Eurasian Journal of Educational Research 104 (2023) 243-266

Eurasian Journal of Educational Research
www.ejer.com.tr

Exploring UTAUT Factors on Lecturers' Adoption of Online Classes During Covid-19 Pandemic

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ARTICLE INFO

Article History:
Received: 10 December 2022
Received in revised form: 15 February 2023
Accepted: 09 April 2023
DOI: 10.14689/ejer.2023.104.014

Keywords
UTAUT, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Attitude, Behavioral Intentions, Quality Education, Online Class During Covid

ABSTRACT

Objective: This study aimed to identify the factors that encourage university lecturers to adopt online courses during the COVID-19 pandemic by studying their perceptions, attitudes, and behavioral intentions **Method/Design:** Data collected through applying convenient sampling technique from 166 voluntary respondents. Based on the exploratory structure, the data were validated using an Equation Model (ESEM), and recent adoptions of respondents were graphed and reported. Used both of quantitative and qualitative analysis result in their analysis. **Findings:** Quantitative analysis results indicates that Respondents' attitudes toward adopting online courses were significantly influenced by their performance expectations, effort expectations, and facilitating conditions. Furthermore, effort expectancy and social influence positively affected the behavioral intention to adopt online courses. Qualitative analysis results indicates that government's mandatory online learning policy was beneficial, but needed to be implemented effectively. They also encountered challenges related to paucity and need for stability, capacity, and ability. **Implications:** The researchers suggested that equitable access to online learning should be addressed to ensure that teachers' and students' needs are met adequately. There is significant significance in the study's results, which could assist in improving the adoption of online courses. These findings will benefit stakeholders, policymakers, and administrators in adapting to online teaching during this pandemic. **Originality/value**: This study investigate in the unexplored territory of lecturer adoption from both of quantitative and qualitative perspective, shedding light on pivotal determinants in this transformative educational shift.

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1. Introduction

The COVID-19 pandemic has caused a sudden disruption in the education system, leading to widespread adoption of online classes. Although this has been a necessary measure to ensure safety, recent studies have shown that online courses have become controversial. Social scientists are now interested in understanding the factors that encourage lecturers to perceive, intend, or adopt online teaching positively. Technology-acceptance models have been developed to establish these factors. These models follow the fundamental premise that external factors cause individual reactions, which in turn cause intentions and, finally, the actual usage of technology. While these models may vary in structure, they seek to understand the underlying factors contributing to user acceptance of technology (Venkatesh et al., 2003).

Before the pandemic, several studies were conducted in higher education to identify the factors that led university lecturers to adopt online classes. These studies have consistently validated their findings through empirical evidence (Mei, Brown, & Teo, 2018; Mosunmola et al., 2018; Tseng et al., 2022). Multiple studies have delved into the intricate relationship between various factors associated with attitude and intention, specifically within the context of the ongoing pandemic. Researchers Lazim, Ismail, and Tazilah (2021) have examined the theorized factors related to attitude, while Tiwari (2020) has explored factors concerning intention. Building upon these investigations, Samat et al. (2020) have further explored the implications of these factors in the current global health crisis. Despite these notable efforts, some studies have not yet reached uniform theoretical explanations regarding this topic (Tandon & Kiran, 2019). The absence of a consensus suggests that the relationship between attitude and intention within the scope of the pandemic remains an area requiring further inquiry (Chayomchai et al., 2020; Sangeeta & Tandon, 2021). Consequently, additional research is warranted to unravel the intricate web of factors that contribute to individuals' attitudes and intentions amidst the pandemic's unique circumstances.

This model integrates factors from previous acceptance theories, which are then organized into similar constructs using the Unified Theory of Acceptance and Use of Technology (UTAUT). There are four exogenous variables in this model that are significantly influencing the two endogenous variables (Venkatesh, Thong, & Xu, 2012). There are also four moderators involved in this model (Dwivedi et al., 2019). Additionally, there are iterations, including the extended UTAUT and revised UTAUT (Sangeeta & Tandon, 2021), which have been adapted for specific situations (Tandon & Kiran, 2019; Tseng et al., 2022; Venkatesh et al., 2003).

In this study, we examined whether revised UTAUT factors would influence lecturers' behavioral intentions toward taking online courses during COVID-19. Several members of the Rajamangala University of Technology, Tawan-ok, responded voluntarily. This study examined lecturers' perceptions regarding their recent adoption of online classes in light of the government's recent initiatives for online instruction (Mala, 2020, 2021).

Investigating technological adoption in the context of online classrooms is the goal of this study. Understanding the elements that affect people's attitudes and intentions to participate in online education is essential given its increasing ubiquity. Through reviewing the pertinent literature, devising a sound methodology, presenting the findings, and providing a detailed analysis of the components that foster a positive mindset and intent to behave regarding online classes, the investigation seeks to add to the body of current research. Furthermore, the study aimed to contribute to better and smoother mitigation of online teaching during this pandemic by university stakeholders, policymakers, and administrators. The study was divided into four next chapters, literature review, research methodology, data analysis and interpretations, discussion and future recommendations.

2. Literature Review

2.1 Theoretical Model

An examination of lecturer behavioural intentions to adopt online classes during COVID-19 was conducted in this study by examining revised UTAUT factors. Researchers conducted a survey of voluntary respondents from Rajamangala University of Technology, Tawan-ok, and multiple victims of the pandemic. This study examined how lecturers perceived their recent adoption of online classes, considering the government's recent push to increase online learning.

The behaviours of users and acceptance of new technologies has been the subject of several separate theoretical frameworks. The 'Theory of Reasoned Action' contends that one's conduct is influenced by their behavioural aim, attitude, and subject norm. According to the Model, a technology's utility and usability influence its level of user adoption. Another model also takes behavioural intention and control perceptions into account. A number of other models have been put out, including the Motivational Model, the Combined TAM & TPB Model, the Model of PC Utilization, and the Innovation Diffusion Theory. Taylor and Todd (1995), Davis, Bagozzi, and Warshaw (1992), Thompson, Higgins, and Howell (1991), Moore and Benbasat (1991), and Compeau and Higgins (1995) are just a few of the studies that have been done on these models throughout the years and are continually being developed to better understand consumer acceptability and technology utilization.

Recently, some interesting studies have been published regarding educators' sudden shift to online teaching. One such study, conducted by Todd (2020), focused on schoolteachers' perceptions of this transition during the COVID-19 pandemic. Various factors influence schoolteachers' adoption of online instruction according to a study published by Sangeeta and Tandon (2021). It is fascinating to see how quickly and effectively teachers adapt to technology in their classrooms. As the pandemic continues, it will be interesting to see more studies using theoretical models to understand the factors driving this sudden acceptance of technology.

