Adoption of Online Classes During COVID-19: An Institution's Investigation on Perception & Behavioral Intention

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Abstract

In the advent of COVID-19, an institution revisits the revised UTAUT in its interest in identifying factors encouraging positive perception and behavioral intention towards adoption of online classes among its learners and lecturers. In doing so, a non-experimental, non-probabilistic, quantitative study gathered online surveys from voluntary 580 samples. Data was later evaluated through the Exploratory Structural Equation Model (ESEM). Results suggested that Performance Expectancy & Facilitating Conditions influenced Attitude, and Effort Expectancy & Social Influence influenced Behavioral Intention – in both groups. Performance Expectancy over Behavioral Intention and Social Influence over Attitude were especially significant among learners; while, Effort Expectancy on Attitude was particularly significant among lecturers. Also, surprisingly, a disconnect among Facilitating Conditions & Behavioral Intention; Attitude & Behavioral Intention were shown in this study. Furthermore, their current adoption was implored. Both groups felt that the current policy was necessary, beneficial but, to an extent, not practical. Both groups believed challenges were related to paucity and capacity in running online classes. Learners specifically addressed future issues in online learning related to its effectiveness, and lecturers emphasized its equity in online teaching if classes were to resume. Practical implications on technology acceptance would contribute significantly towards better adoption of online classes during this outbreak.

Keywords: Unified Theory of Acceptance and Use in Technology, UTAUT, revised UTAUT, Technology Acceptance Model, User Acceptance

JEL Classification Code: I23, I28, O32, O33, O38

1. Introduction

The adoption of online classes caused by the sudden disruption of COVID-19, has become front and center for many recent studies on technology acceptance in education. Whether or not certain factors encourage learners to positively perceive, intend, or adopt online learning; and, educators to positively perceive, intend, or adopt online teaching – had become especially intriguing.

Various technology acceptance models, previously theorized or currently developed, have sought to establish relevant factors leading to user acceptance. And, however they may vary in structure, these models have followed the same basic premise: that external factors cause individual reactions, that individual reactions cause intentions, and that intentions cause actual usage of technology (Venkatesh, Morris, Davis, & Davis, 2003).

Pre-pandemic publications in higher education (Tseng, Lin, Wang, & Liu, 2019; Mosunmola, Mayowa, Okuboyejo, & Adeniji, 2018; Mei, Brown, & Teo, 2018) have consistently established significant results by empirically validating factors that lead university learners and lecturers to eventually adopt online classes. Likewise, recent publications, in the context of the pandemic, have been accounted for in producing positive relationships among theorized factors toward attitude (Lazim, Ismail, & Tazilah, 2021), intention (Tiwari, 2020), and actual use of technology (Samat, Awang, Hussin, & Nawi, 2020). Moreover, there were also publications that have not entirely reached the same theoretical implications. There were conclusions suggesting that some theorized factors had nothing to do with the individual's attitude (Sangeeta & Tandon, 2020; Sukendro, Habibi, Khaeruddin, Indrayana, Syahruddin, Makadada, Hakim, 2020), no connection with their intention (Asvial, Mayangsari, & Yudistriansyah, 2021; Raza, Qazi, Khan, & Salam, 2021; Chayomchai, 2020), and no credibility towards their actual use of technology (Chayomchai, Phonsiri, Junjit, Boongapim, & Suwannapusit, 2020; Sangeeta & Tandon, 2020) during this pandemic.

Majority of these studies adopted The Unified Theory of Acceptance and Use of Technology model (UTAUT) (Venkatesh et al., 2003) for being able to integrate factors from many previous acceptance theories and conveniently organizing them to similar constructs. This model was finalized having four exogenous variables (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions), significantly influencing two endogenous variables (Behavioral Intention, Actual Use), and being affected by four moderators (Gender, Age, Experience, Voluntariness of Use). And from this, iterations such as the extended UTAUT (Venkatesh, Thong & Xu, 2012), and revised UTAUT (Dwivedi, Rana, Jeyaraj, Clement, and Williams, 2019) would become varying models depending on specific contexts.

The researcher was able to develop his own theoretical model, basing it from the revised UTAUT for its suitability in mandatory settings and for being able to empirically establish: 1. that Attitude should be incorporated (Fishbein & Ajzen, 1975) – as it was equally found important along with Behavioral Intention, 2. that moderators should be dropped (Tandon & Kiran, 2019; Tseng et al., 2019) – as they are rendered not too effective to be causing moderation; and 3. that alternative paths should be considered – as they can emerge equally significant with hypothesized paths (Dwivedi et al., 2019). Furthermore, the researcher has also decided to exclude Actual Use, for its questionable relationship with Behavioral Intention (Sangeeta & Tandon, 2020) during the context of this pandemic.

This study was able to investigate the significant influence of the revised UTAUT factors over Behavioral Intention towards adoption of online classes among learners and lecturers during COVID-19 outbreak. Moreover, their perceptions of their current adoption of online classes were also reported. Both sample groups were voluntary respondents from Rajamangala University of Technology, Tawan-ok, currently affected more than a few times by the pandemic with the government's current initiative to implement adoption of online classes (Mala, Covid-19 Fear Pushes Classes Online, 2020) (Mala, Covid Hinders Education Again, 2021).

This paper explores the topic on technology acceptance, reviews related literature, establishes the research methodology, presents results, and discusses analyses for investigating factors that encourage positive Attitude and Behavioral Intention towards adoption of online classes. Likewise, it hopes to help the university's stakeholders, policymakers, and administrators towards a better and smoother mitigation of online learning and online teaching during this educational disruption caused by the COVID-19 outbreak.

* Acknowledgements: My special thanks to Dr. Satha Pongsatha Ph.D, my brilliant adviser at Assumption University of Thailand, the administration of Rajamangala University of Technology, Tawan-ok, especially the Faculty of Liberal Arts, its President - Associate Professor Rerkchai Fooprateepsiri Ph.D., Dean - Asst. Prof. Khanathip Jirasanyansagul Ph.D., Academic Affairs Head - Ms.Piyaporn Boonchuayrod Ph.D., Department Head - Mr. Ingkayut Poolsub, and to Mr. Werachart Muttitanon, the head of the ICT department, who made it possible for me to conduct the study.

