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Through the Lens of Parents: How Preschool Students Adopt U-Learning during COVID-19 in Thailand?

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Abstract

Purpose: This study ains to examine the factors influencing the acceptance and usage of the ubiquitous learning (u-learning) system among parents of preschool students in a private school in Samutprakarn, Thailand during to the COVID-19 pandemic. The Technology Acceptance Model (TAM) and the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) were used to study the parents' behavior in the context of technology acceptance and actual use. **Research design, data, and methodology:** Quantitative research and non-probability sampling techniques were utilized. Item-Objective Congruence and pilot testing were applied to check the content validity and reliability of the questionnaire prior to administering it to 500 respondents via an online survey questionnaire. The data were analyzed using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). **Result:** The findings reveal that perceived usefulness influences attitude and behavioral intention to use u-learning. Performance expectancy directly influences the intention to use the U-learning system. On the other hand, perceived ease of use, effort expectancy, and social influence have no significant impact on behavioral intention. **Conclusions:** The key findings provide technology developers, curriculum designers, and educators with inputs on creating useful and practical strategies to improve the current u-learning system suitable for preschool learners.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The battle against the COVID-19 pandemic has irrevocably altered the education landscape, necessitating incorporating ubiquitous learning (u-learning) as a key pedagogical strategy. As described by Cope and Kalantzis (2013), U-learning mirrors a traditional classroom but allows learners to study anytime and anywhere using digital platforms. This approach to learning emphasizes the seamless integration of learning experiences across various contexts, such as physical, temporal, and social, to enable learners to create meaningful connections with their environment and everyday experiences (Hwang, 2014).

However, the U-learning system is challenging for preschoolers due to their limited ability to use technology. Although many can easily navigate a touchscreen, they may still need help with other aspects of technology use, such as typing or understanding more complex digital interfaces (Plowman et al., 2012). There are also pedagogical challenges in creating U-learning environments, as there is a need to balance children's natural curiosity and play-based learning with specific learning objectives (Marklund & Dunkels, 2019).

Despite these constraints, the education sector had no choice but to implement U-learning due to the school closures. Huang and Lin (2017) highlighted that some parents felt online learning was less effective than traditional, face-to-face education, negatively affecting their child's academic progress. At the same time, other parents felt the strain of juggling the need to provide the required physical

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and technical supervision and support for their preschool children's online learning (Trust & Whalen, 2020).

In this study, the acceptance and usage behavior of the U-learning system has become crucial determinants of the children's learning outcomes. Hence, the Technology Acceptance Model (TAM) and the Extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) are applied to provide established theoretical frameworks in analyzing and predicting the adoption and user behavior toward technological systems. In the context of this study, the U-learning system comprises Google Classroom and Google Meet, wherein learners are provided with a regular timetable. The parents can also let their child attend real-time lessons or use the recorded lessons uploaded in Google Classroom based on their available schedule. Classwork, homework, and other tasks are accessible on the same platform.

Although there are previous studies related to technology acceptance and use of technology in school, these are usually on older learners, especially university students. Studying the adoption and use of U-learning from the perspective of preschool parents provides valuable insights into what factors matter most to them, thereby improving the design and implementation of these technologies (Almaiah et al., 2020). Parents are also recognized to be critical in facilitating their children's learning, especially at the preschool level. Hence their attitudes toward U-learning significantly affect their children's learning outcomes (Lin, 2020).

Understanding their behavior can help to address disparities in access to and use of digital learning technologies, thus promoting equity in education during a crisis (Reich et al., 2020). As a whole, the findings of this study offer additional insights for policymakers, technology developers, curriculum designers, parents, and educators in designing and implementing effective U-learning systems tailored for preschoolers.

The succeeding parts of this paper are organized as follows: Section 2 presents the related literature and research framework, whereas Section 3 describes the methodology with the hypotheses, research design, population and sample size, and sampling technique. Section 4 reports the results and discussion, and Section 5 comprises the conclusion, recommendation, and implications.