The 'Unified Theory of Acceptance and Use of Technology' (UTAUT) is a theoretical framework that was described by Venkatesh et al. (2003). It also highlights supportive environments, societal impacts, and performance expectations in addition to merging previously postulated components.

A model that considers these factors and moderators such as gender, age, experience, and voluntariness, establishes these factors significantly over the behaviours intentions and actual use behaviours. A modified version of UTAUT2 was developed by Venkatesh et al. (2012), which was later modified as revised UTAUT by Dwivedi et al. (2019).

2.2 Hypotheses Development

In this study, the revised UTAUT model was utilized as a tool to measure lecturers' online learning adoption during COVID-19. The model added attitude as a variable to better understand behavioral intention, which has been established as important in previous studies (Davis, 1989). The final dependent variable, use behavior, was excluded because of its insignificance (Taylor & Todd, 1995), especially in mandatory settings where students could not resume their studies online (Rana et al., 2016). The study found that the revised UTAUT factors had a significant influence on lecturers' attitudes and behavioral intentions towards adopting online classes, with attitudes mediating the relationship between exogenous UTAUT factors and behavioral intention (Dwivedi et al., 2017; Fishbein & Ajzen, 1977).

2.2.1 Performance Expectancy → Attitude & Behavioral Intention

In terms of performance expectancy, it refers to how much an individual thinks a system will boost his or her performance at work. Dwivedi et al. (2019) proposed that attitude should be retained in the revised UTAUT, as it had already been included in performance expectancy and effort expectancy. The extent to which technology can improve or worsen one's performance and make their job easier or harder can influence an individual's decisions. According to Venkatesh et al. (2003), both voluntary and mandatory settings determine technology use behavior based on performance expectations.

H_{a1}: Online course adoption is strongly influenced by lecturers' performance expectations during COVID-19.
H_{a2}: COVID-19 pandemic has a significant impact on lecturers' performance expectations.

2.2.2 Effort Expectancy → Attitude & Behavioral Intention

As previously mentioned, the ease of use of a system plays a crucial role in determining its effectiveness. As far as technology usage behaviour is concerned, this is also known as effort expectancy and is just as significant as performance expectations. Users are more likely to accept and keep using a system if it is simple, whether the use is voluntary or required. Since users' views and behavioural intentions toward a technology are greatly influenced by effort anticipation, it follows that effort expectancy is a key element.

Ha3: The COVID-19 epidemic has a big impact on lecturer's attitudes regarding taking online classes.
Ha4: The COVID-19 epidemic has had a significant impact on lecturers' behaviours to participate in online courses.

2.2.3 Social Influence → Attitude & Behavioral Intention

When deciding whether to embrace a new system, a person's choice-making strategy is significantly influenced by social influence. Venkatesh et al. (2003) assert that a person's sense of how important other people consider their usage of the system can have a significant influence on their decisions. Davis (1985) contends that even if a person feels pressured by a referent to adopt a system, it may still be consistent with their own personal ideas, according to Dwivedi et al. (2019). This means that both external and internal pressure can affect an individual's decisions. The revised UTAUT considers an individual's attitude towards the new system, which is an important factor to consider when evaluating adoption.

H_{a5}: A significant degree of social influence influences lecturers' behavior when it comes to adopting online classes during COVID-19.
H_{a6}: COVID-19 has significantly influenced the lecturers' adoption of online classes due to social influence.

2.2.4 Facilitating Conditions → Attitude & Behavioral Intention

System usage is supported by an organizational and technical infrastructure. It plays an important role in both voluntary and mandatory technology use. Recent research by Dwivedi et al. (2019) has identified attitude as an unexpected but influential factor in facilitating conditions. The updated UTAUT model recognizes the importance of assistance and training programs, and helps designers create a positive attitude towards technology use. With the inclusion of attitude, facilitating conditions may not have a direct impact on behavioral intention.

H_{a7}: There is a significant impact of facilitation factors on lecturers' behaviors about adopting online courses during the COVID-19 pandemic.
H_{a8}: COVID-19 pandemic significantly influenced lecturers' behavior to adopt online classes.

2.2.5 Attitude → Behavioral Intention

The presence of organizational and technical infrastructure supports the use of a system Technology use is crucial both for voluntary and mandatory reasons. The attitude of an individual may be an unexpected yet influential factor in facilitating conditions, according to recent research by Dwivedi et al. (2019). The updated UTAUT model recognizes the importance of assistance and training programs, and helps designers create a positive attitude towards technology use. With the inclusion of attitude, facilitating conditions may not have a direct impact on behavioral intention.

H_{a9}: Lecturers' attitudes significantly influence their intention to adopt online classes during COVID-19.

2.3 *Conceptual Framework*

As part of this study, four core constructs of UTAUT were used, all mediated by attitude; using behaviour was not included in the revised model (Dwivedi et al., 2019).

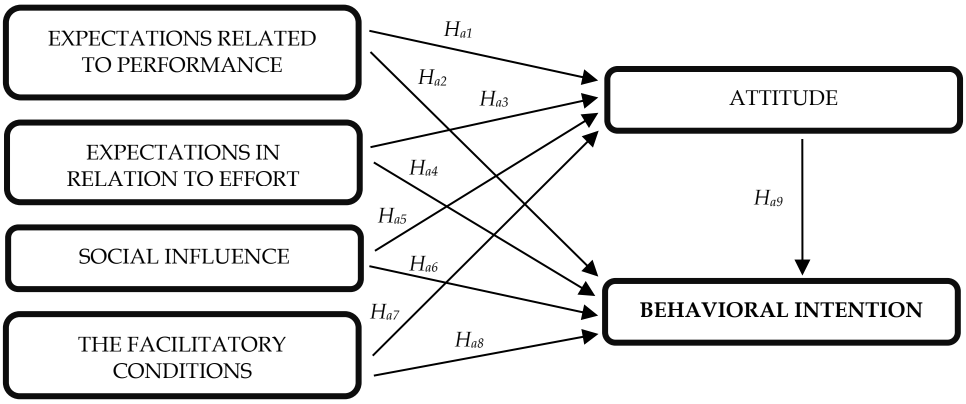

Figure 1. *Proposed model for this study*

3. Research Methodology

This study aimed to identify the factors that encourage university lecturers to adopt online courses during the COVID-19 pandemic by studying their perceptions, attitudes, and behavioural intentions. For this purpose, research applied both of qualitative and quantitative approaches because data collected from both of survey and open ended questions. The researchers used the convenient sampling technique for their data collection.