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2. Literature Review

2.1 Theoretical Models

Studies on technology acceptance have always been interested in use behavior; establishing factors that lead to users' actual usage of information technologies or actual adoption of information systems. Since the 1980s, where the investments in IT & IS boomed (Westland & Clark, 2000), companies understood that a technology's productivity would only be as good as the employee's acceptance of that particular technology. Thus, there have been many theories and theoretical models developed in the past that tested pertinent relationships with use behavior.

The first of them, the 'Theory of Reasoned Action' (Fishbein & Ajzen, 1975) had proposed that a user's behavior is determined by one's behavioral intention and in turn by one's attitude and subject norm. A second theory, the 'Technology Acceptance Model' (Davis, 1989) had suggested that a user's acceptance or adoption is determined by one's perception of the technology's usefulness and ease of use. Another would be an improvement of the first model, the 'Theory of Planned Behavior' (Taylor & Todd, 1995b), which had added perceptions of control as a second factor, besides behavioral intention, in understanding an individual's use behavior. Many more of these theoretical individual models: 'Motivational Model' (Davis, Bagozzi, & Warshaw, 1992), 'Combined TAM & TPB' (Davis, Bagozzi, & Warshaw, 1989), 'Model of PC Utilization' (Thompson, Higgins, & Howell, 1991), 'Innovation Diffusion Theory' (Moore & Benbasat, 1991), 'Social Cognitive Theory' (Compeau & Higgins, 1995), would seek to explain acceptance and usage of technology for several decades and still.

Recent studies have been published, particularly on students' sudden adoption of online learning and teachers' sudden adoption of online teaching. A local journal by Imsa-ard (2020) has reported his university students' perceptions toward the abrupt transition to online learning; and another one by Todd (2020) has identified his schoolteachers' perceptions of the shift from the classroom to online teaching during COVID-19. International journals like the one by Tiwari (2020) have used theoretical models in measuring the impact of the students' attitude towards adoption of online classes; and another by Sangeeta & Tandon (2020), in identifying factors influencing adoption of online teaching by schoolteachers during COVID-19. More of these studies, especially today, would employ theoretical models in understanding factors leading to the sudden acceptance and use of technology especially during the pandemic.

One theoretical model in particular is the 'Unified Theory of Acceptance and Use of Technology' (UTAUT) (Venkatesh et al., 2003), popular for being able to conveniently combine previously theorized factors into similar constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, and establish them significantly over Behavioral Intention and Actual Use, along with moderators: Gender, Age, Experience, Voluntariness. This model would be extended as UTAUT2 (Venkatesh et al., 2012) and later modified as revised UTAUT (Dwivedi et al., 2019) in response to specific settings.

2.2 Hypotheses Development

The hypotheses established in this study were based on a strong foundation derived from very recent studies on education and technology acceptance in the context of COVID-19 outbreak. In achieving the research objectives, this study proposed to use the revised UTAUT theoretical model (Dwivedi et al., 2019). The researcher's decision to exclude the final dependent variable – Use Behavior, was supported as well by results and recommendations in recently concluded researches. Hypothesis 1 to 9 are specific to learners while hypothesis 10 to 18 are to lecturers.

2.2.1 Performance Expectancy on Attitude & Behavioral Intention

Performance Expectancy, the degree to which an individual believes that using the system will help him or her attain gains in job performance (Venkatesh et al., 2003) covers constructs like perceived usefulness (TAM1/TAM2) (C-TAM-TPB), extrinsic motivation (MM), job-fit (MPCU), relative advantage (IDT), and outcome expectations (SCT) from the other individual theories of technology acceptance.

In the original UTAUT, Attitude was treated as already being encompassed in Performance Expectancy and/or Effort Expectancy, and treated not as a direct influence to Behavioral Intention or Use Behavior. On the other hand, Dwivedi et al. (2019) purported for their revision of the UTAUT, that Attitude should be maintained as an individual could be influenced by the extent to which the technology may prove to be useful (better or worse), or the extent to which technology may be easy to use (easy or hard). In other words, the degree to which a technology is capable of performing and easing usage influences how people feel about the technology itself.

Ha1: Performance Expectancy has a significant influence over the learners' Attitude to adopt online classes.

Ha10: Performance Expectancy has a significant influence over the lecturers' Attitude to adopt online classes.

Performance Expectancy is said to be the strongest predictor of Behavioral Intention and remains significant in both voluntary and mandatory settings in technology Usage Behavior (Venkatesh et al., 2003).

Ha2: Performance Expectancy has a significant influence over the learners' Behavioral Intention to adopt online classes.

Ha11: Performance Expectancy has a significant influence over the lecturers' Behavioral Intention to adopt online classes.

2.2.2 Effort Expectancy on

Attitude & Behavioral Intention

Effort Expectancy is defined as the degree of ease associated with the use of the system (Venkatesh et al., 2003). It covers constructs from other technology acceptance theories like perceived ease of use (TAM1/TAM2), complexity (MPCU), ease of use (IDT).

For the justification of Effort Expectancy over Attitude, please refer to section 2.2.1 (Performance Expectancy on Attitude & Behavioral Intention).

Ha3: Effort Expectancy has a significant influence over the learners' Attitude to adopt online classes.

Ha12: Effort Expectancy has a significant influence over the lecturers' Attitude to adopt online classes.

Similar to Performance Expectancy, it is also significant in both voluntary and mandatory contexts in technology Use Behavior. However, Venkatesh et al. (2003) furthered that significance only mattered during the first stage, and then becoming less significant over periods of extended and sustained usage.

Ha4: Effort Expectancy has a significant influence over the learners' Behavioral Intention to adopt online classes.

Ha13: Effort Expectancy has a significant influence over the lecturers' Behavioral Intention to adopt online classes.

2.2.3 Social Influence on

Attitude & Behavioral Intention

Social Influence – the degree to which an individual perceives that important others believe he or she should use the new system (Venkatesh et al., 2003); constitutes subjective norm (TRA, TPB, C-TAM-TPB), social factors (MPCU), and image (IDT) from related individual theories, which contains the same explicit and implicit notion that the individual's behavior is influenced by the way in which they believe others will view them as a result of having used the technology (Venkatesh et al., 2003).

However, Dwivedi et al. (2019) quoted Davis (1985), that although an individual may do what a referent feels he or she must do, the act might also be consistent with the individual's own feelings. Thus, besides the mechanism on compliance, - internalization and identification would be two more identifying social influences as pertaining to the individual (Warshaw, 1980). In other words, there is social pressure and there is internal pressure. It is with the revised UTAUT that not only the context is accounted for, but the individual as well.