2. Literature Review

2.1 Perceived Usefulness

Perceived usefulness is construed as one's conviction wherein a specific process or scheme would continuously improve one's teaching and learning based on the person's trust and confidence towards adopting an automated system to improve one's achievement at a school or workplace (Arteaga Sánchez et al., 2013; Jaiyeoba & Iloanya, 2019). It can also be understood as a user's beliefs about the potential benefits of using U-learning technologies to enhance learning outcomes and effectiveness (Park et al., 2012). In a study among learners, those who perceived u-learning as useful and satisfying exhibited positive attitudes and intentions to recognize and utilize the technology during the global outbreak (Ahsan et al., 2021; Saleh & Bista, 2021; Zhang & Deng, 2021). 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 pertains to an individual's intense feeling that operating an intranet would be uncomplicated (Park & Kim, 2014). Meanwhile, Venkatesh et al. (2003) explained that it was an individual's level of comfort in accepting and applying a certain process or structure. Thus, once a system is perceived as easy to use, it is most likely to generate positive energy among users, develop an intention to use it, and use it (Davis et al., 1989). This was supported in several studies involving students, wherein perceived ease of use influenced their decision to accept and utilize the learning system during the pandemic (Abdelhamid et al., 2020; Ahsan et al., 2021; Wang & Chen, 2020). 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 is the extent to which an individual relies on using a different system to assist in getting benefits in job performance (Davis, 1989). In the workplace, Venkatesh et al. (2003) defined performance expectancy as a user's conviction that a structure or setup was beneficial in completing a task. Escobar-Rodríguez et al. (2014) considered performance expectancy as indicative of the advantages of utilizing social media technology as a learning tool. The users' intention to employ electronic devices when accessing library resources remotely was also influenced by performance expectancy (Chang, 2013). Chao (2019) further noted that performance expectancy positively correlated with the behavioral intention to use mobile learning. Thus, a hypothesis is developed:

H4: Performance expectancy has a significant impact on behavioral intention.

2.4 Effort Expectancy

Effort expectancy is the ease of using a system or technology (Hsiao & Tang, 2014; Venkatesh et al., 2012). Gwebu and Wang (2011) defined effort expectancy as the employment of a new system or machine without difficulty. In the context of mobile government services, a user expects the absence of any difficulty in learning the technology (Talukder et al., 2019a). Davis (1989) characterized effort expectancy as the degree of ease associated with the application of a system. Research has indicated that when U-learning technologies require less effort, the likelihood of students, parents, and educators accepting and using them is higher (Iqbal & Qureshi, 2021; Park et al., 2012). Hence, this study hypothesizes that:
H5: Effort expectancy has a significant impact on behavioral intention.

2.5 Social Influence

Social Influence is modifying one's judgment, emotions, beliefs, or action due to information gathered from others (Talukder et al., 2019). This was further explained as an external motivator to accept a learning technology like Moodle based on the perception of others (Anderson & McKeown, 2016). This was the case in a study of university students whose instructors reminded them to get into the school's learning management system through handheld devices or phones (Hu & Lai, 2019). This was further noted in a study conducted among Taiwanese students on how social Influence affected their intention to use weblog learning (Chao, 2019). Parents and peers also significantly positively affected students' attitudes, intentions, and actual uses of online learning (Zhang & Deng, 2021). Accordingly, this study concludes a hypothesis:
H6: Social Influence has a significant impact on behavioral intention.

2.6 Attitude

Attitude is a user's positive or negative feelings about performing the target behavior, such as using a particular technology or system (Davis et al., 1989; Fishbein & Ajzen, 1975). In the context of U-learning, attitude can thus be understood as the positive or negative feelings toward using U-learning technologies (Park et al., 2012). Two separate studies that explored the attitudes of students toward U-learning during the pandemic showed that students who had positive attitudes toward U-learning were more likely to have higher levels of engagement and satisfaction with the learning materials and were more likely to use the technology regularly (Saade & Bahli, 2005). Consequently, a hypothesis is set:
H7: Attitude has a significant impact on behavioral intention.

