ability to use technology and implement multiple platforms for managing courses, even simultaneously. Therefore, the effectiveness of online learning applications relied on the academician’s acceptance and their use of technology devices (Zanjani et al., 2016).

Several theories of behavioral science explained the acceptance and use of technology for learning purposes, such as the motivational model (Deci & Ryan, 1985), social cognitive (Bandura, 1986), technology acceptance model (TAM) (Davis, 1989), personal computing usage (Thompson et al., 1991), diffusion of innovations (Rogers, 2003), theory of planned behavior (TPB) (Ajzen, 2011), theory of reasoned action (Fishbein & Ajzen, 2010), a combination of TAM-TPB (Taylor & Todd, 1995), and unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003, 2012). Dwivedi et al. (2020) explained that UTAUT is a leading theory commonly used by many scholars when analyzing technological usage in an educational context. It consists of numerous constructs that contribute to individual acceptance and use of technology, including performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and actual use. In this present research, the UTAUT framework is employed to examine the acceptance and use of online learning, specifically to scrutinize the nexus among social influence, effort expectancy, performance expectancy, facilitating conditions, behavioral intention, and online learning application.

The study of UTAUT in the context of online learning adoption is classified into three research streams, such as the perceptions of students and educators (Yahaya et al., 2022), consideration of developed and developing countries (Abbad, 2021; Thongsri et al., 2018), and the use of online learning before and after pandemic situation (Osei et al., 2022; Raza et al., 2021). This research contributes severally to the body of knowledge in behavioral science. First, it contributes to the UTAUT model by analyzing the case of online learning among university lecturers. It is important to note that much of this UTAUT research conducted by many scholars focused on students' perceptions in the promotion of technology application, while the analysis of teaching staff is still underdeveloped (Hu et al., 2020). Second, it concentrates on developing countries, specifically Indonesian universities, which have many problems with information and communication technology (ICT) development. It has been discovered that the majority of previous research focused on the approval and adoption of online learning in developed countries (Tarhini et al., 2017), with none conducted in developing countries. This is the reason Abbad (2021) argued that the examination of the UTAUT model needs to be extended to the developing countries. Therefore, the understanding of the adoption of online learning in developing countries is helpful as the focus is on Indonesia. Third, it focused on the online learning adoption during the COVID-19 crisis. Dhawan (2020) claimed that online learning was a solution for teaching and learning during the pandemic. Finally, this present research not only examines the direct effect of the antecedents of behavioral intention on online learning but also the indirect influences.

This research has three purposes in aiming to contribute; first, it uses the UTAUT model to investigate the direct effect of behavioral predictors on intention. Second, it analyzes the ability of behavioral intention to promote the application of online learning. Third, it examines the role of behavioral intention in mediating the behavioral predictors' impact on intention.

Literature Review

This section elucidates the main theories, concepts, and prior studies underpinning the association between four dimensions of the unified theory of acceptance and use of technology (UTAUT) and behavioral intention and adoption of online learning.

Theoretical Foundations

The UTAUT model was developed by Venkatesh et al. (2003) after reviewing several theories in behavioral sciences, such as theory of reasoned action (TRA), theory of planned behavior (TPB), technology acceptance model (TAM), and diffusion of innovation (DOI). These theories literally elucidated several dimensions that affect human behavior and attitude in performing specific actions. TRA postulates that behavior is driven by subjective attitudes and norms (Fishbein & Ajzen, 2010). Ajzen (2011) developed TRA by introducing perceived behavioral control as a predictor of human intention, known as TPB. Davis (1989) focused on the application of new systems and technologies by implementing TAM, while Rogers (2003) developed DOI. TAM considers perceived ease of use and perceived usefulness as determinants of behavioral intention while the diffusion of innovation theorized that behavioral intention was predicted by advantage, complexity, compatibility, observability, and trialability. Regarding UTAUT, Venkatesh et al. (2003) argued that individuals' motivation to receive and utilize new technology is extremely predisposed by their insights into the technology. This implies that the willingness to use technology is driven by individuals' belief that the technology can improve their performance and effectiveness when performing their tasks. Furthermore, Venkatesh et al. (2003) referred to previous theories in order to formulate several factors determining individuals' acceptance and use of technology, which include performance expectancy, effort expectancy, social influences, and facilitating conditions. These factors encourage individuals' intent to use a specific technology and also to enjoy its usage in the future.