Ha5: Social Influence has a significant influence over the learners' Attitude to adopt online classes.

Ha14: Social Influence has a significant influence over the lecturers' Attitude to adopt online classes.

Compliance causes the individual to simply alter one's intention in response to social pressure as for Warshaw (1980). For voluntary, social influence has become non-significant; yet for mandatory settings, appears important especially during the first stages of individual experience with technology, which eventually wears away over time with sustained usage (Venkatesh & Morris, 2000).

Ha6: Social Influence has a significant influence over the learners' Behavioral Intention to adopt online classes.

Ha15: Social Influence has a significant influence over the lecturers' Behavioral Intention to adopt online classes.

2.2.4 Facilitating Conditions on Attitude & Behavioral Intention

Facilitating Conditions are defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system (Venkatesh et al., 2003). What constitutes facilitating conditions are theoretical constructs such as perceived behavioral control (TPB, C-TAM-TPB), facilitating conditions (MPCU), and compatibility (IDT).

Venkatesh et al. (2003) found it to be significant in both voluntary and mandatory settings of technology usage immediately following training. In addition, Facilitating Conditions, empirically having a direct influence on usage, negates having one with Behavioral Intention. According to the researchers, Behavioral Intention only becomes significant in the absence of core constructs like Performance Expectancy and Effort Expectancy.

Dwivedi et al. (2019) agreed in their earlier study; but later in furthering expansion of the role of Attitude (Dwivedi et al., 2019), the unexpected path between Facilitating Conditions and Attitude became accounted for as well. The revised UTAUT would acknowledge this context in the form of training programs and help desks which may be instrumental in enabling individuals to form positive attitudes about the technology use.

Ha7: Facilitating Conditions has a significant influence over the learners' Attitude to adopt online classes.

Ha16: Facilitating Conditions has a significant influence over the lecturers' Attitude to adopt online classes.

Moreover, because of the inclusion of Attitude as a mediating variable, there is more reason to believe Facilitating Conditions do influence Behavioral Intention of using technology. And because of the addition of Attitude in the revised UTAUT model, the explanatory power of the theoretical model has improved from 38% to 45% variance for Behavioral Intention (Dwivedi et al., 2019).

Ha8: Facilitating Conditions has a significant influence over the learners' Behavioral Intention to adopt online classes.

Ha17: Facilitating Conditions has a significant influence over the lecturers' Behavioral Intention to adopt online classes.

2.2.5 Attitude on Behavioral Intention

Venkatesh et al. (2003) in their establishment of the UTAUT, also recognized Attitude towards using technology as the strongest predictor of Behavioral Intention. However, the researchers have also empirically established that, in one way or another, attitudinal/affective reactions have already been encompassed in the first two core constructs – Performance Expectancy and Effort Expectancy. Therefore, Attitude will only have a direct effect in the absence of the latter mentioned constructs. The non-significance of Attitude has been further supported by previous model tests (Davis et al., 1989; Taylor & Todd, 1995; Thompson et al., 1991)

Although Attitude is deemed an iterating construct in the UTAUT, Dwivedi et al. (2019) believed, as in the previous literature, that it is still significant in determining Behavioral Intention. For the revised UTAUT, the researchers would still maintain that individuals still form intentions to perform behaviors toward which they have a positive attitude about.

Ha9: Attitude has a significant influence over the learners' Behavioral Intention to adopt online classes.

Ha18: Attitude has a significant influence over the lecturers' Behavioral Intention to adopt online classes.

2.3 Conceptual Framework

The final conceptual framework being used is based on the revised UTAUT Model (Dwivedi et al., 2019); four core constructs as exogenous variables being mediated by Attitude to predict Behavioral Intention; final endogenous factor – Use Behavior, being omitted.

3. Research Methodology

This non-experimental quantitative study required non-probabilistic voluntary responses from university learners and lecturers in predicting their perception and Behavioral Intention towards adoption of online classes during COVID-19 outbreak. A valid and reliable questionnaire was operationalized, customized to fit the specific context, and made available online for convenient distribution and solicitation.

The population for this empirical study were 8,142 learners and 621 lecturers as of Semester 2 of the year 2020 at Rajamangala University of Technology, Tawan-ok (RMUTTO) varying in gender, age, and to which faculty and campus they belong. The sample for this empirical study were those who responded to the voluntary public survey; which were 414 learners and 166 lecturers.

The research instrument was a google form-generated questionnaire, which consisted of three parts:
Part 1 – General information such as occupation, gender, age group, and campus they currently belong to;
Part 2 – 23-item Survey on Adoption of Online Class during COVID-19 Outbreak; and
Part 3 – Follow-up open-ended questions for both learners and lecturers.

The validity of the questionnaire was based on the total adoption of items used by Venkatesh et al. (2003) in developing the Unified Theory of Acceptance & Use of Technology (UTAUT) as proposed measurement in their previous study entitled, "User Acceptance of Information Technology: Toward A Unified View". The reliability on the other hand, was based on the previously conducted pilot test among 30 university learners and 30 university lecturers with no scores less than 0.6 Cronbach's Alpha (Cronbach, 1951). Furthermore, the questionnaire was made available in two languages, English and Thai, since the minority consisted of a few hired foreign language teachers and the rest are mostly Thai.

The process started by preparing the questionnaire in google form. The permission to run the study with learners and lecturers as subjects of the study was firstly approved and permitted by the President of the university. The online questionnaire was attached as google form links and sent as emails to all subjects through the assistance of the ICT department of the university. Upon inception, subjects were given two weeks to respond, or until responses suffice data analysis count requirement to conduct SEM analysis. The data was collected as generated summary by google forms; then later interpreted through the appropriate data analysis tools.

Descriptive statistics to describe characteristics and explain central tendencies & variability of data were collected in this study as mean, range, and standard deviation. Data analyses had employed Exploratory Structural Equation Model (ESEM) (Asparouhov & Muthén, 2009) where the data underwent three types of scrutiny: 1. Exploratory Factor Analysis (EFA) (Child, 1990) – to validate the construct items, 2. Confirmatory Factor Analysis (CFA) (Jöreskog, 1969) – to validate the constructs, and 3. Structural Equation Model SEM (Kaplan, 2008) – to validate construct relationships. As for the follow-up questions on the learners' and lecturer' current adoption of online classes, responses were qualified in similar themes and quantified in tabular statistics for reporting.