2.7 Behavioral Intention

Behavioral intention is defined as an individual's subjective probability that a person will perform a specific behavior, such as particular technology or system (Davis et al., 1989; Venkatesh et al., 2012). The stronger an individual's intention to use technology, the more likely they are to use it based on the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975). A study on e-learning participation during the COVID-19 pandemic established that both perceived usefulness including perceived ease of use caused an impact on a user's behavioral intent (Nikou & Maslov, 2021). The same factors were noted to influence the intention of undergraduate students to use a learning management system (LMS) (Hu & Lai, 2019; Min et al., 2023). 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 result of the direct influence of behavior intention (Davis, 1989; Hubert et al., 2017) or when a user's intention is triggered by a positive or negative exposure to a product or service (Moghavvemi & Akma Mohd Salleh, 2014). A study on the adoption of e-learning among university professors showed a strong relationship between their intention to use the technology and their actual usage (Gunasinghe et al., 2020). Similarly, the faculty members' positive behavior intention resulted in using the behavior of interactive whiteboards, as shown in the study by Sumak and Sorgo (2016).

3. Research Methods and Materials

3.1 Research Framework

In developing the conceptual framework for this current study, the researchers used the TAM and UTAUT2 constructs essential in investigating the factors influencing preschool parents' intention and use behavior towards u-learning. The framework allowed the researcher to investigate the current constructs and relationships applicable to a new phenomenon being studied due to a lack of prior information or insufficient theories (Akintoye, 2015; Grant & Osanloo, 2015). The models explain the factors influencing the users' acceptance and use of technology based on their context (Venkatesh et al., 2012).

In the current conceptual framework, there were eight variables wherein five (5) were independent variables, specifically: perceived usefulness, perceived ease of use, performance expectancy, effort expectancy, and social influence. The mediating variable was attitude, while behavioral intention and use behavior were identified as dependent variables. Figure 1 shows the conceptual framework for this study.

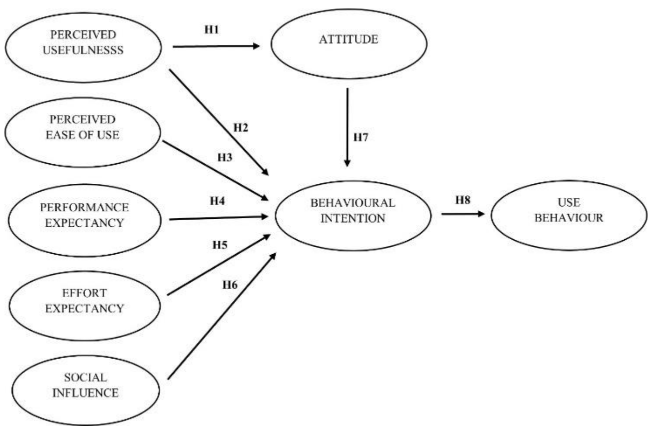

Figure 1: Conceptual Framework

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

The quantitative method was used to provide reliable and objective insights, compare results between groups across different time points, and offer empirical evidence to support or refute the effectiveness of educational policies, strategies, or practices (Creswell, 2014; Hopkins, 2008). Quantitative research often involves larger sample sizes that allow findings to be generalizable, particularly in education research, due to its impact on many students (Teddlie & Tashakkori, 2009).

An online survey questionnaire was used as a tool and administered via Google survey form. This was a convenient method to collect data, and using online applications for administration increased the scope and speed of data collection to avoid errors and provide privacy for respondents (De Jong et al., 2016; Marcano Belisario et al., 2015).

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. The use of IOC in TAM research was highlighted in several studies as important because it evaluated the validity of measures and ensured that the measures were accurately assessing the intended constructs (Venkatesh & Davis, 2000). Similarly, the use of IOC in UTAUT2 research was emphasized by Venkatesh et al. (2012) to evaluate the validity of their measures. Those measures with high item-objective congruence indicated that the intended constructs were accurately measured. Several studies on mobile acceptance used IOC to evaluate the validity of measures (Park et al., 2007; Wu & Chen, 2017).