Since its initial release, the UTAUT model has rapidly grown and has been used in various sectors, such as marketing, education, and finance. Venkatesh et al. (2012) developed the UTAUT model into UTAUT2, by adding several variables, which include hedonic motivation, price value, experience, and habit. This hedonic motivation is a key factor in determining public acceptance of new technology, and how much fun or pleasure individuals derive from using the tools at their disposal. Price value reflects users' primary perception of the difference between the potential benefits of the application and the financial cost of its usage. Experience refers to the possibility of using an intended technology, usually defined by the amount of time that has passed since an individual first used the technology. Habit is the degree to which individuals tend to immediately perform behavioral patterns as a result of their education. Moreover, Gunasinghe et al. (2020b) attempted to further develop UTAUT2 into UTAUT3 by adding a variable known as personal innovativeness. This is a consistent mental condition that motivates people to experiment with new technological advancements (Farooq et al., 2017), that has been tested as an antecedent, mediator, and moderator in diverse studies. This current model is still underdeveloped because many scholars are not interested in it, despite the fact that it has been utilized (Gunasinghe et al., 2020a; Tiwari et al., 2021).

The Effect of Performance Expectancy on Behavioral Intention

Venkatesh et al. (2003) defined performance expectancy as the stage at which users perceive that the utilization of information management practices can benefit their job outcomes and necessarily yield job effectiveness. It is important to note that Venkatesh et al. (2003) adopted performance expectancy from various constructs in several different theories, namely perceived usefulness from Davis (1989), extrinsic motivation from Davis et al. (1992), and job-fit from Thompson et al. (1991). In this present research, the performance expectancy is closely related to the lecturer's belief that online learning usage can boost their teaching performance and also serve as an impetus that increases learning performance and outcomes in the higher education system during COVID-19. During their seminal studies, Venkatesh et al. (2003, 2012) revealed that performance expectancy was the pivotal factor in determining behavioral intention. The theoretical assumptions linking performance expectancy and behavioral attention are supported by prior research, such as Teo and Noyes (2014), Hu et al. (2020), Alshammari (2021), and Sangeeta and Tandon (2021). Therefore, the following hypothesis is proposed.

H1: Performance expectancy has a positive effect on behavioral intention.

The Effect of Effort Expectancy on Behavioral Intention

Venkatesh et al. (2003) developed effort expectancy from TAM, specifically perceive ease of use, which refers to the level of comfort in using technology. The application of this online method changes teaching mechanisms, from direct to indirect teaching. Therefore, many teaching staffs, particularly the older individuals hoped for easy use of the new system. This system is crucial because of its applicability in online learning which encouraged the lecturers to continue using this system, not only for teaching but also for all academic purposes. It is important to note that previous scholars suggested a significant influence of effort expectancy on lecturers' behavioral intention (Dakduk et al., 2018; Durak, 2019; Jameel et al., 2022) thereby leading to the following hypothesis:

H2: Effort expectancy has a positive effect on behavioral intention

The Effect of Social Influence on Behavioral Intention

Social influence is measured by individuals' recognition of other people's beliefs concerning their use of technology (Venkatesh et al., 2003). The support or recommendation from others such as nuclear families, supervisors, and coworkers serve as a notable consideration for lecturers to take advantage of online learning. Prior findings that pointed out the effect of social influence on the behavioral intention of lecturers in using online learning include Buabeng-Andoh and Baah (2020), Kim and Lee (2020), Rahman et al. (2021), and Wijaya et al. (2022). Regarding these theories and empirical evidence, the following hypothesis was formulated as follows:

H3: Social influence has a positive effect on behavioral intention.

The Effect of Facilitating Conditions on Behavioral Intention and Adoption of Online Learning

Venkatesh et al. (2003) highlighted that facilitating conditions are situations where people assume that an organization possesses the necessary facilities to accommodate any use of technology. This is extremely related to all the lecturer's resources in the implementation of online learning, including hardware and software. According to Altalhi (2021), technical infrastructures, such as laptops, tablets, smartphones, earphones, and the internet are an essential part of the online learning context because the adequacy of these facilities serves as a motivation to use online learning. Furthermore, lecturers' knowledge and capacity to entirely operate online platforms are also essential in affecting their motivation to adopt online learning. Venkatesh et al. (2003, 2012, 2016) elucidated that these facilitating conditions do not only affect behavioral intention but also the adoption of online learning. Prior studies that investigated the positive and significant impact of facilitating conditions on behavioral intention and educators' intention to adopt online learning include Herting et al. (2020), Hu et al. (2020), and Gunasinghe and Nanayakkara (2021). Consequently, the following hypotheses were proposed:

H4: Facilitating conditions positively affect behavioral intention.
H5: Facilitating conditions positively affect the adoption of online learning.