4. Results And Discussion

4.1 Demographic Information

All the 580 samples are learners (414) and lecturers (166) from Rajamangala University of Technology, Tawan-ok varying in gender, ages, and campuses to where they currently reside. The chart above shows females significantly more (71%) than males across subgroups, and much more significantly among learners (73%). Across ages, the learners aging 30 and below (69%) are the extreme majority in both subgroups. Moreover, majority of the respondents (50%) came from learners of Chakrabongse Bhuvanat Campus.

4.2 Data Analyses

4.2.1 Construct Items Analysis

The 23 construct items used in the questionnaire were adopted from the UTAUT theoretical model, thus construct and face validity have already been established. Yet, to further validate the items' convergent & discriminant validity, and reliability, the Exploratory Factor Analysis was run. Data adequacy was at .964 KMO with Bartlett's Test at .000 significance; and after elimination of cross-loads, KMO was at .940 with Bartlett's still at .000 significance – indicating that construct items can be grouped and that they are appropriate for identifying relationships (Osei-Kyei et al., 2014).

Data validity was initially determined among construct items with high convergent validity (factor loadings) and minimal discriminant validity (cross-loadings) through the Pattern Matrix (Campbell & Fiske, 1959). After resolution was made to eliminate eight major cross-loaders, convergent validity remained high with no factor loadings lower than 0.7, discriminant validity established despite two constructs minimally correlating at .715 as evidenced by the Component Correlation Matrix (Lyytinen & Gaskin, 2016).

Data Reliability was established separately for both learners and lecturers subgroup, before and after deletion of cross-loading items. The internal consistency of constructs as a measurement of latent variables for both groups were high and remained higher than 0.6 Cronbach's Alpha (Nunnally, 1978) threshold cut-off. The construct items were established to be adequate, valid and reliable after undergoing EFA.

4.2.2 Measurement Model Analysis

After the construct items were established fit, the constructs were run for a measurement model fit through the Confirmatory Factor Analysis. In doing so, factor loadings, model fit, model re-specification, and construct reliability & validity were established. All constructs had items with factor loadings higher than 0.5 (Gao, Mokhtarian, & Johnston, 2008) with standard error, critical ratio (t-value), and p-value supporting significance. Initial model fit was deemed terrible; however, after model re-specification, goodness of fit was reported:

CMIN/DF = 2.281, CFI = 0.985, SRMR = 0.025, RMSEA = 0.056, PClose = 0.191 for learners; and: CMIN/DF = 1.489, CFI = 0.979, SRMR = 0.0594, RMSEA = 0.054, PClose = 0.349 for lecturers – reflecting excellent model fit for both subgroups (Hu & Bentler, 1999).

Construct reliability was established through Composite Reliability (CR) and Maximal Reliability (MaxR(H)) being higher than recommended 0.70 (Awang, 2015). Convergent validity reported Average Variance Extracted (AVE) no value less than 0.50 (Hair, Black, Babin, & Anderson, 2010), and all values for CR were greater than the AVE.

Discriminant validity was assessed through the Heterotrait-Monotrait Ratio of Correlations (HTMT) with no value less than 0.90 (Gold, Malhotra, & Segars, 2001) among constructs. Finally, to know whether the constructs meant the same to both subgroups: learners and lecturers, the configural invariance was identified by comparing model fit per subgroup and as a whole. The model fit among groups were excellent proving that the measurement model was invariant among subgroups.

2.3 Structural Model Analysis

After the data underwent EFA for construct items analysis and CFA for constructs analysis, the model was ready to test pre-theorized relationships through the Structural Equation Model (SEM). In doing so, the structural model fit was tested, hypotheses were concluded, and path analyses were made.

The structural model was found fit for learners at: CMIN/DF = 2.439, CFI = 0.983, SRMR = 0.028, RMSEA = 0.059, PClose = 0.083; and lecturers at: CMIN/DF = 1.489, CFI = 0.979, SRMR = 0.064, RMSEA = 0.054, PClose = 0.349. Hypotheses testing alternative hypotheses as being supported or not supported for both groups as shown in the comparison below:

There were six supported (H1, H2, H4, H5, H6, H7) with three not supported alternative hypotheses (H3, H8, H9) from the learners; and there were five supported (H10, H12, H13, H5, H16) and four not supported (H11, H14, H17, H18) from the lecturers subgroup. Similar hypotheses reflecting acceptance in both groups were: PE to ATT (H1 & H10), EE to BI (H4 & H13), SI to BI (H6 & H15), and FC to ATT (H7 & H16). Hypotheses accepted particular to learners were PE to BI (H2), and SI to ATT (H5); and to lecturers subgroup was EE to ATT (H12). Both subgroups had retained the null hypotheses for FC to BI (H8 & H17), and ATT to BI (H9 & H18).

4.2.4 Path Analysis

Towards path analysis, path coefficients for both subgroups rank were found similar with the first top three correlations namely: Performance Expectancy to Attitude, Effort Expectancy to Behavioral Intention, and Social

Influence to Behavioral Intention. Particularly high coefficient for learners was Performance Expectancy to Behavioral Intention; and for lecturers Effort Expectancy to Attitude. Both subgroups scored negatively for Facilitating Conditions to Behavioral Intention.

4.3 Discussion

4.3.1 Performance Expectancy on Attitude & Behavioral Intention

In the revised UTAUT, Performance Expectancy sought to explain its influence over Attitude and over Behavioral Intention. The extent to which technology is perceived useful influences Attitude (Dwivedi et. al, 2019); and regardless settings being voluntary or mandatory, performance expectancy remained the strongest predictor of Behavioral Intention towards technology use (Venkatesh et. al, 2003). In the context of this study, below is a discussion whether or not Performance Expectancy has significant influence over Attitude and Behavioral Intention.

The hypothesized path between PE and ATT were found the most significant for both learners (H1: $\mu = .514$) and lecturers (H10: $\mu = .491$). This means that the subgroups' attitude on adopting online classes were being influenced by how useful they perceived the technology was in achieving educational goals. Recent studies, during the context of this pandemic, support similar claims (Tiwari, 2020; Sukendro et al., 2020; Maphosa, Dube, & Jita, 2020) that learners' positive attitude with online learning was strongly related with the extent on how helpful they perceived the technology being used; and claims about lecturers (Sangeeta & Tandon, 2020; Lazim et al., 2021), liking the adoption of technology was based on how they believed technology to be supportive in their online teaching endeavors. As for this study, it is concluded that Performance Expectancy does influence Attitude significantly.

