pISSN: 1906 - 3296 © 2020 AU-GSB e-Journal.
eISSN: 2773 – 868x © 2021 AU-GSB e-Journal.
http://www.assumptionjournal.au.edu/index.php/AU-GSB/index

Exploring The View of Parents of Primary School Students on the Use Behavior of U-Learning in Thailand During COVID-19

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Received: June 20, 2023. Revised: September 18, 2023. Accepted: August 26, 2023

Abstract

Purpose: This study explores the factors influencing the behavioral intention and use behavior of primary school parents in a private school in Samutprakarn, Thailand, towards ubiquitous learning (u-learning) during the height of the COVID-19 pandemic. **Research design, data, and methodology:** This quantitative research involved 500 respondents and used an online survey questionnaire. The non-probability sampling technique was used. Item-Objective Congruence and pilot testing were used to check the content validity and reliability of the questionnaire before its administration. The data were analyzed using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). **Results:** The study's findings identified perceived usefulness to influencing attitude and behavioral intention toward u-learning strongly. Effort expectancy was found to influence the intent to accept technology directly. Moreover, behavior intention directly influences the use of behavior towards ubiquitous learning. Factors considered insignificant were perceived ease of use, performance expectancy, social influence, and attitude. **Conclusions:** With perceived usefulness as the strongest factor in technology acceptance and followed by effort expectancy, it is recommended that technology developers, curriculum designers, and educators consider these components in creating effective strategies and u-learning systems suitable for primary school learners during a crisis.

Keywords : Ubiquitous Learning, Technology Adoption, Behavioral Intention, Use Behavior, COVID-19

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Parents of school-age children assisted with the classes at home while juggling work daily during the COVID-19 pandemic. It forced them to take a front seat in their children's education, as teachers conducted lessons remotely. However, despite being forced to take the new role due to the crisis, they expressed concerns about the quality of education, their children's well-being, and the impact of remote learning on their family life. Other parents felt online learning was less effective than on-site learning causing serious effects on their children's academic progress (Huang & Lin, 2017).

Faced with limited options and the adverse effects of school closures, education officials, school administrators, and teachers continued to tap various learning modes, such as digital, TV/radio, and paper, to fill the learning gap.

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According to Cope and Kalantzis (2013), ubiquitous learning (u-learning) contains the elements of a traditional classroom where a teacher, student, lessons, class work, assessments, and even group work exist. However, it differs from a brick-and-mortar school because a student can study anywhere and anytime with technology.

Haythornthwaite (2019) notes that the main features of U-learning include learning location, time, process, output, and even the key people managing the flow of knowledge. Learners can study at their own pace and space by accessing a common online learning platform, yet attend a virtual class with a teacher in real-time. Meanwhile, Li et al. (2005) states that technology plays a vital part in u-learning, as the learner has to pay more attention to the task involved, and the knowledge acquisition process is authentic, instinctive, and unconstrained. Simultaneous participation is done through various platforms such as Google Meet, Microsoft Teams, Zoom, Cisco Webex, Skype, FB Messenger, Line, and Discord (Ironsi, 2021).

In contrast, as learners do not necessarily share the same time zone or simply due to unavailability, the u-learning system offers opportunities for asynchronous learning that takes place via numerous Learning Management Systems (LMS) that package course materials in bite-size modules that can be comprehended and completed easily (Serdyukov, 2021). Popular digital solutions for schools involve Google Classroom, Microsoft 365 Education's Team, Moodle, Blackboard, Schoology, Canvas, and Edmodo, which permits the posting and sharing of multimedia files between learners and teachers.

Despite the promise of a successful learning experience, there is a need to consider the resources available such as teachers, infrastructures, technology, and the parent's capacity to support their children regarding electronic devices, space, time, and skills.

For the locale of this study, parents and guardians expressed concerns about longer screen times, lack of technical skills in navigating the digital learning platforms, and limited understanding of the whole system.

However, as more COVID-19 cases claimed lives, parents barely had a choice and faced head-on the use of technology in their children's classes. With the limited exposure to U-learning, parents bombarded the schools with requests for 24/7 technical assistance and on-site and off-site training on U-learning while observing social distancing.

In this study, u-learning was conducted via Google Meet and Google Classroom, and a regular timetable was set. Parents could allow their child to skip the Google Meet session and use the recorded Meet sessions uploaded in the Google Classroom to watch at their own pace. All learners must submit their independent or collaborated work via Google Classroom and other tasks the teachers assign.