Cronbach's Alpha method was utilized for both the evaluation of validity and reliability. To assess the questionnaire's reliability, an initial examination involved the Index of Item-Objective Congruence (IOC) and a pilot test. In the IOC analysis, three experts independently rated each item on the scale, resulting in all items receiving scores of 0.67 or higher, signifying strong consensus. Subsequently, a pilot test was conducted with 50 participants, and the reliability of the questionnaire was confirmed using the Cronbach alpha coefficient. The outcomes demonstrated robust internal consistency for all questionnaire items, with a reliability score of 0.60 or greater.

A formal request to conduct the research was submitted to the school management. After ethics approval was granted, the online survey was sent to 500 preschool parents with prior experience with u-learning for at least one (1) academic term or approximately four (4) months. The participants were also informed in the short letter and the survey questionnaire that answering the survey was voluntary and responses were considered confidential. The respondents were given one (1) month to complete the questionnaire to allow them sufficient time to answer the questions.

3.3 Population and Sample Size

The target population was preschool parents in a private school in Samutprakarn, Thailand, with one academic term or four (4) months of exposure to U-learning to guarantee that they were aware and familiar with the technology and learning platform.

The online A-priori Sample Size Calculator for SEM was used to determine the minimum sample size. With eight (8) latent variables, 40 observed variables, and a probability level 0.05, the recommended sample size was 444. The Social Science Citation Index (SSCI) recommended that 100 – 400 respondents are needed to attain highly significant statistical analyses like structural equation modeling (SEM)

(Lund, 2021). A more complex model would require more samples. Hence, the online survey questionnaire was finally administered and screened for valid responses to 500 preschool parents.

3.4 Sampling Technique

The researcher employed non-probability sampling techniques, particularly purposive and convenience sampling. The first method is defined as intentionally selecting specific individuals due to their traits and based on the researcher's judgment (Garg, 2016; Roberts, 2010). Purposive sampling is choosing the units according to personal judgment instead of randomization. This allowed a researcher to choose from the group identified based on interest, and no random sampling was needed. The method was often used by researchers when a limited location was involved. Next was convenience sampling by including members of a population who were available to the researcher and conveniently located around an accessible locale (Edgar & Manz, 2017; Galloway et al., 2005). Hence, the author identified preschool parents located in Samutprakarn, Thailand, as the study samples due to the proximity and availability of the said group to the researchers.

4. Results and Discussion

4.1 Demographic Information

Table 1 summarizes the complete demographic information of the 500 respondents. Among the respondents, 40 percent were male, and 60 percent were female. For the frequency of u-learning, 51.8 percent is 4-6 days/week, 29.8 percent use three days/week, and 18.4 percent use seven days/week.

Table 1: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	200	40.0%
	Female	300	60.0%
Frequency Use of U-Learning	3 days/Week or Below	149	29.8%
	4-6 Dyas/Week	259	51.8%
	7 Days/Week	92	18.4%

Source: Constructed by author.

4.2 Confirmatory Factor Analysis (CFA)

The Confirmatory Factor Analysis (CFA) is used to confirm whether or not the data fit the hypothesized measurement and establish the instrument's construct validity (Brown, 2015). The authors conducted the fit model, convergent and discriminant validity; the results are shown in Table 2.

Based on the CFA results, all items of each construct are significant with a factor loading that comply with discriminant validity. Item loadings greater than 0.40 with a p-value lower than 0.05 are considered satisfactory items (Stevens, 1992).

A Composite Reliability (CR) of 0.7 or above is acceptable, indicating good internal consistency among the items (Fornell & Larcker, 1981). This is achieved in the results of the current study with CR ranging from 0.734 to 0.900, as shown in the table.

The Average Variance Extracted (AVE) was between 0.380 to 0.565. Although the AVE was lower than the cut-off points of 0.4, the Composite Reliability (CR) was still higher than 0.6. Hence, the convergent validity of the construct was still adequate.

For valid and generalizable results, Cronbach's Alpha is widely used to measure internal consistency reliability for scales and questionnaires, such as in education research (Tavakol & Dennick, 2011). A high Cronbach's Alpha value of more than 0.7 gives researchers a reliable instrument to synthesize findings (Nunnally & Bernstein, 1994). The preschool group achieved this required value, with the CA ranging between 0.731 to 0.900.