As part of this study, 166 lecturers from Rajamangala University of Technology, Tawan-ok (RMUTTO) were asked to complete a voluntary survey. It was a diverse group of lecturers based on their gender, age, faculty affiliation, and campus. An online questionnaire generated with Google Form was used, including a preface, demographics, a 23-item Likert scale survey, and three open-ended questions. A study by Venkatesh et al. (2003) titled "User Acceptance of Information Technology: Toward a Unified View," was used to develop the questionnaire items, and two professors from Assumption University of Thailand determined their face validity. In a pilot study conducted among 30 university lecturers, no score below 0.6 Cronbach's Alpha was obtained (Cronbach, 1951).

The instrument's reliability is shown in Table 1.

Constructs	*A*
The performance expectation	.739
Amount of effort expected	.864
Aspects of social influence	.736
Conditions that facilitate learning	.892
Attitude	.878
Behavioral Intentions	.944

The ESEM data analysis was conducted two weeks after the researcher determined that the respondent count was sufficient for this study. Because all the samples were Thai lecturers, the questionnaire was also available in Thai. Upon availability of the questionnaire on Google Forms, the university president granted permission to conduct the study. With the assistance of the university's IT department, Google Forms was sent to all students as links and attachments in emails, and descriptive statistics were collected to describe the characteristics and explain the central tendencies and variability of the data, including mean, range, and standard deviation. This study utilized the Exploratory Structural Equation Model (ESEM), which examines the data in three different ways: Exploratory Factor Analysis (EFA) validated construct items, Confirmatory Factor Analysis (CFA) validated constructs, and Structural Equation Model (SEM) validated deviation. Follow-up questions on lecturers' recent adoption of online courses yielded quantitative responses in the tabular statistics.

4. Data Analysis Results

The results were analysed from both perspectives namely descriptive and inferential statistics. The results were further analysed on two perspectives qualitative and quantitative analysis. In first section discussed about quantitative analysis and in next section discussed about the qualitative analysis.

4.1 Descriptive Statistics

Table 2

Demographic Information

N = 166	Lecturers	
	f	**%**
Gender		
Male	56	34
Female	110	66
Age		
Those under 30	14	8
Between 31 and 40	70	42
Between 41 and 50	61	37
Above 51 years old	21	13
Campus		
Bang Phra University Campus	38	23
The campus at Chantaburi	38	23
Chakrabongse Bhuvanat Campus	73	44
Campus of Uthen Thawai	17	10

There were 166 university lecturers of different sexes, ages, and campuses. The majority of lecturers (66%) were female, as shown in Table above in 2. There are 42% of the lecturers were between 31 and 40 years old. Furthermore, 44% of the sample population was drawn from the Chakrabongse Bhuvanat Campus.

Table 3

Mean & Standard Deviation

Construct Items		Lecturers	
		$\bar{x}$	Σ
Performance Expectancy			
1. *When an outbreak like COVID-19 occurs, I would find it useful to take classes online.*	PE01	4.22	.999
2. *I can complete tasks more quickly by taking classes online.*	PE02	3.60	1.175
3. *My productivity has increased since I began taking classes online.*	PE03	3.28	1.175
4. *It is possible for me to achieve better educational results by taking classes online.*	PE04	3.13	1.219
Effort Expectancy			
5. *It would be easier and clearer to adopt online classes.*	EE01	3.08	1.175
6. *I am confident that I will be able to adapt to online classes easily.*	EE02	2.71	1.393
7. *My experience with adopting classes online is positive.*	EE03	3.72	1.106
8. *I am comfortable adapting classes online.*	EE04	3.89	1.096
Social Influence			
9. *If an outbreak like COVID-19 occurs, I should consider online classes.*	SI01	4.14	.953
10. *I am being encouraged to adopt online courses by people who are important to me.*	SI02	3.90	1.016

11. People around me have been helpful in my adoption of online classes.	SI03	3.88	1.032
12. I have been able to adopt online classes with the support of the university.	SI04	3.84	1.155
Facilitating Conditions			
13. As a result of resources, I have available, I can adopt online classes during outbreaks such as COVID-19.	FC01	3.17	1.324
14. Taking online classes is something I am familiar with.	FC02	3.87	.969
15. I can adopt online classes with other technologies that I use.	FC03	3.96	.907
16. In the event that I have trouble adopting online courses, I can seek assistance.	FC04	3.60	1.032
Attitude Towards Use of Technology			
17. In the case of an outbreak such as COVID-19, online classes may be a good idea.	ATT01	4.34	.925
18. It is more interesting to take classes online.	ATT02	3.15	1.282
19. Online classes make learning more enjoyable.	ATT03	3.06	1.315
20. Online classes sound like a good idea to me.	ATT04	3.28	1.263
Behavioral Intention			
21. During an outbreak such as COVID-19, I intend to take classes online.	BI01	4.47	.836
22. My intention is to transition to online classes if there is an outbreak like COVID-19.	BI02	4.52	.736
23. In the event of an outbreak such as COVID-19, I plan to adopt online classes.	BI03	4.52	.761

Respondents were asked to rate 23 items from strongly disagree to strongly agree on a scale of one to five. According to PE04, lecturers scored between 3.13 and 4.22, indicating that they were generally neutral about online classes improving their educational results, but generally in agreement that online classes were helpful during the pandemic despite generally being neutral about them. According to the effort expectancy, the range was between 2.71 (±1.393) EE02 and 3.89 (±1.096) EE04. A score of just under neutral and more towards disagreement (2.71) was almost a consensus on EE02, "easily skillful at online classes." However, adapting to online courses was relatively straightforward (3.89).

As shown in the table above, lecturers have a relatively tight range of means across SI04 and SI01 (3.84% and 1.155). According to their statements, they felt positive regarding the university's support for online learning during the pandemic and positive about those who influence their behaviour encouraging them to take online classes.

Also shown in the table are medians ranging between 3.17 (±1.324) for FC01 and 3.96 (±.907) for FC03. In response to the question of whether they have the necessary resources to adopt online courses, they scored lower and relatively neutral. Their adoption of online classes also scored higher when asked if they were compatible with other types of technology. As a result of a comparison of lecturers' means of attitude, the mean ATT03 was 3.06 (+1.315) and the mean ATT01 was 4.34 (+0.925). According to lecturers, online classes are fun but are not as effective as traditional classrooms, while the mean-variance of online courses during this pandemic suggests that online courses would be a better option.

4.2 Inferential Statistics

4.2.1 Construct Items Analysis

Asparouhov and Muthén's (2009) research explores the use of the Exploratory Structural Equation Modeling (ESEM) method through the application of a Factor Analysis (Child, 1990). This method focuses on more than just identifying pre-theorized question items under their respective constructs. Instead, it aims to validate these items by testing and fitting them during the confirmation factor analysis process (Marsh et al., 2010). This approach offers a valuable contribution to the field as it goes beyond traditional factor analysis techniques. By incorporating structural equation modelling, Scholars can examine the connection among variables that can be seen and concepts that underlie them more thoroughly. Through ESEM, the validity of these factors can be confirmed, ultimately enhancing the reliability of the measurement instrument.