The hypothesized path between PE and BI was found significant for learners (H2: $\mu = .263$), but not for lecturers (H11: $\mu = -.082$). This means that while the Behavioral Intention was directly affected by how the learners appreciate the usefulness of the technology, the lecturers were not as affected. Several recent studies supported how strong as a predictor Performance Expectancy was over Behavioral Intention for both learners and lecturers, especially in the context of the pandemic (Tiwari, 2020; Samat et al., 2020; Raza et al., 2020). The studies have shown that both subgroups showed more intention to adopt online classes if they believed the technology was helping them in getting positive online learning or online teaching results. However, a few studies in the same context of the present pandemic revealed otherwise. The educational technology gap in Jakarta Indonesia middle school being a disadvantage (Asvial et al., 2021), and Performance Expectancy being moderated by perceived risk in some 390 adults in Bangkok Thailand as being debunked (Chayomchai et al., 2020) – are two occasions Performance Expectancy surprisingly uncorrelated with Behavioral Intention. As for the lecturers of this study, a possible reason might be that the respondents were mostly middle-aged and had strong positive responses on Performance Expectancy having no qualms about appreciating the importance of technology unlike the older groups (Venkatesh et al., 2019), which is the minority in this study. Thus, their intention to adopt online classes would have nothing to do with biases about performance expectations from the technology. As for the conclusion, the decision is split between learners and lecturers.

4.3.2 Effort Expectancy on Attitude & Behavioral Intention

With its significance on Attitude, a group of researchers were able to prove how one sees technology as easy or hard directly affects how one feels about using the technology (Dwivedi et al., 2019). As towards Behavioral Intention, the UTAUT established Effort Expectancy as significant in voluntary and mandatory settings and declining over periods of extended and sustained usage (Venkatesh et al., 2003). In the context of this study, it is paramount to know whether Effort Expectancy significantly influence Attitude and Behavioral Intention.

The hypothesis established between EE and ATT showed insignificant for learners (H3: $\mu = .030$), yet otherwise for lecturers (H12: $\mu = .228$). How learners felt about the adoption of online classes had nothing to do with it being easier or harder. However, for lecturers, technology being easier or harder directly and proportionally affected how they would feel about the adoption. The potential reason might be found in the comparison itself, that younger generation of learners don't feel much burdened about the intricacies of technology unlike older generation of lecturers. Age being a moderator affecting Attitude explains Effort Expectancy being more significant along age brackets (Venkatesh et al., 2012). Effort Expectancy and Attitude in lecturers were found significant as evidenced in similar recent publications (Lazim et al., 2021; Sukendro et al., 2020; Sangeeta & Tandon, 2020), stating that it mattered to them how easy, user-friendly and convenient to use the system. The decision was split among groups for this study; the learners' Effort Expectancy has nothing to do with their Attitude in adopting online classes; as for lecturers, the opposite is true.

The hypothesis about EE and BI were both strongly significant for learners (H4: $\mu = .332$) and lecturers (H13: $\mu = .500$). This means that learners' intention to adopt online classes were strongly influenced by how convenient the adoption would be; and similarly true among lecturers as well. Recent publications (Chayomchai, 2020; Chayomchai et al., 2020; Raza et al., 2021; Tiwari, 2020) have proven perceived ease of use, factored in the construct Effort Expectancy, significantly influencing Behavioral Intention to use technology. As for this study, a strong conclusion is made that Effort Expectancy significantly influences Behavioral Intention to adopt online classes among learners and lecturers during the current pandemic.

4.3.3 Social Influence on Attitude & Behavioral Intention

It's influence on Attitude and Behavioral Intention is explored here. On a personal level, scientists believed that identification with people that mattered to them, their opinions, had a say in how they felt (attitude) about using technology (Dwivedi et at., 2019); but the individual, as part of the bigger functional workforce, make decisions more as a mechanism of compliance rather than just identification or internalization of how they felt, which eventually shapes their intention to use technology (Venkatesh et al., 2012). In this study, it's essential to know whether Social Influence has significant influence over Attitude and eventually over Behavioral Intention.

The hypothesis between SI and ATT had been explored as significant for learners (H5: $\mu = .185$), and not at all true for lecturers (H14: $\mu = .070$). This means that the learners' Attitude in the sudden adoption of online classes was significantly related to how their important loved ones, like friends and family, thought about the idea of learning online during the pandemic. Previous study supported this claim among learners (Dwivedi, Rana, Janssen, Lal, Williams, & Clement, 2017; Mosunmola et al., 2018; Tseng et. al., 2019), that relating to their classmates (identification) and understanding their parents' concern (internalization) had an impact on how they felt about accepting technology. Surprisingly for lecturers, Social Influence did not impact their Attitude at all in adopting technology. A similar study had the same result during the context of this pandemic (Sangeeta & Tandon, 2020), that some teachers in Rajpura, India did not base their attitude on how important people in their lives thought of their adoption of technology. This said much about how they were able to do things during this pandemic out of compliance, rather than out of biased perception (Dwivedi et al., 2019). The conclusion for Social Influence on Attitude holds true for learners but not for lecturers towards their adoption of online classes during this pandemic.

The hypothesis established between SI and BI were significant for learners (H6: $\mu = .298$) and lecturers (H15: $\mu = .292$). For both, it meant that how their important others believe in adopting of online classes during the pandemic, shape their Behavioral Intention significantly. Recent studies (Samat et al., 2020; Raza et al., 2021; Asvial et al., 2021) support the claim that both learners and lecturers were more likely to comply with the policy of adopting online classes as being positively reinforced by their loved ones who were concerned about their safety during pandemic. Therefore, it is concluded in this study that Social Influence significantly influences Behavioral Intention towards adopting online class for both learners and lecturers during COVID-19 outbreak context.

4.3.4 Facilitating Conditions on Attitude & Behavioral Intention

Facilitating Conditions is proven for its relationship with Attitude and Behavioral Intention. As an emergent path in Dwivedi et al.'s (2019) meta-analysis of UTAUT and the addition of Attitude as a mediating factor, Facilitating Conditions in the forms of help desks and customer support were proven instrumental in how users felt about the use of technology. Furthermore, the same researcher believed that, although Facilitating Conditions was only linked with Use Behavior as the final endogenous construct in UTAUT, it was however also proven significantly related with Behavioral Intention – only because Attitude was introduced in the first place (Dwivedi et al., 2019). The relationships are being explored whether there is a significance between Facilitating Conditions and Attitude & Facilitating Conditions and Behavioral Intention.