Hence, this study further explores the behavioral intention and use behavior of primary school parents toward the role of technology in bridging the gap between the teacher and the learner during the global health crisis. It zeroed into the perception of the parents who had experience using ubiquitous learning (u-learning) as they assisted their children who had to stay home due to the pandemic.

2. Literature Review

2.1 Perceived Usefulness

Perceived usefulness implies the scale of an individual's belief towards the effectiveness of utilizing a specific procedure or structure to be more productive in completing a certain task (Davis, 1989). It is believed that using technology in education leads to improved learning performance, better communication, and increased efficiency in completing educational tasks (Venkatesh & Davis, 2000). Other research results show perceived usefulness as a sound forecast of the behavioral intention of learners towards using an automated system in accessing coursework on computers, laptops, tablets, mobile phones, etc. (Hu & Lai, 2019). In the study of Lourenço and Jayawarna (2011), perceived usefulness is a determining factor for learners to be more motivated in their schooling. Therefore, below hypotheses can be stated:
H1: Perceived usefulness has a significant impact on attitude.
H2: Perceived usefulness has a significant impact on behavioral intention.

2.2 Perceived Ease of Use

Perceived ease of use refers to a user's comfort level in controlling or managing a learning platform or system (Lin, 2013). In other words, it is a user's degree of ease in using a certain technology or structure due to the absence of any difficulty (Davis, 1989). Perceived ease of use of online learning during the same global health crisis is necessary to develop an affirmative attitude and intention toward it (Alqahtani et al., 2021). Davis (1989) considers it as the user's perception of how easy it is to learn and operate technology. Based on the previous studies, this research can put forward a hypothesis:
H3: Perceived ease of use has a significant impact on behavioral intention.

2.3 Performance Expectancy

Performance expectancy pertains to how a user embraces technology based on its performance of certain actions (Venkatesh et al., 2012). It is also defined as one's standard in accepting a specific product or service, such as a digital resource, to improve one's academic achievement (Chiu & Wang, 2008). Teo et al. (2003) consider it a strong influence on the intention to use technology in teaching based on perceived benefits among pre-service teachers. It is also described as a factor influencing the usage of e-learning systems among students due to the high expectations of improved learning outcomes (Al-Emran et al., 2016). Thus, a hypothesis is developed:
H4: Performance expectancy has a significant impact on behavioral intention.

2.4 Effort Expectancy

Effort expectancy is the level of comfort user experiences in operating a new device (Venkatesh et al., 2012). Among younger generations, effort expectancy is important in motivating them to conduct online banking transactions, while another study proves that it induced consumers to use virtual dressing rooms (Gupta & Arora, 2019). Effort expectancy significantly influences willingness to use animation in learning due to existing skills in using technology (Dajani & Abu Hegleh, 2019). In e-learning, using less effort encourages an individual to have a positive attitude toward the technology and will more likely use it (Iqbal & Qureshi, 2021). Hence, this study hypothesizes that:
H5: Effort expectancy has a significant impact on behavioral intention.

2.5 Social Influence

Social influence is the degree of control of relatives and inner social circle over one's decision to utilize a new system or machine (Venkatesh et al., 2012). For Davis (1989), social Influence pertains to making decisions to accept or reject a new system based on the encouragement of significant people in one's life. An investigative study by Zhang and Deng (2021) shows that the social Influence of parents and peers significantly positively affected students' attitudes, intentions, and actual uses of online learning. Moreover, the social Influence of professors and peers has a significant positive effect on students' attitudes and intentions toward u-learning and their actual usage of the technology during the pandemic (Lee et al., 2020). Accordingly, this study concludes a hypothesis:
H6: Social influence has a significant impact on behavioral intention.

2.6 Attitude

Attitude refers to one's idea or emotion about a thing, person, or concept being scrutinized (Davis, 1989). Fishbein and Ajzen (1975) propose that an individual's attitude toward a behavior, such as online learning and subjective norms, influences their behavioral intention toward actual use. In the realm of education, using a learning platform was determined by the attitude of the users and related to how teachers persuaded these learners to use e-learning when revising and completing the course (Arteaga Sánchez et al., 2013). The same observation was noted in how instructors influenced learners' positive reception in patronizing new online learning platforms for independent study (Lai et al., 2020). Consequently, a hypothesis is set:
H7: Attitude has a significant impact on behavioral intention.