Table 4

SPSS: KMO and Bartlett's Test Final Results

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.940
Bartlett's Test of Sphericity	Approx. Chi-Square	8054.223
	df.	105
	Sig.	.000

It was found that data adequacy was at .964 KMO, indicating a robust construct item grouping and accurate relationships between construct items when cross-loading was eliminated (Arsham & Lovric, 2011).

Table 5

Result of the component correlation matrix using SPSS

Component Correlation Matrix						
Component	**1**	**2**	**3**	**4**	**5**	**6**
1	1.000	.548	.606	.452	.650	.629
2	.548	1.000	.715	.634	.627	.660
3	.606	.715	1.000	.588	.651	.671
4	.452	.634	.588	1.000	.507	.584
5	.650	.627	.651	.507	1.000	.646
6	.629	.660	.671	.584	.646	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.

Campbell and Fiske (1959) *recommended examining factor loadings and cross-loadings in the Pattern Matrix as a preliminary measure of data validity. A high level of convergent validity was maintained after removing eight major cross-loaders (*Lyytinen & Gaskin, 2016*). In addition to establishing discriminant validity, the Component Correlation Matrix also confirmed the minimal correlation between the two constructs at .715, which* Gaskin and Lim (2016) *deemed negligible. The validity of the data was rigorously assessed, and it was found to be reliable.*

Table 6

A Comparison of Construct Reliability Before and After Item Deletion

Cronbach's a	*Deleted Items*	*Lecturers*	
		A	*a after deletion*
The performance expectation	PE04	.860	.786
Amount of effort expected	EE01 EE02	.871	.886
Aspects of social influence	SI03 SI04	.751	.765
Conditions that facilitate learning	FC02 FC03	.827	.782
Attitude	ATT01	.855	.911
Behavioral Intentions	-	.919	No items deleted

The items that were cross loaded were deleted before and after the reliability of the data was established. Based on the EFA process, construct items have been established to be valid, reliable, and adequate. A high level of internal consistency was found between latent variables and constructs, as measured by Cronbach's Alpha, which remained above the threshold of 0.6 (Nunnally, 1978).

4.2.2 Measurement Model Analysis

After the measurement model was established, a Confirmation Factor Analysis (CFA) was conducted. The model was then respecified based on construct reliability, validity, factor loadings, and model fit. The Table 7 predicted values indicates that all constructs factor loadings are greater than 0.5 which shown that construct is reliable for further analysis.

Table 7

Demonstrates and Summarizes the Standardized Factor Loadings

Construct Items	Standard Estimates	Standard Error	Critical Ratio	p-value
PE01	.737			
PE02	.823	.063	19.801	***
PE03	.887	.060	21.387	***
PE04	.889	.067	21.476	***
EE01	.883			
EE02	.832	.034	27.073	***
EE03	.778	.035	23.707	***
EE04	.754	.037	23.161	***
SI01	.829			
SI02	.849	.043	24.434	***
SI03	.689	.046	18.248	***
SI04	.719	.047	19.097	***
FC01	.759			
FC02	.861	.048	21.321	***
FC03	.831	.043	20.444	***
FC04	.785	.049	21.321	***
ATT01	.689			
ATT02	.928	.071	20.652	***
ATT03	.911	.073	20.307	***
ATT04	.882	.075	19.606	***
BI01	.918			
BI02	.962	.023	42.551	***
BI03	.949	.031	40.655	***

Moreover, constructs were significant (t-values, standard error, and p-values) with factor loadings over 0.5. These are considered to good for further analysis Gao, Mokhtarian, and Johnston (2008).