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	0.853	0.672 – 0.724	0.853	0.492
Perceived Ease of Use (PEOU)	Park et al. (2015)	7	0.900	0.650 – 0.820	0.900	0.565
Performance Expectancy (PE)	Talukder (2019)	4	0.764	0.630 – 0.711	0.766	0.450
Effort Expectancy (EE)	Hew et al. (2015)	5	0.747	0.637 – 0.803	0.846	0.525
Social Influence (SI)	Sobti (2019)	4	0.731	0.504 – 0.754	0.734	0.413
Attitude (A)	Fatima et al. (2017)	4	0.773	0.619 – 0.730	0.776	0.465
Behavioral Intention (BI)	Lin (2013)	5	0.844	0.519 – 0.728	0.752	0.380
Use Behavior (UB)	Sitar-Taut et al. (2021)	5	0.864	0.695 – 0.802	0.864	0.561

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 as of Table 3.

Table 3: Goodness of Fit for Measurement Model

Index	Acceptable Criteria	Statistical Values
CMIN/DF	<3.00 (Hair et al., 2006)	1.255
GFI	>0.90 (Hair et al., 2006)	0.920
AGFI	>0.90 (Hair et al., 2006)	0.908
NFI	>0.85 (Kline, 2011)	0.892
CFI	>0.85 (Kline, 2011)	0.976
TLI	>0.85 (Kline, 2011)	0.973
IFI	>0.85 (Kline, 2011)	0.976
RMSEA	<0.05 (Browne & Cudeck, 1993)	0.023
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

Table 5 illustrates the inquiry's results in the discriminant validity presentation. The coefficients connecting any two latent variables were smaller than 0.80, and the diagonally defined quantity is the variables' AVE square root. The discriminant validity was established as a result.

Table 4: Discriminant Validity

	EE	PU	PEOU	PE	SI	UB	BI	A
EE	**0.724**							
PU	0.508	**0.702**						
PEOU	0.210	0.239	**0.752**					
PE	0.542	0.519	0.217	**0.671**				
SI	-0.007	0.033	-0.084	-0.014	**0.643**			
UB	0.361	0.147	0.121	0.446	0.004	**0.749**		
BI	0.004	-0.002	0.010	0.030	0.175	0.034	**0.617**	
A	0.599	0.538	0.195	0.591	0.040	0.317	0.021	**0.682**

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 Structural Equation Model (SEM) was used to analyze the data to provide valuable insights into the factors influencing technology acceptance and use, enhancing the understanding of these models (Hair et al., 2010). It also allows real-time approximation of multiple relationships (Kline, 2015) and can explain measurement errors in estimating relationships among TAM and UTAUT2 constructs (Hair et al., 2010).

SEM allows the examination of mediation and moderation effects and a rigorous statistical approach to test and validate the theoretical model (Hair et al., 2010; Kline, 2015). It also can compare rivalling models and assess the overall fit of the models to the data (Hu & Bentler, 1999).

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<3.00 (Hair et al., 2006)	1.360
GFI	>0.90 (Hair et al., 2006)	0.912
AGFI	>0.90 (Hair et al., 2006)	0.901
NFI	>0.85 (Kline, 2011)	0.880
CFI	>0.85 (Kline, 2011)	0.965
TLI	>0.85 (Kline, 2011)	0.962
IFI	>0.85 (Kline, 2011)	0.965
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

The significance of the variables based on the standardized path coefficient (ß) and t-value is presented in Table 7, 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	0.567	8.592*	Supported
H2: PU→BI	0.145	2.080*	Supported
H3: PEOU→BI	0.051	1.155	Not Supported
H4: PE→BI	0.284	4.520*	Supported
H5: EE→BI	-0.009	-0.193	Not Supported
H6: SI→BI	-0.015	-0.332	Not Supported
H7: A→BI	0.381	5.738*	Supported
H8: BI→UB	0.377	7.028*	Supported

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

The discussion that followed explains the hypotheses testing results of the structural model.