The Effect of Behavioral Intention on the Adoption of Online Learning

Behavioral intention is defined as a situation whereby an individual made intentional decisions about whether or not to conduct something in the long term (Venkatesh et al., 2003). Furthermore, Venkatesh et al. (2003, 2012, 2016) investigated the effect of users' behavioral intentions on online learning adoption and found that behavioral intention elevates online learning applications. Several scholars also discovered a positive connection between the behavioral motive and the actual application of online learning by the academicians (Gunasinghe et al., 2020b; Sangeeta & Tandon, 2021; Tiwari et al., 2021). Therefore, the hypothesis is proposed as:

H6: Behavioral intention has a positive effect on the adoption of online learning.

The Mediating Effect of Behavioral Intention

Venkatesh et al. (2003, 2012) theorized the direct effect of UTAUT dimensions on behavioral intention and use behavior. In the earlier model, Venkatesh et al. (2003) proposed that performance expectancy, effort expectancy, and social expectancy had a direct effect on behavioral intention while facilitating conditions are linked to user behavior. Venkatesh et al. (2012) further revised the earlier model into UTAUT-2 by adding new predictors and prepositions. In this UTAUT-2, Venkatesh et al. (2012) postulated that performance expectancy, effort expectancy, social expectancy, and facilitating conditions had an impact on behavioral intention. Furthermore, facilitating conditions, hedonic motivation, price value, and habit were associated with user behavior while behavioral intention affected user behavior. Moreover, Venkatesh et al. (2003, 2012) had not conceptualized the indirect effects of behavioral intention predictors on user behavior but Venkatesh et al. (2012) posited a variety of demographical backgrounds, such as age, gender, and experience as a moderator in buffering the relationship between facilitating conditions, hedonic motivation, price value, habit, and user behavior.

It is important to note that Venkatesh et al. (2003, 2012) did not originally design the mediation, meanwhile, recent findings have promoted various mediators from the model in the case of online learning. Dwivedi et al. (2019) conducted a meta-analysis of UTAUT's research from 162 papers and found that attitude is a mediating condition in the impact of social influence and facilitating conditions on behavioral intention. Altalhi (2021) used UTAUT to shed light on the factors determining the adoption of online courses in Saudi Arabia and revealed that attitude plays a mediating role in the nexus between performance expectancy and actual use. Twum et al. (2021) analyzed e-learning applications in higher education during COVID-19 and suggested that performance expectancy had a mediating impact on the relationship between personal innovativeness and intention. Based on this theoretical point of view and previous studies, the following hypotheses were proposed:

H7: The effect of performance expectancy on the adoption of online learning is mediated by behavioral intention.
H8: The effect of effort expectancy on the adoption of online learning is mediated by behavioral intention.
H9: The effect of social influence on the adoption of online learning is mediated by behavioral intention.
H10: The effect of facilitating conditions on the adoption of online learning is mediated by behavioral intention.

Method

Participants

This research was conducted at a public university in Indonesia because it is one of the public universities in the country that enormously implement online learning during COVID-19 through a learning management system (LMS), that has been used even before the pandemic. The populations are the permanent lecturers in the university across the department, the field of study, faculty, school, and graduate. Data were gathered from 342 lecturers using a purposive sampling approach from July to August 2021. Among these staff, the majority of the respondents were male indicating 60.12% and those from socio-humanities subject are 48.67%, while 37.18% of them are between 41 to 51 years old. Most of these participants' experience in teaching and research was in the range of 11-15 years indicating 28.03%, while those having Ph.D. qualifications are 65%, associate professors are 37.86%, and assistant professors are 32.86%, as illustrated in Table 1.

Table 1
Respondent's Profile

Variable	Item	Frequency	Percentage
Sex	Male	206	60.12
	Female	136	39.88
Age	< 30 years old	34	10.04
	31-40 years old	83	24.40
	41-50 years old	127	37.18
	51-60 years old	62	18.06
	> 60 years old	35	10.32
Tenure	< 5 years	35	10.10
	5-10 years	90	26.45
	11-15 years	96	28.03
	16-20 years	69	20.25
	> 20 years	52	15.17
Academic Position	Lecturer	90	26.46
	Assistant Professor	112	32.86
	Associate Professor	128	37.55
	Professor	11	3.13
Subject	Science and Technology	97	28.47
	Social and Humanities	166	48.67
	Health	78	22.86

Instruments

Measurement items were entirely adopted from Venkatesh et al. (2003), and the indicators had been validated by prior research in developing countries, such as Sri Lanka (Gunasinghe et al., 2020a) and India (Tiwari et al., 2021). It is important to note that this present research had six variables in total, which include performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and online learning application. Based on Table 2, each variable had four items with 24 positive questions or statements in total.