The alternative hypothesis between FC and ATT were accepted for both learners (H7: µ = .240) and lecturers (H16: µ = .184). This meant that for both groups, the availability and unavailability of support in using technology has some influence in how positive or negative they felt about using the technology. The study by Sangeeta and Tandon (2020) reciprocated this result expressing the teachers of Rajpura, India felt encouraged in using the program during the pandemic because of training programs being made available as well. As for subjects of this study, it is solidly concluded that Facilitating Conditions significantly influenced both groups' Attitude towards adoption of online classes during the context of the pandemic.

The alternative hypotheses between FC and BI were rejected for both learners (H8: µ = -.122) and lecturers (H17: µ = -.035). This meant that the provision of facilities and organizational support did not reinforce their intentions to use technology. Similar recent studies during this pandemic (Chayomchai et al., 2020; Asvial et al., 2021) did not support the claim likewise concluding that Facilitating Conditions had more to do with the Actual Use rather than with Behavioral Intention to use technology. This was originally premised in the UTAUT (Venkatesh et al., 2003) were Facilitating Conditions could hold significance on Behavioral Intention only in the absence of first two constructs - Performance Expectancy and Effort Expectancy, as previous empirical studies were concerned (Eckhart et al., 2009; Foon & Fah, 2011; Yeow & Loo 2009). This study concludes Facilitating Condition on Behavioral Intention not significant for both sample groups towards their adoption of online classes during COVID-19 outbreak.

4.3.5 Attitude on Behavioral Intention

Attitude and Behavioral Intention are the final two constructs in the revised UTAUT that deemed to have significant relationship. Although Attitude is deemed an iterating construct in the UTAUT, Dwivedi et al. (2019) believed, as in the previous literature, that it is still significant in determining Behavioral Intention. These group of researchers would still maintain that individuals still form intentions to perform behaviors toward which they have a positive attitude with. For this study, Attitude is tested for significance on Behavioral Intention.

The hypothesis between ATT and BI came out insignificant for both learners (H9: µ = .061) and lecturers (H12: µ = -.004). This meant that there is a clear disconnect on how both groups felt about the use of technology and their intentions to use the technology. A recent study (Asvial et al., 2021) produced similar claims among Indonesian middle schoolers in their acceptance of online classes during COVID-19. It was concluded that because of the existing gap in using technology (being not ready), Attitude and Behavioral Intention could not be established. The reason might be the same as for this study, as COVID-19 context has put learners and lecturers in a limitation which is a disadvantage of choice; states of their present attitude don't say much towards their intention to use. Another plausible reason could be based in the original UTAUT findings by Venkatesh et al. (2003), stating that Attitude had similar indicators that of Performance Expectancy and Effort Expectancy, and thus its redundance did not contribute well to the establishment of the unified model of technology acceptance. For the record, this study has concluded that Attitude has no significant influence over Behavioral Intention towards adoption of online classes among learners and lecturers in the present context of Covid-19 outbreak.

5. Conclusions

5.1 Summary of Key Findings

This study initially identified factors as prescribed by the revised UTAUT in determining the learners' and lecturers' Attitude and Behavioral Intention to adopt online classes in the context of COVID-19 outbreak. Furthermore, it sought to report their differing perceptions on their actual current adoption of online classes. Below are the summarized results of this study:

There were two endogenous variables in this study – Attitude and Behavioral Intention. Over Attitude, the following had direct effects: Performance Expectancy, Social Influence, and Facilitating Conditions; leaving Effort

Expectancy rejected. Over Behavioral Intention, the following had significant influences: Performance Expectancy, Effort Expectancy, and Social Influence; leaving two others: Facilitating Conditions and Attitude not supported.

The learners' perception of adopting online classes had opinions that the policy was necessary, beneficial, yet not so practical amidst COVID-19 outbreak. Furthermore, they believed the greatest challenge of adopting online classes were related to paucity and capacity, and that a possible issue might be related to effectiveness of online classes if it were to continue longer in the future.

As for the lecturers, the same four exogenous and two endogenous variables were at play. Performance Expectancy, Effort Expectancy, Facilitating Conditions, but except Social Influence, were found to have significant effects on Attitude. In addition, Effort Expectancy and Social Influence, were found having influence over Behavioral Intention; Performance Expectancy, Facilitating Conditions and Attitude having none.

When asked about their perceptions about the current policy, the majority felt it was strongly necessary, beneficial, yet not as practical as hoped. When asked what challenges they were currently facing with the adoption, the bigger majority believed them to be related to paucity and capacity; while a high minority accounted infrastructure as contributing factors to problems in running online classes. When asked about probable issues they could think of if the adoption persisted longer, most lecturers believed them having to do with equity, sustainability and effectiveness.

5.2 Implications for Practice

There were significant relationships made during the testing of the hypotheses, and the results have clearly shown what the university could do to encourage learners' and lecturers' adoption of the government's mandate to resume classes during the pandemic.

5.2.1 Practical Implications for Learners

Performance Expectancy was found to be the strongest indicator for Attitude and equally significant on Behavioral Intention towards adoption of online classes. Now that this study has proven how learners see the adoption as being useful, causing them to feel accomplished, increasing their productivity, bettering their learning results – all these, influence the extent of their preference and intention amidst being mandated; thus, an effort should be made to improve their online learning experience. Although the vast majority of learners perceived adoption of online classes as necessary and beneficial, they also thought the initiative as not practical, since there were problems related to unpreparedness in the sudden implementation. Challenges they thought were related to paucity – setbacks due to instability (weak internet, log-in errors, lags), and capacity – setbacks due to inability (first timer, not computer proficient); a dominant issue they thought needed looked at for the future, is the adoption's effectiveness. All of these are only saying that for them to be able to appreciate the adoption of online classes, the quality of adoption itself is needed to be better and more.

Effort Expectancy was the second strongest indicator found significantly influencing Behavioral Intention. This study has proven that the extent to how learners saw the adoption of online classes as simpler, clearer and more understandable will have impacted their intention more towards adoption itself. Therefore, an effort should be made to make adoption of online classes easier and user-friendly for them. The administration may choose a unified digital platform with occasional tutorials where learners be able to navigate conveniently.