H1 confirmed the significant influence between perceived usefulness and attitude for preschool parents wherein a user's feeling and viewpoint affects the total evaluation of the usefulness of u-learning during the pandemic. This was supported by other studies that established a strong relationship between the two constructs that would result in the adoption of a technology or system (Abaido & Al-Rahmi, 2021; Alqahtani et al., 2021; Hsiao & Tang, 2014; Moon & Kim, 2001; Venkatesh & Davis, 2000).

H2 proved the significant relationship between perceived usefulness and behavioral intention in which the more useful technology is perceived by preschool parents, the higher the intention to use it for u-learning (Alqahtani et al., 2021; Alqahtani & Alamri, 2021; Bhattacherjee, 2001; Moon & Kim, 2001; Murugesan et al., 2021; Venkatesh & Davis, 2000; Zhang & Deng, 2021).

H3 was not supported as no significant influence was found between perceived ease of use and behavioral intention. The former was defined as a user's perception of a technology's ease before adopting the U-learning system. Other studies revealed that perceived ease of use could not be used as a predictor of adopting U-learning, as the users' familiarity or prior experience with the technology did not affect their intention to use it (Alalwan et al., 2017a; Alqahtani & Alamri, 2021; Bhattacherjee, 2001; Kim & Shin, 2017; Lee et al., 2020; Taylor & Todd, 1995; Venkatesh et al., 2003).

H4 showed a significant influence between performance expectancy and behavioral intention which pertained to the level of productivity or academic performance that a user expected from using U-learning during the pandemic. Various studies showed that even if the technology was complex and difficult to use, there was a strong intention to use U-learning (Alalwan et al., 2017b; Alqurashi, 2020; Bhattacherjee et al., 2008; Gao et al., 2015; Venkatesh & Bala, 2008).

H5 was found to be invalid, and findings showed no relationship between effort expectancy and behavioral intention, as users placed less importance on the simplicity or complexity of using the U-learning system. The assumption for the insignificant influence could be attributed to the high digital literacy of preschool parents, who were mostly in the age range of 35 years old to 44 years old, as well as having high educational attainments (Ahsan et al., 2021; Alalwan et al., 2017c; Huang et al., 2018; Saade & Bahli, 2005; Taylor & Todd, 1995; Zhang & Deng, 2021).

H6 was not supported as there was no significant effect between social influence and behavioral intention of the preschool parents toward the adoption of u-learning. It was assumed that the opinions and preferences of friends or peers were irrelevant to the parent's decision to adopt U-learning during the pandemic (Alqahtani et al., 2021; Al-Somali et al., 2009; Iqbal & Qureshi, 2021; Salloum et al., 2021; Venkatesh et al., 2012).

H7 validated the strong relationship between attitude and behavioral intention as preschool parents held a constructive view of the U-learning system that eventually convinced them to make use of the technology while they assisted the children, who were studying at home during the global health crisis (Alqahtani & Alamri, 2021; Davis, 1989; Salloum et al., 2021; Venkatesh et al., 2012).

H8 had established a strong relationship between behavioral intention and use behavior as preschool parents strongly intended to accept and adopt the u-learning system, which eventually affected their final decision to use it during the pandemic. Similar studies supported this theory that the stronger the intention of a user to embrace U-learning, then the likelihood of actual usage is also high (Abaido & Al-Rahmi, 2021; Akour et al., 2020; Al-Fraihat et al., 2020; Al-Gahtani, 2016; Alzahrani et al., 2020; Kusuma et al., 2020; Venkatesh & Davis, 2000).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This research established a strong positive relationship between perceived usefulness and attitude, which supports similar studies that showed a substantial and constructive upshot on the users' intention to use the system due to their positive attitude (Venkatesh & Davis, 2000). This could eventually impact children's learning experiences and outcomes (Huang et al., 2007).

It can be concluded that based on TAM, it is important to design systems that are perceived as useful by potential users in order to increase their positive attitude towards the system and their intention to use it (Kim et al., 2013; Kim & Lee, 2012). In TAM, perceived usefulness and ease of use are considered key determinants of attitude, while in UTAUT2, they are identified as key determinants of performance and effort expectancy. For this reason, understanding the role of attitude in technology adoption is essential for developing effective strategies to promote technology acceptance and use.