Furthermore, confirmatory factor analyses were conducted using structural equation modeling with AMOS 24.0 software because it was important to ensure the validity and reliability of the data before analyzing the data. Convergent validity, discriminant validity, and internal consistency were therefore applied in measuring the validity and reliability. The convergent validity was inspected using average variance extracted (AVE), while reliability was examined to identify whether the data have internal consistency or not. Cronbach's alpha (α) and composite reliability (CR) were computed to ensure internal consistency. The AVE is greater than .50 (Fornell & Larcker, 1981), and since Cronbach's alpha and composite reliability exceed .70, the data meet internal consistency (Yudiatmaja, 2019). Performance expectancy was measured to determine the ability of online to improve lecturers' performance in teaching and learning. It consisted of four items. It was valid and reliable (AVE = .64, Cronbach's α = .90, CR = .88). Effort expectancy evaluated the opportunity for the usability of the system comprising four statements.

It was valid and reliable (AVE = .65, Cronbach's α = .92, CR = .88). Social influence analyzed the effect of other people on the lecturer's decision to use online learning. It comprised four items. It was valid and reliable (AVE = .68, Cronbach's α = .94, CR = .86). Facilitating conditions refer to the resources owned by the lecturer in implementing online learning. It included four items. It was valid and reliable (AVE = .63, Cronbach's α = .52, CR = .87). Behavioral intention examined the lecturer's tendency to use online learning in the future comprising four items. It consisted of four, but two items were removed from the model because its standardized factor loadings were less than 0.5. The rest of the items were valid and reliable (AVE = .66, Cronbach's α = 1.32, CR = .78). The adoption of online learning is described as the actual behavior of the lecturer regarding the use of online learning during COVID-19. It comprised four items. It was valid and reliable (AVE = .62, Cronbach's α = .80, CR = .87).

The questionnaire items that are in English were translated into the Indonesian language using back-to-back translation, as recommended by Brislin (1988) and Yudiatmaja, Edison, et al. (2021) to ensure content validity. Respondents were asked to answer these items in the questionnaire based on their preferences using five Likert scales, including (1) strongly disagree, (2) disagree, (3) moderate, (4) agree, and (5) strongly agree. After conducting confirmatory factor analysis, two items were deleted from behavioral intention because factor loadings were lower than the rule of thumb of .50 as shown in Table 2.

Procedure

A survey approach was used to collect data through a self-administered questionnaire which was distributed in the late second semester of the 2019/2020 academic year to obtain respondents' opinions. The questionnaire was provided in an online version through Google docs because of the COVID-19 pandemic and was distributed through the official WhatsApp group account of the university's management, such as faculty, school, and graduate school management. Based on the data from the Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia (2022), the number of permanent lecturers at the university was 1,489 persons. The progress of the data collection was evaluated monthly which includes the equality of the questionnaire distribution in three fields of studies, specifically science and technology, health, as well as social and humanities. In total, three evaluations were conducted every two months at three different times, specifically during the first, middle, and last semester. Based on the evaluation of the last semester, only 243 responses were collected and distributed via WhatsApp message to contact some other colleagues in different departments, faculty, and school at the university to obtain a maximum response. This strategy was very effective in increasing the number of filled-out questionnaires. Subsequently, 342 valid questionnaires were successfully obtained with a response rate of 21.76%. This number was satisfactory for behavioral science research (Hendra & Hill, 2019), specifically during the COVID-19 period.

Ethical Considerations

This research fulfilled strictly ethical clearance in the data collection process because it relates to humans. Before conducting the initial survey, the ethical clearance and study protocol by the ethical committee of the Faculty of Social and Political Sciences, Andalas University were applied to obtain ethical approval with Reference No. 001/04/Ethical-Committee/2021, date 14 June 2021. It is important to note that informed consent was provided at the beginning of the questionnaire due to the use of an online survey, and data were only collected from respondents that are willing to participate in the research. This implies that the individuals that are not willing to participate are permitted to opt-out of the survey. Therefore, all respondents in this study agreed with informed consent.

Results

Descriptive Analysis

The descriptive statistics of each item are elucidated in Table 2, where the mean, standard deviation (SD), and standardized factor loadings (SFL) have been calculated. These results showed that the mean of each variable ranged from 3.20 to 3.38, thereby, indicating that the respondents gave a positive response and are averagely satisfied with the indicators. The standard deviation is narrowly spread around the mean, ranging from .59 to .80. The results of the mean and standard deviation of UTAUT's items are very similar to Reyes et al. (2022). However, it is in contrast to Garone et al. (2019) and Gunasinghe and Nanayakkara (2021) that revealed the mean and standard deviation of UTAUT's dimensions to be above 3.60. Based on CFA's results, the SFL of all items ranged from .73 to .85, thereby indicating a good convergent validity because the SFL was above .70 as suggested by Hair et al. (2010).