This study found Social Influence impacting Attitude and Behavioral Intention. It has proven that the degree to which the learners' friends and family believed the adoption of online classes also influenced their preference and intention towards actual adoption. Hence, extra efforts can be made to encourage important people to theses learners to continually give their utmost support in learning online. Somehow, the best way to do this is to send them emails of gratitude, as thanking them would be the best means of getting more of their support for the learners.

The significance of Facilitating Conditions in the formation of the learners' attitude toward adoption of online learning was proven in this study. This meant that the availability of resources, knowledge, compatibility and assistance during online learning impact their preference to adopt online learning. Hence, an effort must be made on providing learners the necessary resources, pertinent knowledge, and assistance especially during their troubles in adopting online classes. Administrators may establish a system to provide timely updates, offer mini-trainings, and offer call support whenever students are at loss with online classes.

5.2.2 Practical Implications for Lecturers

Performance Expectancy was found to be a strong indicator for Attitude towards adoption of online classes. Now that this study has proven how lecturers see the adoption as being instrumental, helpful, giving good teaching results or better – all these influence the extent of their preference despite the policy being abruptly enforced; thus, an effort should be made to improve their online teaching experience. Although the vast majority of lecturers perceived adoption of online classes as necessary and beneficial, they also thought the initiative as not practical, since there were difficulties related to the sudden implementation. Challenges they thought were related to paucity – setbacks due to instability (weak internet, log-in errors, lags), and capacity – setbacks due to inability (first timer, not computer proficient); a dominant issue they thought needed looked at for the future, is the adoption's sustainability. All of these are only saying that for them to be able to appreciate the adoption of online classes, the quality of adoption itself is needed to be better and maintained at standard.

Effort Expectancy was the strongest indicator found significantly influencing Attitude and Behavioral Intention in lecturers. This study has proven that the extent to how they saw the adoption of teaching online as simple, clear and understandable to follow will have an impact in their preference and intention towards adoption itself. Therefore, an effort should be made to make online teaching easier and user-friendly. The perceptions of the lecturers confirmed this issue as equity – that when initiative was made to enforce online teaching, corresponding effort to make it easier and faster to adopt was equally important to them. Next to quality, convenience of adopting online classes should be in the checklist as well.

This study found Social Influence impacting Behavioral Intention. It has proven that the degree to which the lecturers' friends and family believed the adoption of online classes also influenced their preference towards actual adoption. Hence, an effort can be made to boost morale among lecturers by keeping open a forum where communal discussions about the policy during COVID-19 is openly tabled for everyone's discussion; a chance to express their thoughts among colleagues and peers and get to listen from each other would likely boost their preference to support adoption of online classes.

The significance of Facilitating Conditions in the formation of the learners' Attitude toward adoption of online learning was proven in this study. This meant that the availability of resources, knowledge, compatibility and assistance during online learning impact their preference to adopt online learning. Hence, an effort must be made on providing lecturers the necessary resources, pertinent knowledge, and assistance especially during troubleshooting problems in online teaching. Administrators may establish a system to provide timely updates, offer mini-trainings, and offer call support whenever lecturers are at loss with online classes.

5.3 Recommendations for Further Research

Despite the success of this research in arriving at significant conclusions, the researcher felt more could be achieved with: 1. the addition of moderators, 2. addition of Actual Use of Behavior, 3. addition of parameters more specific to subgroups, 4. having a more demographically represented sample population; and 5. Having results for indirect and mediating effects as well.

The addition of moderators and the final endogenous construct, Actual Use of Behavior, is as suggested in original UTAUT model. Although reasons have been established to exclude them from the start, incorporating them in a further similar study may contribute well to establishing theoretical implications. Their inclusion could be lent insignificant because of the nature of this study being mandatory, nevertheless, additional theoretical basis would be established.

Parameters specific to learners and online learning (COVID-19 anxiety, perceptions about the lecturer, perceived cost), and parameters specific to lecturers and online teaching (readiness, administration support, project team capability) should be included for future studies; thus, making results more meaningful and specific for the current context.

Employing more samples that fairly represents demographic information among groups is one thing to add in further studies. Although, this study is successful in explaining significant relationships among technology acceptance constructs, it is also much better put if the samples were dispersed equitably among age, gender and subgroups; consideration of bias is better addressed.

Finally, besides identifying direct effects – indirect and mediating effects can be further explored for more meaningful internal relationships hypotheses testing as well.

References

Asparouhov, T., & Muthén, B. (2009). Exploratory structural equation modeling. Structural Equation Modeling, 16(3), 397-438.

Asvial, M., Mayangsari, J., & Yudistriansyah, A. (2021). Behavioral Intention of e-Learning: A Case Study of Distance Learning at a Junior High School in Indonesia due to the COVID-19 Pandemic. International Journey of Technology, 54-64.

Awang, Z. (2015). SEM made simple: a gentle approach to learning Structural Equation Modelling. Bandar Baru Bangi: MPWS Rich Publication.

Campbell, D. T., & Fiske, D. W. (1959). Convergent and Discriminant Validation by the Multitrait-Multimethod Matrix. Psychological Bulletin, 56, 81-105.

Chayomchai, A. (2020). The Online Technology Acceptance Model of Generation-Z People in Thailand during Covid-19 Crisis, Management & Marketing. Challenges for the Knowledge Society, 15, 496-513.

Chayomchai, A., Phonsiri, W., Junjit, A., Boongapim, R., & Suwannapusit, U. (2020). Factors Affecting Acceptance & Use of Online Technology in Thai people during COVID-19 Quarantine Time. Management Science Letters, 10, 3009-3016.

Child, D. (1990). The essentials of factor analysis. (2nd ed). New York, US: Cassell Educational.

Compeau, D. R., & Higgins, C. A. (1995b). Computer Self-efficacy: Develpoment of a Measure and Initial Test. MIS Quarterly, 19, 189-211.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. Psychometrika, Vol.16, 297-334.

Davis, F. (1985). A Technology Acceptance Model for Empirically Testing New End-User Information Systems - Theory and Results, PhD thesis. Massachusetts: Massachusetts Institute of Technology.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319-340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. Management Science, 35 (8). 982-1003.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and Intrinsic Motivation to Use Computers in the Workplace. Journal of Applied Psychology, 11, 1111-1132.

Dwivedi, Y. K., Rana, N. P., Janssen, M. L., Lal, B., Williams, M. D., & Clement, M. (2017). An Empirical Validation of the Unified Model of Electronic Governmenet Adoption (UMEGA). Government Information Quarterly, 1-20.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a Revised Theoretical Model. Information Systems Frontier, 21:719-734.