2.7 Behavioral Intention

Behavioral intention refers to an individual's plan or motivation to achieve certain conduct, like using a system or technology (Davis, 1989; Venkatesh et al., 2012). It is also defined as a projection of one's conscious full awareness and action about utilizing a new application or system (Chau & Hu, 2002). When there is high-performance expectancy, effort expectancy, social influence, and facilitating conditions, the likelihood of positive intent toward the technology is also higher (Alamri & Alqahtani, 2021). Zhong et al. (2022) conceptualized that "behavioral intention to use online learning system is the contribution of perceived usefulness, perceived ease of use, trust, attitude and satisfaction." Therefore, this study proposes a below hypothesis:
H8: Behavioral intention has a significant impact on use behavior.

2.8 Use Behavior

Use behavior is the regularity, period, and strength of a person's relations and connection with a specific structure (Venkatesh et al., 2012). It refers to the outcome of behavioral intention to use a technology, which is influenced by perceived ease of use, perceived usefulness, and attitude towards using the technology (Davis, 1989). In the context of e-learning adoption, the actual usage of the digital learning system is influenced by students' behavioral intention, which is also affected by perceived usefulness, perceived ease of use, and social influence (Sumak & Sorgo, 2016). Alzahrani et al. (2020) have also identified perceived usefulness, ease of use, and support by the university as factors that influence the user behavior of online learning during the COVID-19 crisis.

3. Research Methods and Materials

3.1 Research Framework

The current research presents a modified conceptual framework based on the core theories of the Technology Acceptance Model (TAM) and the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) Model.

The first model has been used in various studies to present the relationship between the introduction and use of technology and the behavior of users.

Davis (1989) explains that adopting and using technology can be described through TAM. Constructs like perceived usefulness, perceived ease of use, intention, belief, and attitude can lead toward using technology. TAM has shown that perceived usefulness and ease of use as independent variables have a direct relationship with respect to behavior intention and use behavior, which is the dependent variable.

On the other hand, UTAUT2 explains the factors that influence a consumer's acceptance and use of technology in a consumer context (Venkatesh et al., 2012). It has seven (7) key constructs, namely: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. This model has been widely applied in various contexts to study technology acceptance and use, including mobile learning, e-commerce, and e-health.

In order to reinforce the existing research model, seven (7) theoretical frameworks from related studies were used as a basis by the researcher. The conceptual framework is presented in Figure 1.

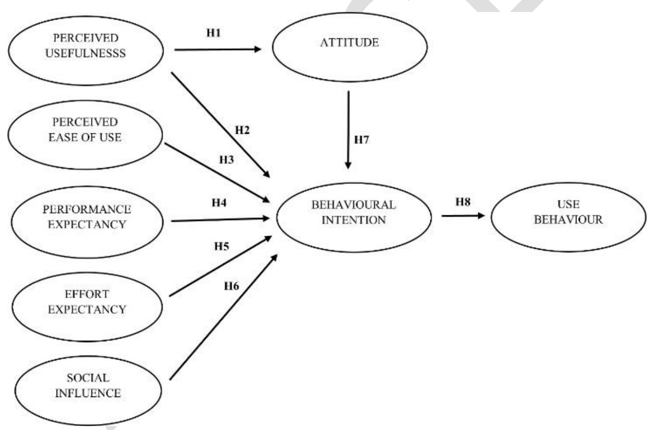

Figure 1: Conceptual Framework

H1: Perceived usefulness has a significant impact on attitude.
H2: Perceived usefulness has a significant impact on behavioral intention.
H3: Perceived ease of use has a significant impact on behavioral intention.
H4: Performance expectancy has a significant impact on behavioral intention.
H5: Effort expectancy has a significant impact on behavioral intention.
H6: Social influence has a significant impact on behavioral intention.
H7: Attitude has a significant impact on behavioral intention.
H8: Behavioral intention has a significant impact on use behavior.

3.2 Research Methodology

This study used the quantitative method through online questionnaires via Google Forms. A set of scale items adapted from previous studies on the use of technology in learning was generated and then subjected to Item-Objective Congruence (IOC) test and Cronbach's Alpha test. Once the reliability testing was concluded, the online survey was sent to 500 primary school parents of students in a private school who had at least one (1) academic term or approximately four (4) months of exposure to U-learning.