Table 2

Mean, Standard Deviation, and Standardized Factor Loading of Each Measurement Item

Construct and Item	Mean	SD	SFL
Performance Expectancy (PE)			
PE1: Online learning helps the learning process during the pandemic	3.25	.73	.80
PE2: The teaching process can be improved by using online learning	3.27	.71	.82
PE3: Online learning can help improve student performance	3.29	.80	.82
PE4: Online learning can help record an assessment of students	3.31	.72	.77
Effort Expectancy (EE)			
EE1: Lecturer-student interaction through online learning runs clearly	3.27	.73	.82
EE2: Teaching using online learning is easy	3.23	.70	.84
EE3: The use of online learning can be learned easily	3.28	.77	.81
EE4: Online learning features can be used easily	3.32	.73	.77
Social Influence (SI)			
SI1: My family advised me to use online learning	3.28	.79	.85
SI2: My colleagues motivate me to use online learning d	3.27	.76	.85
SI3: Colleagues who I respect encourage me to use online learning	3.28	.76	.83
SI4: Overall, the university supports to use of online learning	3.31	.76	.77
Facilitating Conditions (FC)			
FC1: I have sufficient facilities to use online learning	3.32	.69	.70
FC2: I have the necessary knowledge to use online learning	3.27	.71	.77
FC3: Help is available if I have problems using online learning	3.35	.76	.80
FC4: Online learning according to various technologies	3.25	.74	.82
Behavioral Intention (BI)			
BI1: I intend to continue using online learning in the future	3.34	.73	.84
BI2: I will always attempt to use online learning	3.38	.69	.78
Adoption of Online Learning (AO)			
AO1: I use online learning regularly	3.20	.69	.83
AO2: I prefer to use online learning rather than face to face	3.20	.66	.79
AO3: Currently I am still using online learning	3.21	.59	.73
AO4: Most of my lectures use online learning	3.26	.73	.82

Note. SD, standard deviation; SFL, standardized factor loadings

Measurement Model Assessment

The model appropriateness was measured to determine whether the model fitted with the data. Also, the goodness-of-fit of the data was checked using several parameters such as chi-square (χ^2), degrees of freedom (df), chi-square/degrees of freedom (χ^2/df), normed fit index (NFI), comparative fit index (CFI), Tucker Lewis Index (TLI), and root-mean-square error of approximation (RMSEA). To fulfill the goodness of fit, the data need to pass these parameters as suggested by structural equation modeling scholars, which include the *p*-value of χ^2 must be higher than .05 (Kline, 2015), χ^2/df need to be lower than 2.00 (Bagozzi & Yi, 1988), NFI must be higher than .90, CFI ought to be greater than .90, TLI must be above .90, and RMSEA need to be less than .08. Meanwhile, the data revealed that $\chi^2 = 243.74$ with $p < 0.01$, df = 194,

χ^2/df = 1.26, NFI = .95, CFI = .99, TLI = .99, and RMSEA = .03. The results of the goodness-of-fit measurement and the thresholds were presented in Table 3.

Confirmatory factor analyses (CFA) using SEM were conducted before analyzing the data. It was important to ensure the validity and reliability of the data before further analysis. We applied convergent validity, discriminant validity, and internal consistency to measure the validity dan reliability. Convergent validity was inspected using standardized factor loadings (SFL) for each item and average variance extracted (AVE). Reliability was examined to identify whether the data have internal consistency or not. Composite reliability using Cronbach's alpha was computed to ensure internal consistency. Based on CFA's results in Table 2, the SFL of all items ranged from .73 to .85. All items showed good convergent validity because the SFL was above .70 as suggested by Hair et al. (2010).

Table 3

Goodness-of-Fit Measures of the Full Model

Parameter	Cut-off Value		Calculated Value	
	Requirement	Reference	Results of This Study	Interpretation
χ^2	$p > 0.05$	Kline (2015)	243.74**	Good
df	n.a	n.a	194	n.a
χ^2/df	<2.00	Bagozzi and Yi (1988)	1.26	Good
NFI	>.90	Byrne (2016)	.95	Good
CFI	>.90	Kline (2015)	.99	Good
TLI	>.90	Hair et al. (2010)	.99	Good
RMSEA	<.08	Kline (2015)	.03	Good