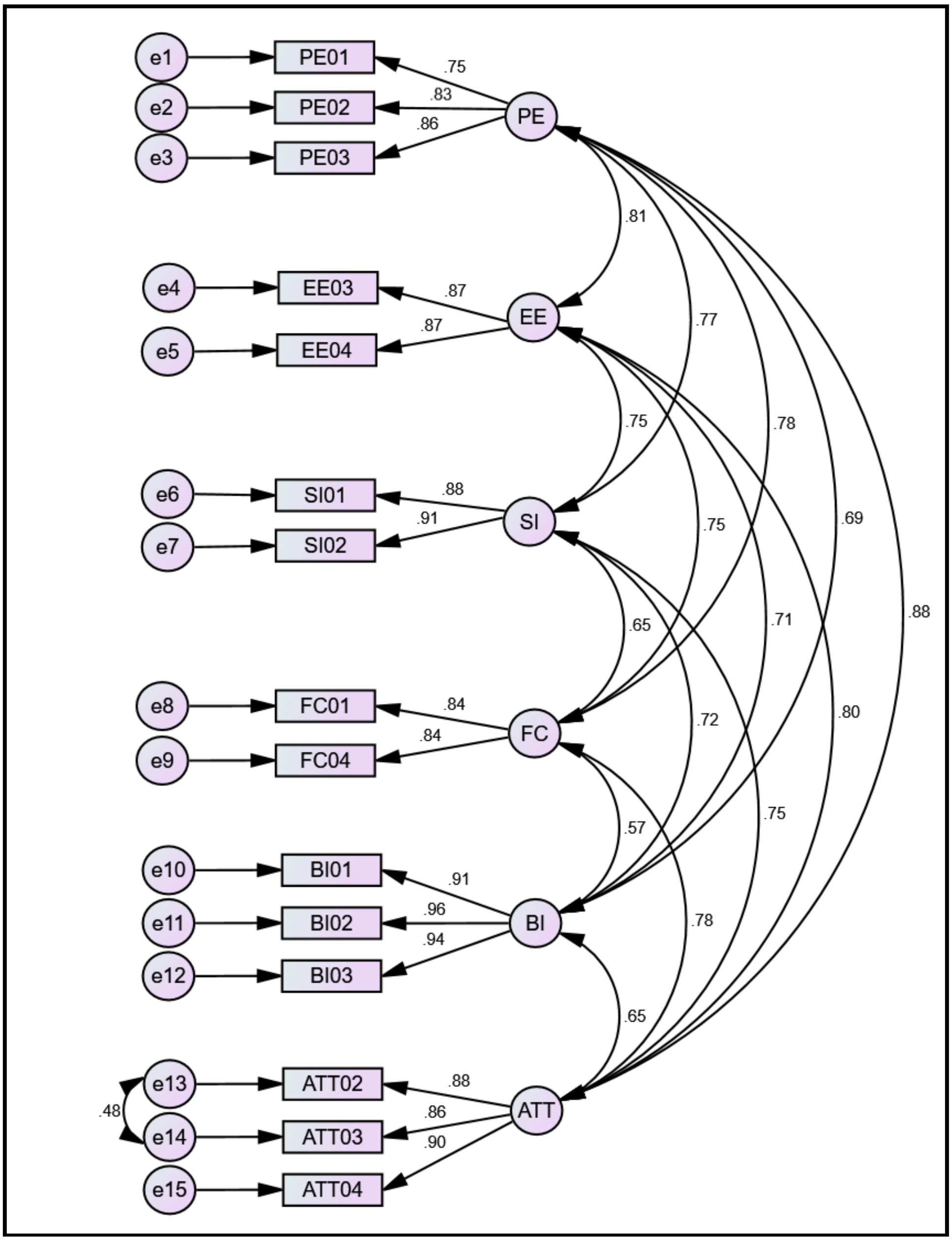

Figure 2. *Shows the measurement model for the finalized constructs*

After the initial model fit was assessed, it was deemed terrible. However, with some re-specification of the model, the goodness of fit was excellent. CMIN/DF, CFI was 0.979, SRMR was 0.0594, RMSEA was 0.054, and PClose were 1.489, 0.979, 0.0594, 0.054, and 0.349, respectively. These results reflect an excellent model fit, and we are pleased with the outcomes (Hu & Bentler, 1999).

Table 8

Shows the Compiled Reliability, Average Variance Extracted, and Maximum Reliability are presented

Constructs		Lecturers		
		CR	**AVE**	**MaxR(H)**
The performance expectation	PE	0.867	0.626	0.905
Amount of effort expected	EE	0.886	0.796	0.890
Aspects of social influence	SI	0.790	0.659	0.890
Conditions that facilitate learning	FC	0.796	0.661	0.796
Attitude	ATT	0.943	0.847	0.966
Behavioral Intentions	BI	0.927	0.810	0.957

Reliability measures such as Composite Reliability (CR) and Maximal Reliability (MaxR(H)) had higher values than the recommended threshold of 0.70, indicating that the construct was reliable (Awang, 2015). According to Hair et al. (2010), the average variance extracted (AVE) did not fall below 0.50, indicating robust convergence. Furthermore, all CR values exceeded AVE, further proving the construct's reliability.

Table 9

Shows the Heterotrait-Monotrait Ratio of Correlations

	Lecturers					
	PE	**EE**	**SI**	**FC**	**ATT**	**BI**
PE						
EE	0.557					
SI	0.552	0.412				
FC	0.769	0.461	0.598			
ATT	0.736	0.535	0.631	0.714		
BI	0.493	0.545	0.387	0.415	0.597	

As measured by the Heterotrait-Monotrait Correlation (HTMT), no value beyond 0.90 was found (Gold, Malhotra, & Segars, 2001) among constructs in terms of discriminant validity.

4.2.3 Structural Model Analysis

SEM (Structural Equation Model) was used to test the model after EFA (element-by-element analysis) and CFA (construct-by-construct analysis). A comprehensive understanding of the pre-theorized relationships within the data was gained by assessing the structural model fit, formulating hypotheses, and performing path analyses.

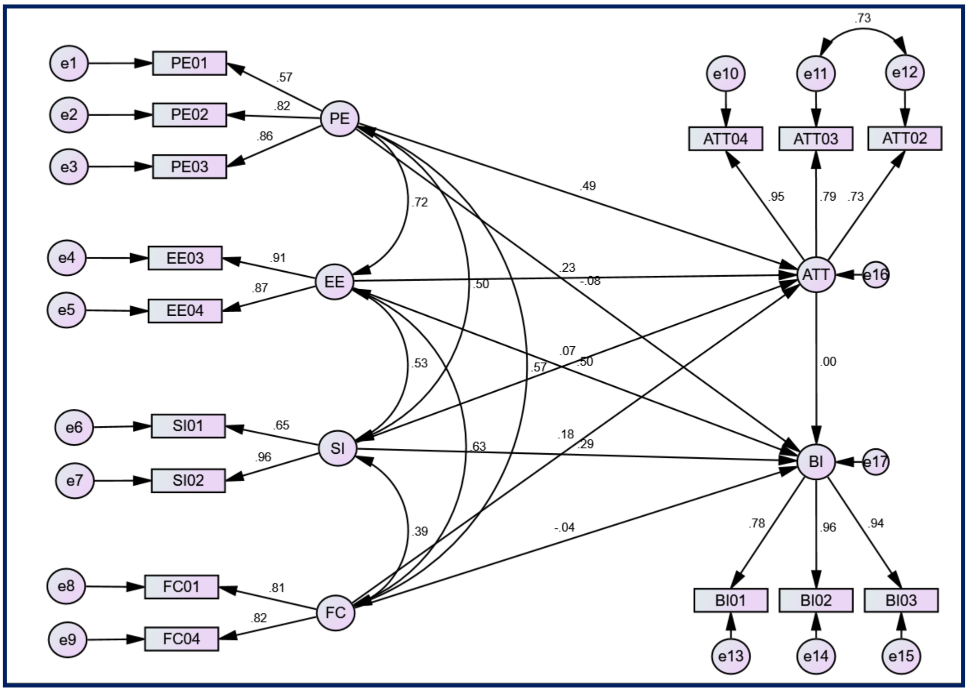

Figure 3. *Structural Model*

The results of the analysis indicate that the structural model has a good fit, as shown in the figures above. There was no need to delete any variables or add any additional covariance to maintain the minimum level of model fit. The goodness of fit was computed using several different indices, including CMIN/DF, CFI, SRMR, RMSEA, and PClose. All these indices reported excellent results according to the recommended thresholds. Overall, these findings suggest that the structural model provides a strong and reliable representation of data (Hu & Bentler, 1999).

Table 10

Hypotheses Against Regression Weights

No.	Hypothesis	Standard Estimates	Standard Error	Critical Ratio	p-value	Decision
H1	PE → ATT	.489	.200	4.070	***	SUPPORTED
H2	PE → BI	-.089	.172	-.547	.587	NOT SUPPORTED
H3	EE → ATT	.231	.097	2.154	.032	SUPPORTED
H4	EE → BI	.503	.093	3.578	***	SUPPORTED
H5	SI → ATT	.071	.104	1.027	.307	NOT SUPPORTED
H6	SI → BI	.293	.097	3.153	.001	SUPPORTED
H7	FC → ATT	.187	.075	2.145	.031	SUPPORTED
H8	FC → BI	-.032	.068	-.322	.748	NOT SUPPORTED
H9	ATT → BI	-.005	.107	-.023	.989	NOT SUPPORTED

*** *P-value < 0.001 indicates significance*

Based on the regression weights generated by Structural Equation Modeling (SEM), the hypotheses from the table above are evaluated. The postulated claims between constructs that have been supported include Performance Expectancy leading to attitude (H1), Effort Expectancy leading to attitude (H3), Effort Expectancy leading to Behavioral Intention (H4), and Social Influence leading to behavior, indicating that Performance Expectancy has a significant influence on attitude. This suggests that when individuals perceive a higher degree of expected performance from using a particular product or service, their attitude towards it becomes more positive. Similarly, Effort Expectancy also plays a role in shaping attitude. When individuals perceive that using a product or service requires less effort, their attitude towards it tends to be more favorable. This study reveals that Effort Expectancy has a positive and significant impact on Behavioral Intention. This implies that when individuals perceive a product or service to be easy to use, they are more likely to have the intention to engage in the desired behavior related to it.