Structural Equation Modeling (SEM) was used through SPSS and AMOS for Confirmatory Factor Analysis (CFA) to analyze the data gathered to establish convergent validity. Next was to conduct SEM to find the causal relationship between all the constructs presented in the conceptual model and test the significant influences and hypotheses. SEM provides valuable insights into the factors influencing technology acceptance and use, enhancing our understanding of TAM and UTAUT2 (Hair et al., 2010).

3.3 Population and Sample Size

For this research, the target population is primary school students' parents in a private school located in Samutprakarn, Thailand, with one academic term or four (4) months of exposure to u-learning to ensure that they are familiar with the technology and learning platform. The online A-priori Sample Size Calculator for SEM was used to get the minimum sample size. With eight (8) latent variables, 40 observed variables, and a probability level 0.05, the recommended sample size was 444. Hence, the online survey questionnaire was administered and screened for valid responses from 500 primary school parents.

3.4 Sampling Technique

In this study, the researcher utilized non-probability sampling techniques, specifically purposive sampling and convenience sampling. The first method is intentionally selecting specific individuals due to their traits (Roberts, 2010). Purposive sampling identified respondents based on interests, qualifications, or typicality as they fit a general profile of participants who would use a product (Wilson, 2014).

Next was convenience sampling by including members of a population who were available to the researcher. Wilson (2014) describes it as obtaining respondents who meet at least some basic screening criteria. At the same time, Link (2018a) deduces that this form of sampling favored researchers due to its comfort, quickness, and minimal expenditure. The Google form was used in administering the questionnaires for four (4) weeks via the students' Google Classroom for easy and convenient posting and gathering of results.

4. Results and Discussion

4.1 Demographic Information

Table 1 summarizes the complete demographic information of the 500 respondents. Among the respondents, 60.6 percent were male, and 39.4 percent were female. 24.6 percent of students are in Grades 1-2, 42.6 percent are in Grades 3-4, and 32.8 percent are in Grades 5-6. For the frequency of u-learning, 45.6 percent is 4-6 days/week, 33 percent use three days/week, and 21.4 percent use seven days/week.

Table 1: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	303	60.6%
	Female	197	39.4%
Grade	Grade1-2	123	24.6%
	Grade3-4	213	42.6%
	Grade5-6	164	32.8%
Frequency Use of U-Learning	3 days/Week or Below	165	33%
	4-6 Dyas/Week	228	45.6%
	7 Days/Week	107	21.4%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

The Confirmatory Factor Analysis (CFA) is deemed a crucial analysis tool among social and behavioral scientists due to its ability to bridge the gap concerning theory and observation (Mueller & Hancock, 2001). The researcher carried out the fit model, convergent, and discriminant validity to fully validate the model.

Results of the CFA reveal that all items of each construct are significant with a factor loading that comply with discriminant validity. Stevens (1992) considered a satisfactory item when loadings are greater than 0.40 with a p-value lower than 0.05.

The Composite Reliability (CR) must exceed the cut-off point of 0.70, as established by Fornell and Larcker (1981). This is achieved in the results of the current study with CR ranging from 0.712 to 0.856, as shown in Table 2.

Although data show that AVE is between 0.369 to 0.576, under the required value of at least 0.4, the Composite Reliability (CR) is still higher than 0.6, which satisfies the convergent validity of the constructs in the study.

Cronbach's Alpha is another widely used measure of internal consistency reliability for scales and questionnaires, such as in education research, to produce valid and generalizable results (Tavakol & Dennick, 2011). By reporting a high Cronbach's Alpha, generally above 0.7, researchers enable comparisons of the reliability of different instruments used in U-learning research and synthesizing the findings across studies (Nunnally & Bernstein, 1994). The current study shows that all constructs' reliability analysis values are between 0.705 to 0.856, as presented in Table 2. Hence, the instrument is reliable.