Eckhardt, A., Laumer, S., & Weitzel, T. (2009). Who INfluences Whom? Analyzing Workplace Referents' Social Influence on IT Adoption and Non-Adoption. Journal on Informational Technology, 24(1), 11-24.

Fishbein, M., & Ajzen, I. (1975). Belief, Attitude, Intention, and Behavior: An Introduction to Theory & Research. Addison-Wesley Publication Company.

Foon, Y. S., & Fah, B. C. (2011). Internet Banking Adoption in Kuala Lumpur: An Application of UTAUT Model. International Journal of Business and Management, 6(4), 161-167.

Gao, S., Mokhtarian, P. L., & Johnston, R. A. (2008). Nonnormality of data in structural equation models. Transportation Research Record, 2082, 116-124.

Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organizational capabilities perspective. Journals in Management Information Systems.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Englewood Cliffs: Prentice Hall.

Hu, & Bentler. (1999). "Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives".

Imsa-ard, P. (September 2020). Thai University Students' Perceptions Towards The Abrupt Transition To 'Forced' Online Learning in th Covid-19 Situation. Journal of Education Khon Kaen University, 43, 30-44.

Jöreskog, K. G. (1969). A general approach to confirmatory maximum likelihood factor analysis. Psychometrika, 34(2), 183-202.

Kaplan, D. (2008). Structural Equation Modeling: Foundations and Extensions (2nd ed.). SAGE.

Lazim, C. S., Ismail, N. D., & Tazilah, M. D. (2021). Application of Technology Aceeptance Model (TAM) Towards Online Learning During COVID-19 Pandemic: Accounting Students' Perspective. International Journal of Business Economics and Law, 24(1), 13-20.

Lyytinen, K., & Gaskin, J. (2016). Exploratory Factor Analysis (EFA).

Mala, D. (2020, March 12). Covid-19 Fear Pushes Classes Online. Retrieved from Bangkok Post: https://www.bangkokpost.com/thailand/general/1876594/covid-19-fear-pushes-classes-online

Mala, D. (2021, January 4). Covid Hinders Education Again. Retrieved from Bangkok Post: https://www.bangkokpost.com/thailand/general/2045015/covid-hinders-education-again

Maphosa, V., Dube, B., & Jita, T. (2020). A UTAUT Evaluation of WhatsApp as a Tool for Lecture Delivery During the Covid-19 Lockdown at a Zimbabwean University. International Journal of Higher Education, 84-93.

Mei, B., Brown, G. T., & Teo, T. (2018). Journal of Educational Computing Research, 56(1), 74–104.

Moore, G. C., & Benbasat, I. (1991). Development of Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. Information Systems Research, 2, 192-222.

Mosunmola, A., Mayowa, A., Okuboyejo, S., & Adeniji, C. (2018). Adoption and use of mobile learning in higher education: The UTAUT model. Proceedings of the 9th International Conference on E-Education, E-Business, E-Management and e-Learning, (pp. 20-25).

Nunnally, J. C. (1978). Psychometric theory. 2nd ed. New York: NY: McGraw-Hill.

Osei-Kyei, R., Dansoh, A., & Ofori-Kuragu, J. (2014). Reasons for adopting public-privatepartnership (PPP) for construction projects in Ghana. International Journal of Construction Management, Vol. 14 No. 4, pp. 227-238.

Raza, S. A., Qazi, W., Khan, K. A., & Salam, J. (2021). Social Isolation and Acceptance of the Learning Management System (LMS) in the time of COVID-19 Pandemic: An Expansion of the UTAUT Model. Journal of Educational Computing, 59(2), 183-208.

Samat, M., Awang, N. A., Hussin, S. N., & Nawi, F. A. (2020). Online Distance Learning Amidst Covid-19 Pandemic Among University Students: A Practicality of Partial Least Squares Structural Equation Modelling Approach. Asian Journal of University Education, 16(3), 220-233.

Sangeeta, G., & Tandon, U. (2020). Factors Influencing Adoption of Online Teaching by School Teachers: A Study During Covid-19 Pandemic. Wiley & Sons Ltd., 1-11.

Sukendro, S., Habibi, A., Khaeruddin, K., Indrayana, B., Syahruddin, S., Makadada, F. A., & Hakim, H. (2020). Using an Extended Technology

Acceptance Model to Understand Students' Use of E-learning During Covid-19: Indonesian Sport Science Education Context. Heliyon, 1-9.

Tandon, U., & Kiran, R. (2019). Factors impacting customer satisfaction: an empirical investigation into online shopping in India. Journal of Information Technology Case and Application Research, 21:1, 13-34.

Taylor, S., & Todd, P. A. (1995b). Understanding Information Technology Usage: A Test of Competing Models. Information Systems Research, 6, 144-176.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal Computing: Toward a Conceptual Model of Utilization. MIS Quarterly, 15, 124-143.

Tiwari, P. (2020). Measuring the Impact of Students' Attitude towards Adoption of Online Classes during Covid 19: Integrating UTAUT Model with Perceived Cost. TEST Engineering & Management, 8374-8382.

Todd, R. W. (2020). Teachers' Perceptions of the Shift from the Classroom to Online Teaching. International Journal of TESOL Studies, 2, 4-16.

Tseng, T. H., Lin, S., Wang, Y. S., & Liu, H. X. (2019). Investigating teachers' adoption of MOOCs: The perspective of UTAUT2. Interactive Learning Environments, 1-16.

Venkatesh, V., & Morris, M. G. (2000). Why Don't Men Ever Stop to Ask for Directions? Gender, Social Influence, and Their Role in Technology Acceptance & Usage Behavior. MIS Quarterly (24:1), 115-139.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward A Unified View. MIS Quarterly, 27, 425-478.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly, 36(1), 157-178.

Warshaw, P. R. (1980). A New Model for Predicting Behavioral Intentions: An ALternative to Fishbein. Journal of Marketing Research (17:2), 153-172.

Westland, J. C., & Clark, T. H. (2000). Global Electronic Commerce: Theory and Case Studies. Cambridge: MIT Press.

Yeow, P. H., & Loo, W. H. (2009). Acceptability of ATM and Transit Applications Embedded in Multipurpose Smart Identity Card: An Exploratory Study in Malaysia. International Journal of Electronic Government Research, 5(2), 37-56.