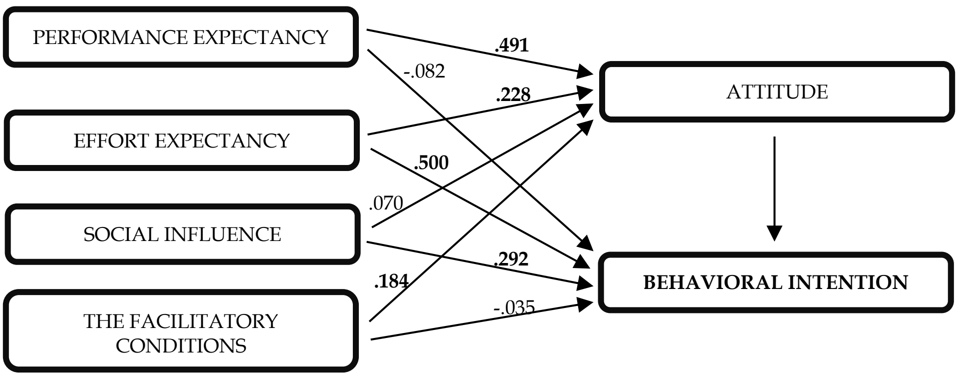

Figure 4. *Squared multiple correlations between learners' paths and learning*

As illustrated in the conceptual framework above, all constructs in the study are significantly influenced by the lecturers' path coefficients. From highest to lowest: EE to BI (.500), PE to ATT (.491), SI to BI (.292), EE to ATT (.228), FC to ATT (.184), SI to ATT (.070), FC to BI (-.035), PE to BI (-.082), and ATT to BI (-.004), were reported. The first five relationships are significant with critical ratio t-value > ±1.96 and p-value < 0.05.

4.3 An overview and analysis of the open-ended questions

There are three follow-up questions intended to gauge lecturers' perceptions of how online classes have affected their recent experience with COVID-19. An expert translator translated 166 Thai responses into English; their answers have been categorized according to specific themes.

4.3.1 " In the midst of this COVID-19 pandemic, how do you feel about online education?

During this pandemic, the government abruptly mandated online classes for lecturers. In the first question, it sought demographic information about the lecturers' awareness of the mandate. Policy Debates (Bellon, 2008) establishes a framework for categorizing subgroups' opinions into themes based on whether two opposing beliefs deem a policy necessary, beneficial, practical, or otherwise.

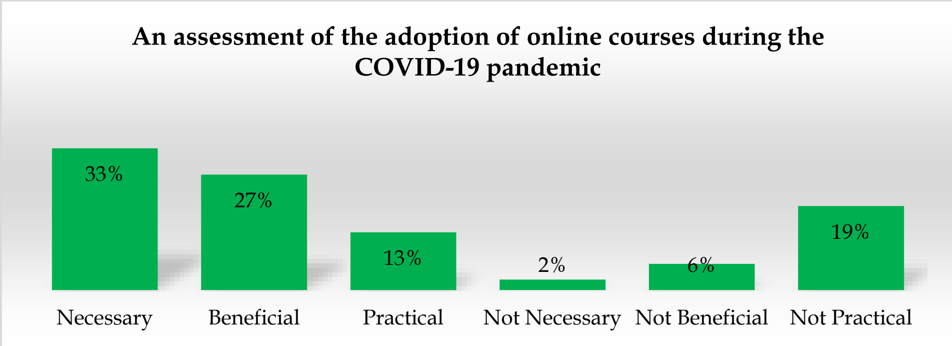

Figure 5. *Shows an overview of the responses to Question 1*

The lecturers felt that adopting online classes was *necessary* (33%) for their teaching endeavors. They felt the move to online classes was basically for public safety – able to distance themselves from others, reducing chances of getting infected. Moreover, they also thought it was the most appropriate measure, provided that technology is already incorporated into almost everyone's daily life.

The second majority also felt adoption was *beneficial* (27%). Technology helped them prepare digital teaching materials, and digital platforms like Zoom or MS Teams were user-friendly. Furthermore, lecturers felt that adopting online classes is generically good, as it served its purpose during distance learning.

A third majority also felt that adopting online classes was not practical (19%) due to certain inconveniences caused by the stability of the internet or the inability to teach certain practical subjects. Regardless, the minority reported the policy of adoption as being practical (13%), not beneficial (6%), and the least being not necessary (2%) at all.

4.3.2 "What challenges have you encountered with adopting online classes?"

In the second question, lecturers were asked to summarize their challenges into categories. Several themes are derived from Tinio (2002)'s discussion of using ICT in higher education and issues and challenges. Infrastructure, capacity, cost, and paucity were identified as challenges within this context.

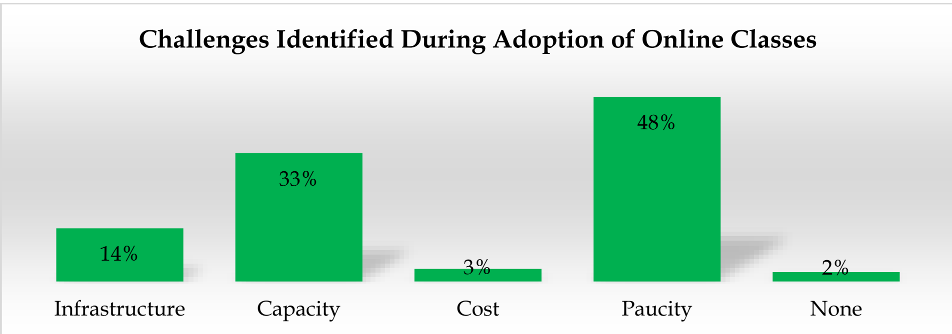

Figure 6. *Responses to Question 2*

There is a majority of respondents (48%) who believe that implementing online courses is challenging due to paucity - problems with internet connectivity, virtual logins, and occasional lag times. Another majority believed the challenge was related to *capacity* (33%) – that most of them felt they lacked the readiness to move classes to online platforms; or were not competent enough.