Table 2: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Usefulness (PU)	Arteaga Sánchez et al. (2013)	6	0.793	0.524-0.725	0.792	0.391
Perceived Ease of Use (PEOU)	Park et al. (2015)	7	0.823	0.472-0.772	0.800	0.369
Performance Expectancy (PE)	Talukder (2019)	4	0.803	0.490-0.874	0.786	0.495
Effort Expectancy (EE)	Hew et al. (2015)	5	0.856	0.656-0.807	0.856	0.544
Social Influence (SI)	Sobti (2019)	4	0.828	0.582-0.937	0.839	0.576
Attitude (A)	Fatima et al. (2017)	4	0.705	0.545-0.665	0.712	0.383
Behavioral Intention (BI)	Lin (2013)	5	0.739	0.510-0.693	0.747	0.374
Use Behavior (UB)	Sitar-Taut et al. (2021)	5	0.815	0.534-0.863	0.820	0.486

Moreover, the indices used for measurement are CMIN/DF, GFI, AGFI, NFI, CFI, TLI, IFI, and RMSEA. The statistical values are all in harmony with the empirical data and have attained goodness of fit.

Table 3: Goodness of Fit for Measurement Model

Index	Acceptable Criteria	Statistical Values
CMIN/DF	<3.00 (Hair et al., 2006)	1.333
GFI	>0.90 (Hair et al., 2006)	0.918
AGFI	>0.90 (Hair et al., 2006)	0.904
NFI	>0.85 (Kline, 2011)	0.878
CFI	>0.85 (Kline, 2011)	0.966
TLI	>0.85 (Kline, 2011)	0.962
IFI	>0.85 (Kline, 2011)	0.967
RMSEA	<0.05 (Browne & Cudeck, 1993)	0.026
Model Summary		**In harmony with empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, IFI = Incremental Fit Index, and RMSEA = root mean square error of approximation

In this study, the values of discriminant validity (Table 4) were all larger than inter-construct correlations. Therefore, the discriminant validity was acceptable.

Table 4: Discriminant Validity

	EE	PU	PEOU	PE	SI	UB	BI	A
EE	**0.737**							
PU	0.064	**0.625**						
PEOU	-0.035	0.177	**0.608**					
PE	-.0.028	0.439	0.318	**0.704**				
SI	0.003	0.177	0.205	0.154	**0.759**			
UB	0.039	0.248	0.016	0.275	0.122	**0.697**		
BI	0.171	0.253	0.139	0.224	0.101	0.223	**0.611**	
A	-0.031	0.319	0.144	0.276	0.223	0.136	0.136	**0.619**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

The current study adopted the Structural Equation Model (SEM) to analyze the gathered data. It provides valuable insights into the factors influencing technology acceptance and use, enhancing understanding of these models (Hair et al., 2010). It also allows the simultaneous estimation of multiple relationships (Kline, 2015), and it can account for measurement errors in estimating relationships among TAM and UTAUT2 constructs (Hair et al., 2010).

SEM also enables researchers to compare competing models and assess the overall fit of the models to the data (Hu & Bentler, 1999). Other than that, it allows for examining mediation and moderation effects and a rigorous statistical approach to test and validate the theoretical model (Hair et al., 2010; Kline, 2015).

The goodness of fit for the structural model is measured and presented in Table 5. Results of the structural model are as follows: CMIN/DF= 1.355, GFI= 0.915, AGFI= 0.901, NFI= 0.874, CFI= 0.963, TLI= 0.960, IFI= 0.964, and RMSEA= 0.027. The results depict acceptable values specified for each index.

Table 5: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<3.00 (Hair et al., 2006)	1.355
GFI	>0.90 (Hair et al., 2006)	0.915
AGFI	>0.90 (Hair et al., 2006)	0.901
NFI	>0.85 (Kline, 2011)	0.874
CFI	>0.85 (Kline, 2011)	0.963
TLI	>0.85 (Kline, 2011)	0.960
IFI	>0.85 (Kline, 2011)	0.964
RMSEA	<0.05 (Browne & Cudeck, 1993)	0.027
Model Summary		**In harmony with empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, IFI = Incremental Fit Index, and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

Table 4 provides the significance of each variable based on its standardized path coefficient (ß) and t-value. which shows the relationships between the constructs, wherein a p-value of <0.05 is required to support each hypothesis. A solid line depicts the validity of the premise, while a dashed line proves otherwise.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PU→A	0.367	5.426*	Supported
H2: PU→BI	0.178	2.371*	Supported
H3: PEOU→BI	0.068	1.113	Not Supported
H4: PE→BI	0.130	1.935	Not Supported
H5: EE→BI	0.166	2.988*	Supported
H6: SI→BI	0.032	0.587	Not Supported
H7: A→BI	0.033	0.507	Not Supported
H8: BI→UB	0.245	3.858*	Supported

Note: * $p<0.05$
Source: Created by the author

The result of the hypotheses testing of the structural model for primary school parents is as follows:

H1 established the presence of a significant influence between perceived usefulness and attitude for primary school parents with an optimistic mindset of using technology instead of face-to-face lessons. They believed their children would achieve their learning goals by using U-learning at home during the pandemic (Chen & Wu, 2020; Hung et al., 2014).