Note. n.a means not available; ** $p < 0.01$

Table 4

Inter-Correlations among the Constructs

Construct	Correlations Matrix					
	1	2	3	4	5	6
(1) Performance Expectancy	**.80**					
(2) Effort Expectancy	.21***	**.80**				
(3) Social Influence	.36***	.31***	**.82**			
(4) Facilitating Conditions	.73***	.30***	.40***	**.79**		
(5) Behavioral Intention	.62***	.25***	.40***	.67***	**.81**	
(6) Adoption of Online Learning	.68***	.28***	.38***	.71***	.69***	**.79**

Note. *** represents significance at the level .001 ($p < 0.001$). The bold value in the diagonal is the square root of AVE

Table 4 shows the bivariate correlations among the constructs. It was observed that all the relationships among variables have strong bivariate correlations because p-values were less than .001, thereby indicating that all relationships were positively and strongly correlated. The relationships with robust correlations include performance expectancy and facilitating conditions (r = .73, p < 0.001), facilitating conditions and adoption of online learning (r = .71, p < 0.001), behavioral intention and adoption of online learning (r = .69, p < 0.001), performance expectancy and adoption of online learning (r = .68, p < 0.001), facilitating conditions and behavioral intention (r = .67, p < 0.001), as well as performance expectancy and behavioral intention (r = .62, p < 0.001). Furthermore, the square root of AVEs in diagonal values was higher than off-diagonals in the correlation among the variables, indicating that the data adequately met discriminant validity (Yudiatmaja, Salomo, et al., 2021).

Structural Model Assessment

In this study, the structural model was evaluated utilizing SEM with a maximum likelihood technique prediction. The structural model fit indices were calculated before testing the hypotheses and the following results were obtained, $\chi^2 = 251.42$ ($p < 0.01$), df = 197, χ^2/df = 1.28, NFI = .95, CFI = .99, TLI = .99, and RMSEA = .03. These results exhibit satisfactory fit indices in terms of the goodness indices criterion required by the scholars as discussed in the measurement model assessment.

The research hypothesis was later calculated using SEM with 5,000 bootstrapped sample and 95% confidence interval (CI) (Hayes, 2018). The results of hypotheses assessment were summarized in Table 5, which consist of the coefficient or Beta (β), 95% bias corrected-confidence interval (CI), *t*-value, and conclusion. The 95% CI was utilized because the path coefficient and *t*-value were insufficient to determine the hypothesis as proposed by Hair et al. (2010). The SEM's results indicate that the performance expectancy has a positive and significant effect on behavioral intention (β = .30, $t = 3.14$, $p < 0.01$) (95% CI = .07, .50), therefore H1 was approved. The effort expectancy has no significant effect on behavioral intention (β = .03, $t = .56$, $p = .58$) (95% CI = -0.12, .20), thereby causing H2 to be rejected. Social influence positively and significantly impacts behavioral intention (β = .14, $t = 2.27$, $p = .02$) (95% CI = -.00, .29), hence H3 was accepted. Facilitating conditions had a positive and significant impact on behavioral intention (β = .41, $t = 4.37$, $p < 0.001$) (95% CI = .24, .63) and adoption of online learning (β = .76, $t = 11.45$, $p < 0.001$) (95% CI = .63, .92), thereby confirming H4 and H5. Behavioral intention (β = .14, $t = 2.52$, $p = .01$) (95% CI = .03, .25) had a positive and significant effect on adoption of online learning, thereby justifying H6.

Table 5
Hypotheses Testing

Hypothesis	Path	Coefficient	CI (95%)	*t* value	*p* value	Result
H1	PE → BI	.30	[.07, .50]	3.14^{**}	.00	Accepted
H2	EE → BI	.03	[-0.12, .20]	.56	.58	Rejected
H3	SI → BI	.14	[-0.00, .29]	2.27^{*}	.02	Accepted
H4	FC → BI	.41	[.24, .63]	4.37^{***}	***	Accepted
H5	FC → AO	.76	[.63, .92]	11.45^{***}	***	Accepted
H6	BI → AO	.14	[.03, .25]	2.52^{*}	.01	Accepted

Note. * Significance at the level .05 ($p < 0.05$); ** Significance at the level .01 ($p < 0.01$); *** Significance at the level .001 ($p < 0.001$); Critical *t* value is 1.96; PE, performance expectancy; EE, effort expectancy; SI, social influence; FC, facilitating conditions; BI, behavioral intention; AO, adoption of online learning