A minority of respondents identified *cost* (3%) to be a challenge as they felt they needed to pay for higher internet consumption than before. Another few said no challenges (2%), yet a high minority of lecturers felt there was a lack of *infrastructure* (14%) to set up and sustain online classes. Thus, adoption becomes challenging (no internet, no personal computers at home, or the university needed to assess feasibility before adopting online classes).

4.3.3 "What can you suggest about adopting online classes if they resume in the future?"

The third question asked learners to report issues you considered if online classes remained suspended for longer than expected. Based on Tinio's (2002) account of issues and challenges associated with the use of ICT in higher education, the themes reflected in this article are taken from his work. Efficacy, cost, equity, and sustainability were the defining attributes of this context.

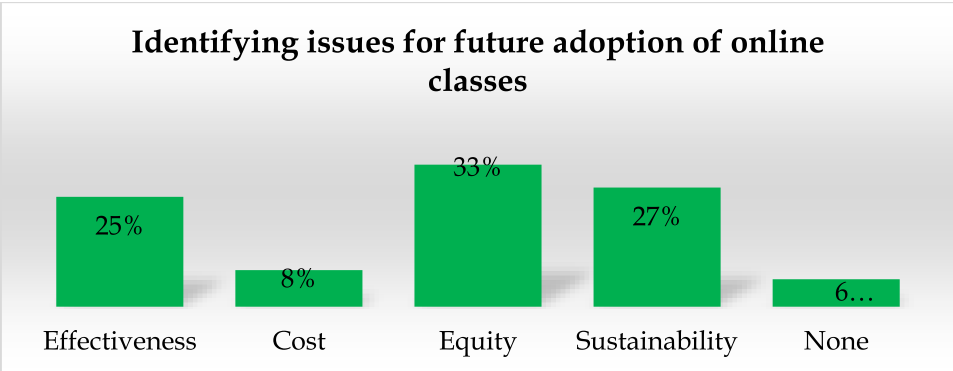

Figure 7. *Shows the responses to question 3*

Most lecturers believed that *equity* (33%) might be an issue in prolonging online classes in the future. Sentiments were made about carrying out a policy carefully regarding learners' and lecturers' ability and capability to comply. Some lecturers highlighted that most learners could not have good Wi-Fi signals and that some need the means to learn digitally.

Another majority talked about *sustainability* (27%) – that if online classes were to resume, there should be a need to upgrade the ability to sustain the policy, such as provision for a stronger internet connection and a means for learners or lecturers to borrow laptops or tablets for online learning.

A third majority believed that effectiveness (25%) should be an issue for resuming online classes; lecturers can build enough competence to teach online and guide learners to navigate online learning.

A minority mentioned cost (8%), believing that some budget allocation can be relocated towards supporting the policy to adopt online classes, especially for adding or supporting infrastructures for learning and teaching to be effectively adapted online. The least of the lecturers (6%) thought there were no issues to consider.

5. Discussion

In the revised UTAUT, Performance Expectancy was found to play a crucial role in determining attitudes and behavioural intentions. The perception of technology as useful has a significant impact on attitude, as demonstrated by Dwivedi et al. (2019). Venkatesh et al. (2003) found that this influence is strong regardless of whether it is voluntary or mandatory. For lecturers, the path between PE and ATT was particularly significant (H10: $\mu = .491$). The way they perceived the technology to be useful in attaining their educational goals heavily influenced their attitude towards online courses. In addition, Sangeeta and Tandon (2021) and Lazim et al. (2021) have found that lecturers adopt technology when it is perceived to benefit their online teaching efforts, especially during pandemic.

These findings demonstrate that there is no significant relationship between lecturers' PE and their BI. This suggests that their appreciation of the usefulness of technology does not directly impact their behavioral intentions. It is interesting to note that while many recent studies have shown that performance expectancy is a strong predictor of behavioral intention, especially during the pandemic, a few studies have contradicted this. There are two instances in which Performance Expectancy unexpectedly did not correlate with Behavioral Intention, including the educational technology gap in Jakarta middle schools and the debunking of the notion that Perceived Risk moderated Performance Expectancy in Bangkok adults (Chayomchai et al., 2020; Raza et al., 2021; Samat et al., 2020; Tiwari, 2020).

In contrast to the older groups, the middle-aged respondents showed a strong appreciation for technology, as well as very positive responses to PE (Venkatesh et al., 2012). This would eliminate any biases in performance expectations from the technology that might influence their intention to adopt online classes (Venkatesh et al., 2012).

Furthermore, willingness to use technology could be directly affected by how one perceives technology (Dwivedi et al., 2019). As a result of prolonged and sustained use of UTAUT, effort expectancy declines both in voluntary and mandatory settings (Venkatesh et al., 2003). A significant effect of effort expectancy on attitude and behavior intention is crucial in this study. Thus, based on the research conducted on the hypothesis between EE and ATT, it was found that there was significance for lecturers (H12: $\mu = .228$). According to recent findings (Lazim et al., 2021), lecturers highly prioritize ease of use, user friendliness, and convenience when it comes to selecting educational systems. Acknowledging the significance of these qualities, Sangeeta and Tandon (2021) published insightful studies that shed light on the impact of these features in the realm of education technology. Lazim et al. (2021) examines the importance of ease of use in educational systems, emphasizing how this aspect significantly affects both lecturers and students. This study highlights the positive influence of user-friendly interfaces, noting how they contribute to enhanced engagement, higher effectiveness, and ultimately, improved learning outcomes. Similarly, Sukendro et al. (2020) delved into the significance of user-friendliness in educational platforms, exploring the factors that contribute to a positive user experience. Hence, the importance of Effort Expectancy and Attitude among lecturers could be explained by the fact that the younger generation of learners may not find technology as challenging as their older counterparts. The influence of age on attitude is also significant, explaining why effort expectancy varies with age (Venkatesh et al., 2012).

Using a mean value of.500, the hypotheses EE and BI were shown to have a significant influence on lecturers. Convenience played a big role in their choice to take online classes. The course's ease had a big impact on their decision to accept online learning. According to recent research by Chayomchai (2020) and Chayomchai et al. (2020), the impression of ease of use is a critical factor in determining people's propensity to utilize technology. The effort expectation construct, a critical factor in determining how readily people embrace and utilize technology, includes the idea of ease of use as a core component. People are more likely to have favourable views regarding technology when they believe it to be simple to use, which increases their intention to utilize it (Tiwari, 2020). The user interface's intuitiveness, ease of interactions, as well as clarity of instructions or features are only a few of the variables that affect how users perceive a product.

However, latest research has shown that individuals prefer to identify with the people who are important to them personally, and that their opinions have a big impact on how they feel about utilizing technology (Dwivedi et al., 2019). In a bigger workforce, people frequently make decisions based on compliance rather than opinion, which has an impact on how they use technology (Venkatesh et al., 2012). It is crucial to determine if social effects have a major impact on attitudes and behavioral intentions.