H2 ascertained that the parents' belief that U-learning would improve their children's academic performance and achievement influenced their purpose to accept U-learning during the health crisis. This significant relationship between perceived usefulness and the behavioral intention was proven by similar studies conducted to ascertain technology acceptance (Davis, 1989; Wang & Chen, 2020).

H3 did not hold among primary school parents, and the assumption of a significant influence between perceived ease of use and the behavioral intention was not supported. It was posited that parents valued other factors in their plan to use U-learning rather than considering their comfort level (Alzaza & Yaakub, 2018; Kim & Park, 2018).

H4 was proven incorrect as results opposed the belief that any technology that promised to improve learning performance would gain the support of primary school parents. Despite the assumption that U-learning would provide better academic results, this was not proven true by the current study, and similar results were recorded in other related literature (Liu, 2015; Ma & Li, 2011).

H5 sustained the validity of the relationship between effort expectancy and behavioral intention as primary school parents perceived u-learning as effortless. This belief would eventually affect their decision to accept using the U-learning system while their children stayed home during the pandemic (Liu et al., 2021; Ma & Li, 2011).

H6 had not gained any traction in the current study as primary school parents needed to consider external opinions and social influence in their intent to allow their children to use U-learning during the global health crisis. Other studies have shown similar results regarding the insignificant relationship between social influence and behavioral intention (Kim & Park, 2018; Song & Lee, 2020).

H7 highlighted the lack of relationship between attitude and behavioral intention as primary school parents did not consider attitude in their resolution to allow their children to participate in u-learning. The link between positive feelings and the plan to use technology was also missing in other U-learning studies involving primary and university students (Abaido & Al-Rahmi, 2021; Iqbal & Qureshi, 2021).

H8 provided proof of the effect of higher intention on the actual use of the technology as demonstrated by the primary school parents whose purpose and plan to use U-learning resulted in their full participation in the system. Other studies among the same age group or older learners validated the same conclusions (Baturay & Bayir, 2019; Hwang et al., 2021).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

According to the study results, there were significant relationships between perceived usefulness and attitude, perceived usefulness and behavioral intention, effort expectancy and behavioral intention, and behavioral intention and use behavior. The TAM and UTAUT2 frameworks supported these relationships.

Various research found a significant positive relationship between perceived usefulness and attitude, wherein users who perceived technology as useful would develop a positive attitude towards it. This would increase the likelihood that they would adopt and use the technology (Davis, 1989; Venkatesh & Davis, 2000).

Other literature on technology adoption consistently proved that perceived usefulness significantly predicted the behavioral intention and use behavior of U-learning (Al-Fraihat et al., 2020; Hung et al., 2014). Such results supported the assumption that users were more likely to adopt and use U-learning if they perceived it would help them achieve their learning goals and improve their academic performance.

Additionally, effort expectancy was considered a critical predictor of behavioral intention and use behavior, wherein users were willing to adopt and use U-learning based on their perception that it was easy to use and required minimal effort (Al-Fraihat et al., 2020; Lee et al., 2020).

These findings confirmed that the factors identified in TAM and UTAUT2, specifically perceived usefulness and effort expectancy, had an influence on behavioral intention and use behavior. The outcomes suggested that designers and educators had to focus on developing and promoting U-learning technologies that users would perceive as useful, easy to use, and positively evaluated.

On the other hand, the implications for the TAM and UTAUT2 theories based on the insignificant influences between perceived ease of use and behavioral intention, performance expectancy and behavioral intention, social influence and behavioral intention, and attitude toward behavioral intention were also tackled.

Some studies provided evidence that perceived ease of use had no relationship to the behavioral intention or used the behavior of u-learning (Al-Fraihat et al., 2020; Hung et al., 2014), while others had a significant relationship (Lee et al., 2020)

Performance expectancy was also found inconsequential in technology adoption and use of U-learning (Wu et al., 2013), yet Hung et al. (2014) proved such an important relationship between the constructs identified.