Table 6 shows that the total effect of connection was counted from the amount of direct and indirect effects among the studied constructs. It was observed that the total effect of social influence, effort expectancy, performance expectancy, and facilitating conditions were .34, .04, .16, and .47 respectively. The data shows that effort expectancy has the smallest total effect compared to others. It is important to note that the significance of the indirect effect of the relationship among the studied variables through behavioral intention was tested using Hayes and Preacher's (2014) guidelines. The results indicate that the relationship between performance expectancy and adoption of online learning is mediated by behavioral intention (β = .04, $t = 1.97$, $p = .02$) (95% CI = .01, .10), thereby indicating that H7 was accepted. Behavioral intention also mediates the connection between facilitating conditions and adoption of online learning (β = .06, $t = 2.19$, $p = .01$) (95% CI = .02, .12), which confirmed H10. Meanwhile, this behavioral intention has no mediating effect in the relationship between effort expectancy and adoption of online learning (β = .01, $t = .54$, $p = .69$) (95% CI = -0.01, .04), as well as social influence and adoption of online learning (β = .04, $t = 1.68$, $p = .08$) (95% CI = .01, .05), indicating that H8 and H9 were rejected.

Table 6
Direct, Indirect, and Total Effect

Hypothesis	Path	Direct Effect	Indirect Effect	CI (95%)	*p* value	Total Effect
H7	PE → BI → AO	.30**	.04*	[.01, .10]	.02	.34
H8	EE → BI → AO	.03	.01	[-0.01, .04]	.69	.04
H9	SI → BI → AO	.14*	.02	[.01, .05]	.08	.16
H10	FC → BI → AO	.41***	.06*	[.02, .12]	.01	.47

Note. * Significance at the level .05 ($p < 0.05$); Critical *t*-value is 1.96; PE, performance expectancy; EE, effort expectancy; SI, social influence; FC, facilitating conditions; BI, behavioral intention; AO, adoption of online learning

Discussion

This research aims at examining the use of online learning by using the unified theory of acceptance and use of technology (UTAUT) model from the educators' perspective. It investigates the link between four constructs of UTAUT and behavioral intention and adoption of online learning. Also, it explores the mediating role of behavioral intention in the linkage. From the results, this study notes several key points to be discussed. First is the performance expectancy, which plays a key role in leveraging behavioral intention. In this scenario, the lecturer's desire for optimum performance in the teaching and learning process was the reason for the use of online learning. Therefore, the expectation of maximizing performance tends to encourage an online learning system. This result is in line with the findings of Teo and Noyes (2014), Hu et al. (2020), Alshammari (2021), and Sangeeta and Tandon (2021) that performance expectancy has a significant impact on the behavioral intention of academic staff in adopting online learning. However, the results do not conform with that of previous studies by Herting et al. (2020) and Rahman et al. (2021) because they claimed that performance expectancy had no direct effect on lecturers' intention to use online learning.

Furthermore, this result shows that effort expectancy has no significant impact on behavioral intention reason being that the key role of effort expectancy in predicting online learning requires few exceptions for the academic staff. In this situation, the lecturers do not perceive the ease of use of the new system as a crucial factor in its adoption. This finding is in contrast with the UTAUT model developed by Venkatesh et al. (2003, 2012, 2016) which asserts the crucial role of expectation endeavor in determining behavioral intention. However, the result is similar to previous studies, such as Šumak and Šorgo (2016), Hu et al. (2020), and Sangeeta and Tandon (2021). Šumak and Šorgo (2016) found an insignificant effect of effort expectancy on teachers' behavioral intention to use interactive whiteboards in Slovenia. Meanwhile, Hu et al. (2020) explained that effort expectancy has an insignificant effect on mobile learning adoption among lecturers in China. Sangeeta and Tandon (2021) also showed that effort expectancy is not sufficient enough to explain the behavioral intention and use of online teaching in India.

Results showed that social influence has the lowest impact on online learning, even though the relationship is still significant. This also confirmed the findings of previous studies such as Kim and Lee (2020), Buangeng-Andoh and Baah (2020), Rahman et al. (2021), and Wijaya et al. (2022). Moreover, Kim and Lee (2020) showed that social influence can predict the adoption of ICT-based classes among Filipino teachers. Buangeng-Andoh and Baah (2020), in their research conducted in Ghana, found that social influence is connected to the intention to use a learning management system by pre-service teachers. Rahman et al. (2021) explained that behavioral intention to use flipped studying among Malaysian lecturers was notably determined by the societal environment. Sangeeta and Tandon (2021) pointed out that social influence has a significant effect on the behavioral intention of Singaporean teachers in using online teaching. Wijaya et al. (2022) sought the application of micro-lecturer among the teachers in China and found that social influence was the greatest predictor of behavioral intention. However, these results differ from the research that found that social influence had no significant effect on behavioral intention to adopt e-learning among universities lecturer (Herting et al., 2020; Jameel et al., 2022).