In the case of lecturers, the relationship between social influence and attitude was found to be insignificant (H14: μ = .070). Therefore, they were not influenced by how their family and friends felt about online classes during the pandemic, which means that they had no influence on what they thought about them. Technology adoption attitudes were not influenced by social influence in the study. Researchers in Rajpura, India, found that some teachers were not influenced by their loved ones' views on technology adoption during the pandemic. There was more compliance than prejudice in many teachers' decisions (Dwivedi et al., 2019).

Lecturers, however, showed a significant relationship between social influence and behavior intentions (H15: μ = .292). Accordingly, the importance others place on adopting online courses during the pandemic greatly influences their behavior in the use of technology during the crisis. According to investigations (Asvial, Mayangsari, & Yudistriansyah, 2021; Raza et al., 2021; Samat et al., 2020), students and lecturers have been more likely to abide by this policy whenever loved ones which were worried regarding their safety throughout the pandemic beneficially reinforced their choices to take online classes.

In other words, Dwivedi et al. (2019) further argued that attitudes and behavioral intentions were significantly influenced by facilitating conditions. It has been proven that facilitating conditions affect the attitude of users towards technology at help desks and in customer support. When attitude was introduced into UTAUT, facilitating conditions were also significantly related to behavioral intention as the final endogenous construct. Technology usage was positively or negatively affected by lecturers' access to and availability of support. Sangeeta and Tandon (2021) found that training programs enabled teachers in Rajpura, India to use technology during the pandemic. However, Behavioral intentions were found not to be related to facilitating conditions Thus, providing facilities and support for technology usage did not increase user intentions. It has also been reported that studies during the pandemic failed to support this claim, concluding that facilitating conditions are determined more by actual behavior than by behavioral intentions. Facilitating circumstances may nevertheless be important even in the absence of performance anticipation and effort expectancy (Eckhardt, Laumer, & Weitzel, 2009; Foon & Fah, 2011; Yeow & Loo, 2009).

Lastly, an important relationship is expected to exist between attitude and behavioral intention based on the revised UTAUT. According to Dwivedi et al. (2019), attitude still plays a crucial role in determining behavioral intentions even though it was originally considered iterative in UTAUT. A positive attitude increases the likelihood that people will perform desired behaviors. The proposed study, however, found no significant association between ATT and BI for lecturers (H12: $\mu = -.004$). Their attitudes towards using technology and their intent to use it are not connected. The COVID-19 pandemic was observed to have similar effects on Indonesian middle school students (Asvial et al., 2021). There is a gap in technology use that prevented attitude and behavioral intention from being established. A possible explanation could be that learners and lecturers have been adversely affected by the pandemic, which restricts their options. They may not be inclined to use technology much in the current state of their attitudes.

The initial research by Venkatesh et al. (2003), which shows a connection between attitude and performance expectancy and effort expectancy, serves as the foundation for a different interpretation. Therefore, its redundancy had no effect on the creation of a uniform technology acceptance model. The findings support the necessity to investigate contextual elements in the link between attitudes and behavioral intentions.

5.1 Implications for Practice

During the testing of the hypotheses, significant relationships were formed, which demonstrated how the university could encourage lecturers to adopt online classes during the pandemic. Performance expectancy was found to play a substantial role in shaping attitudes toward adoption. Lecturers saw the adoption of online courses as instrumental, helpful, and effective in producing good teaching results. This influenced their preference for online classes, despite the policy being enforced abruptly. Thus, it is crucial to continually improve their online teaching experience and ensure that it remains effective in the long run.

Online classes were generally regarded as helpful and necessary by lecturers, but the sudden implementation of the initiative caused difficulties. The difficulties encountered were largely caused by lack of resources (weak Internet, log-in errors, and lags) and insufficient capacity (first-timers or incompetent computer users). Future efforts will need to address the sustainability of adoption. Therefore, it is important to maintain a high level of quality when implementing online classes for lecturers.

As per the outcomes of the study conducted on lecturers, it has been established that effort expectancy is the primary factor influencing their attitude and behavioral intention toward adopting online teaching. Study results confirm that lecturers' preferences and intentions towards online teaching will be positively imoactyed by a perception that online teaching is simple, clear, and understandable. It is therefore crucial to make online teaching more accessible and user-friendly to encourage its adoption.

Moreover, the study found that social influence impacts behavioral intention. Lecturers are likely to adopt online classes if their friends and family believe in their adoption. There could be a forum where lecturers can openly discuss to boost morale and encourage adoption. This allows lecturers to share their thoughts among their colleagues and peers and listen to one another, which ultimately makes online classes more appealing to lecturers.

Finally, the study confirms that facilitating conditions play a significant role in developing lecturers' attitudes toward adopting online learning. Students' preferences for online learning are influenced by resources, knowledge, compatibility, and assistance available to them. Administrators must therefore provide lecturers with the necessary materials, knowledge, and support, particularly when implementing online courses. The system can be setup to provide timely updates, mini-training, and tele support whenever lecturers have problems with online courses, ensuring a smooth adoption.

5.2 Recommendations for Further Research

Although this research has yielded significant conclusions, there is still room for improvement. The researcher suggests adding moderators and incorporating use behavior, as initially indicated in the UTAUT model. While these factors were excluded from the current study, including them in future research could contribute to the theoretical implications. Additionally, future studies should consider parameters specific to lecturers and online teaching, such as COVID-19 anxiety and readiness for online teaching. It would also be helpful to have a more demographically representative sample population to address the potential bias. Finally, exploring the mediating effects, in addition to the direct impacts, would lead to more meaningful internal relationship hypothesis testing. Overall, these additions have enhanced the quality and specificity of the research findings.

5.3 Conclusions

In the revised UTAUT, several factors determining lecturers' attitudes toward online classes during the COVID-19 pandemic were identified. This study also aimed to investigate lecturers' perceptions regarding online learning. Lecturers were impacted by four exogenous and two endogenous variables. There was a significant relationship between attitudes and performance expectations, effort expectations, and enabling conditions but not with social influence. Behavior intention, performance expectations, facilitating needs, and attitude were also influenced by effort expectancy and social influence. When asked about the current policy, most lecturers saw online learning as necessary and beneficial during the COVID-19 pandemic. In addition, they felt it could have been more practical. Most lecturers have identified capacity and paucity as the most challenging aspects of adopting online classes. Most students also reported infrastructure issues that contributed to their difficulties running online classes. Most lecturers believed that there would be problems with equity, sustainability, and effectiveness of adoption continued for a long time. This would be confirmed in a Delphi method study (Tee et al., 2022) where technology optimization was a second critical positive consequence where e-learning infrastructures and online learning tools would naturally be quite the landscape in this new normal teaching and learning.

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