Social influence was also noted as irrelevant in persuading users to accept and use U-learning, which meant that peer pressure or the influence of others might not be a strong factor in the adoption and use of U-learning (Al-Fraihat et al., 2020; Hung et al., 2014). In contradiction to this result was the study by Kim and Park (2018) that identified social influence as important in mobile social networking.

While most studies validated the strong relationship between attitude and the adoption and use of technology, there were instances where attitude had no impact on behavioral intention. This was real in the study of Kim and Kankanhalli (2009), proving that attitude did not significantly influence the behavioral intention to use web-based learning.

A possible reason for the lack of effect between behavioral intentions was that the impact of attitude might be more complex and dependent on other factors such as the specific technology, user characteristics, and context. In some cases, users might have positive attitudes toward technology but opt not to use it due to other factors such as cost, time constraints, or social norms.

In summary, although the relationship between perceived ease of use, performance expectancy, social influence, and attitude towards behavioral intention and use behavior of u-learning were important constructs in TAM and UTAUT2, further research on the specific factors that influenced technology adoption and use in the context of u-learning in primary school during a crisis would be beneficial to gather a comprehensive understanding of the factors that influence adoption and use of u-learning.

5.2 Recommendation

The results of the current study contributed several inputs on how technology acceptance and usage could be increased based on the different factors identified by the author. Hence, the following recommendations based on the factors identified as having no or weak influence on the adoption and use of U-learning were provided as follows.

First, designers could simplify the user interface because perceived ease of use was insignificant toward acceptance and use of U-learning among primary school parents during the COVID-19 pandemic. This could be done by reducing the clicks required to navigate the platform, using clear and concise language, and minimizing visual clutter. User support could also be provided in the form of online tutorials or helpdesk in order to improve the perceived ease of use. It would help learners troubleshoot technical issues and increase their confidence in using it.

Second, performance expectancy was identified as not influencing the adoption of U-learning among primary school parents. It was recommended that learning content should be relevant, up-to-date, and engaging for the learners to increase the perceived value and performance of u-learning. The more interactive and engaging the learning activities, the more learners would increase the performance expectancy of the platform. This could be achieved through gamification elements such as leaderboards, badges, or points that make learning more enjoyable and motivate learners to engage with the U-learning system.

Third, the social influence factor was identified to have no impact on behavioral intention and use behavior with preschool and primary school learners; it could be improved by encouraging social learning through collaborative work such as paired tasks, online discussions, and group projects, which were the main components of a learner-centered classroom instead of the traditional teacher-centered approach. Providing opportunities for learners to provide feedback to their classmates through peer review would help learners feel more connected to each other and increase their motivation to participate despite the absence of face-to-face interactions. Integrating social media tools for learners to connect, share resources, and provide support and feedback to one another could improve social influence.

Fourth, the attitude was considered insignificant among primary school parents in adopting U-learning. Thus, there was a need to highlight the benefits of u-learning, specifically its convenience, flexibility, cost-effectiveness, and possibility of benefiting from personalized learning and increased engagement. Improvement in attitude would also happen when user support is provided, such as tutorials, online help desks, and technical assistance to help learners overcome any challenges while using the system.

By better understanding the factors that influenced technology acceptance models that accounted for the unique challenges and opportunities presented by the pandemic, researchers and educators could develop more effective strategies for promoting the adoption and use of U-learning platforms that would benefit primary school learners.

5.3 Limitation and Further Study

This study focused on the factors influencing behavior intention and use behavior of U-learning among primary school parents in a private school in Samutprakarn, Thailand. The research methodology could be expanded beyond the quantitative approach to expand the scope and generalizability of the study. The additional use of a qualitative approach, such as conducting Key Informant Interviews (KIIs) involving parents, educators, and students, would increase the scope of research and lessen the limitations. A Focus Group Discussion (FGD) involving parents from both preschool and primary school would provide an in-depth analysis of the responses. These mixed methods would be useful in recognizing inconsistencies in both quantitative and qualitative findings.

Next is to widen the scope, participants, and locale of the future study by involving teachers, students, administrators, and technology designers and including different school types, such as government and private schools in urban and rural areas, for more comprehensive research. The study could also involve participants from different economic backgrounds better to understand the degree of acceptance and use of U-learning, as some learners might need equal access to the technology.

Finally, future studies could look into the inclusivity of the U-learning system. It would be interesting to look into how learners with physical impairments and learning difficulties respond and use U-learning. The result would eventually guide designers in refining the platform and content or system suitable to their needs.

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