Further, this research found that facilitating conditions have the highest effect on lecturers' acceptance of online learning. For example, the availability and adequacy of resources in using electronic learning strongly affect the lecturer's behavioral intention and use. This result confirms previous research that highlights the positive contribution of facilitating conditions on the behavioral intention of teaching staff to adopt online learning, such as Hu et al. (2020), Herting et al. (2020), Gunasinghe and Nanayakkara (2021), and Sangeeta and Tandon (2021). Herting et al. (2020) found that facilitating conditions influenced the behavioral intention of professors in Spain. Meanwhile, Gunasinghe and Nanayakkara (2021) demonstrated the significant role of facilitating conditions in elevating lecturers' intention to use virtual learning in Sri Lanka. However, various results obtained previously showed an insignificant influence of facilitating conditions on behavioral intention, such as Teo and Noyes (2014), Alshammari (2021), and Rahman et al. (2021).

This research discovered that behavioral intention affects the actual use of online learning. In this scenario, the lecturer's intention influences their willingness to thoroughly use online learning for academic purposes in higher education. This result is in line with several findings that show a positive and significant relationship between intention to use and online learning acceptance, such as Gunasinghe et al. (2020b) that found the significant impact of behavioral intention on the user behavior of virtual learning in the case of Sri Lankan lecturers. Tiwari et al. (2021) also revealed that behavioral intention significantly predicted the effect of behavioral intention on the manner of technology adoption during COVID-19 by the teachers in India.

The mediating role of behavioral intention in the relationship among facilitating conditions, social influence, performance expectancy, and online learning application was also highlighted. However, the mediating effect of behavioral intention in the connection between effort expectancy and online learning has not been discovered. The results complement the UTAUT model evolved by Venkatesh et al. (2003) because they had never examined its indirect effect. Also, subsequent research has failed to pay attention to the problem rather than expanding the theory (Tamilmani et al., 2021).

Limitations and Future Research

This research has several limitations and these include, first, a classical UTAUT model developed by Venkatesh et al. (2003) was used but it has been extended into UTAUT 2 (Venkatesh et al., 2012) and UTAUT3 (Gunasinghe et al., 2020b). Several constructs were introduced into the new model such as hedonic motivation, price value, habit, and personal innovativeness. In the future, analyses of these new variables are needed when studying online learning in order to complete this knowledge of the UTAUT model. Second, this research did not identify the potential moderators in the relationships, such as gender, age, tenure, experience, etc. Meanwhile, the assessment of these variables is essential to conceive the function of dummy and moderating variables in using an online system for teaching and studying (Hu et al., 2020). Third, this research only focused on one public university, thereby causing the prediction power of the analysis to be very limited. Therefore, comparative research between public and private universities even across the countries is needed in order to broaden the investigation. Finally, it performed a quantitative analysis to examine the acceptance and use of online learning. Quantitative methods are sufficient to test different independent and dependent variables without understanding the meaning and reason behind the variables. This issue is solely addressed by a qualitative approach (Yudiatmaja et al., 2018; Yudiatmaja, Kristanti, et al., 2021), thereby, indicating the high demand for this method in the future.

Implications for Behavioral Science and Conclusion

Academic Contributions

The results point to several implications for the theory and practice. In terms of behavioral science, this study contributes in two ways, first is that it corroborates the theory of UTAUT by providing a case of online learning among the professional teaching staff of higher education in a developing country. It confirms that the UTAUT dimensions are sufficiently acceptable not only in developed but also in developing countries. Second, the research contributes to the understanding of UTAUT by focusing on the COVID-19 pandemic.

Practical Contributions

Considering the practical perspective, this research shows that facilitating conditions have a greater impact on behavioral intention and lecturers' motivation to use online learning during the COVID-19 period. Therefore, the government and university administrators need to pay special attention to the availability of digital devices, such as laptops, the internet, smartphones, tablets, etc. not just in number, but also the capacity to use every device. The university's management also needs to provide several tools required by the lecturer to apply digital teaching during COVID-19 and the supporting staff in every faculty to assist any lecturer facing technical problems regarding online learning. This assistance is essential to increase lecturers' confidence in the effectiveness of online learning usage as an academic tool.

Conclusion

This current research examines the lecturer's intention to use and adopt online learning using the UTAUT model. Specifically, the effect of performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention on online learning applications was examined. The results show that performance expectancy, social influence, facilitating conditions, and behavioral intention have a positive and significant influence on the adoption of online learning meanwhile, effort expectancy has no positive impact on behavioral intention. Furthermore, it shows the mediating effect of behavioral intention in the nexus between performance expectancy and adoption of online learning, social influence, and online learning, as well as facilitating conditions and online learning but the behavioral intention has no mediating impact on the effect of effort expectancy and social influence on online learning adoption.

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