Performance expectancy was also confirmed to significantly affect users' intention to use U-learning systems, as parents expect the technology to enhance their children's educational performance (Kim et al., 2013; Kim & Lee, 2012; Venkatesh et al., 2003). Thus, technology design should be aligned with the expectations and objectives of the U-learning system. There is also a need to continuously improve the platform based on user feedback and technological advances to meet and exceed performance expectations to make it relevant and effective (Venkatesh &

Bala, 2008).

Another implication for the TAM and UTAUT2 theories was the insignificant influence of perceived ease of use, effort expectancy, and social influence on preschool parents' behavioral intention and use behavior. The lack of a significant relationship suggests that there may be other concerns for parents regarding u-learning acceptance. They might place greater value on other aspects, such as the perceived usefulness or effectiveness of the platform in enhancing their children's learning (Davis, 1989; Venkatesh et al., 2003).

It is also possible that parents have a reasonable level of technical proficiency; thus, the ease of use and effort expectancy are not significant barriers to them. In today's digital age, many people have become familiar with using various digital platforms, reducing the impact of these factors (Venkatesh et al., 2012). This was true in other studies wherein performance expectancy positively affected technology acceptance and usage, but perceived ease of use and effort expectancy did not, while social influence had a considerable negative effect (Al-Fraihat et al., 2020; Hung et al., 2014).

The insignificant relationship with social influence might suggest that parents' decisions to use U-learning platforms are more independent and less affected by others' opinions or societal norms. Parents may make decisions based on their evaluations of the benefits and costs rather than societal pressures (Venkatesh & Davis, 2000).

5.2 Recommendation

There is a need for technology designers to simplify the user interface. 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 preschool parents to troubleshoot technical issues and increase their confidence in using it.

In terms of increasing the significance of effort expectancy, this can be done by emphasizing the benefits of U-learning through increased flexibility, convenience, and access to a wider range of learning resources. Establishing a supportive learning environment could also enhance u-learning acceptance by providing learners with opportunities for collaboration, creating a sense of community, and offering regular opportunities for feedback and reflection.

The social influence factor could be increased by letting teachers, administrators, and other staff members discuss the benefits with parents and provide reassurances, creating a supportive social environment that encourages u-learning adoption. Success stories can also be featured on school websites, and testimonials from prominent personalities can be shared with parents.

5.3 Limitation and Further Study

The limitation of the study and how to improve future research. As this is primarily quantitative research, expanding the research methodology by mixing both quantitative and qualitative approaches will be beneficial. Including Key Informant Interviews (KIIs) and Focus Group Discussions (FGDs) involving parents, educators, and students can provide an in-depth analysis of the responses.

There is also a need to widen the scope, participants, and locale of the future study by involving teachers, students, administrators, and technology designers, as well as the inclusion of different school types, such as government and private schools in urban and rural areas for more comprehensive research. So, it is hoped that the insights provided by this study could help educators, policymakers, and developers create and adjust better platforms and develop guidelines, training programs, and support systems for parents to boost their acceptance and usage of U-learning for their children's education.

References

Abaido, M. A., & Al-Rahmi, W. M. (2021). Investigating the factors affecting university students' adoption of e-learning during the COVID-19 pandemic: An extended TAM model. *Interactive Learning Environments, 17*(1), 84-100. https://doi.org/10.1080/10494820.2021.1900921

Abdelhamid, M. K., Ibrahim, H. M., & Sharaf, S. (2020). E-learning critical success factors during the COVID-19 pandemic: A comprehensive analysis of e-learning managerial perspectives. *Journal of Educational Technology Systems, 49*(1), 85-106. https://doi.org/10.1177/0047239520968606

Ahsan, M. N., Hoque, R., & Islam, M. R. (2021). An empirical investigation of the adoption of online learning during the COVID-19 pandemic: An extended technology acceptance model. *Education and Information Technologies, 20*(4), 1-20. https://doi.org/10.1007/s10639-021-10587-6

Akintoye, A. (2015). *Developing theoretical and conceptual frameworks.* www.jedm.oauife.edu.ng>uploads

Akour, A., Al-Tammemi, A., Barakat, M., & Kanj, R. (2020). The Impact of the COVID-19 Pandemic and Emergency Distance Teaching on the Psychological Status of University Teachers: A Cross-Sectional Study in Jordan. *The American journal of tropical medicine and hygiene, 103*(6). 2391-2399.

Alalwan, A. A., Baabdullah, A. M., Rana, N. P., Tamilmani, K., & Dwivedi, Y. K. (2017). Factors influencing the adoption of mHealth apps: A review of the literature. *Journal of Health Informatics in Developing Countries, 11*(2), 1-17.

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management, 37*(3), 100-110.

Alalwan, A. A., Rana, N. P., Dwivedi, Y. K., & Algharabat, R. (2017). Examining factors affecting customer intention to use mobile healthcare services in Saudi Arabia. International *Journal of Information Management, 37*(3), 127-139.

Al-Fraihat, D., Joy, M., Masadeh, R., & Sinclair, J. (2020). Evaluating E-learning systems success: An empirical study. *Computers in Human Behavior, 102,* 67-86. https://doi.org/10.1016/j.chb.2019.08.004

Al-Gahtani, S. S. (2016). Empirical Investigation of e-Learning Acceptance and Assimilation: A Structural Equation Model. *Applied Computing and Informatics, 12,* 27-50. https://doi.org/10.1016/j.aci.2014.09.001

Almaiah, M. A., Al-Khasawneh, A., & Althunibat, A. (2020). Exploring the critical challenges and factors influencing the E-learning system usage during COVID-19 pandemic. *Education and Information Technologies, 25*(6), 5261-5280. https://doi.org/10.1007/s10639-020-10219-y

Alqahtani, M. A., & Alamri, M. M. (2021). Investigating Students' Perceptions of Online Learning Use as a Digital Tool for Educational Sustainability During the COVID-19 Pandemic. *Educational Psychology, 13,* 1-10. https://doi.org/10.3389/fpsyg.2022.886272

Alqahtani, M., Al-Khalifa, H. S., & Al-Qahtani, A. (2021). Primary school teachers' perceptions of using online learning during the COVID-19 pandemic: An application of the technology acceptance model. *Journal of Educational Computing Research, 59*(7), 1258-1280. https://doi.org/10.1177/07356331211006436

Alqurashi, E. (2020). What do students engage with the most? A comparative study between high and low achieving students within online learning environments. *Open Learning, 37*(5), 1-16. https://doi.org/10.1080/02680513.2020.1758052

Al-Somali, S. A., Gholami, R., & Clegg, B. (2009). An Investigation into the Online Banking Acceptance in Saudi Arabia. *Tec novation, 29*(2), 30-141.

Alzahrani, A. M., Hakami, A., Alhadi, A., & Ali Batais, M. (2020). The interplay between mindfulness, depression, stress, and academic performance in medical students: A Saudi perspective. *PLoS ONE, 15*(4), e0231088.

Anderson, M., & McKeown, T. (2016). UTAUT: Capturing differences in undergraduate versus postgraduate learning? *Education + Training, 58*(9), 945-965. https://doi.org/10.1108/ET-07-2015-0058

Arteaga Sánchez, R., Duarte Hueros, A., & García Ordaz, M. (2013). E-learning and the University of Huelva: A study of WebCT and the technological acceptance model. *Campus-Wide Information Systems, 30*(2), 135-160. https://doi.org/10.1108/10650741311306318

Bhattacherjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model. *MIS Quarterly, 25,* 351-370. http://dx.doi.org/10.2307/3250921

Bhattacherjee, A., Perols, J., & Sanford, C. (2008). Information technology continuance:a theoretical extension and empirical test. *Journal of Computer Information Systems, 49*(1), 17-26. https://doi.org/10.1080/08874417.2008.11645302

Brown, T. A. (2015). *Confirmatory factor analysis for applied research.* Guilford Publications.

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen and J. S. Long (Eds.), *Testing structural equation models* (pp. 136-162). Sage.

Chang, C. C. (2013). Library mobile applications in university libraries. *Library Hi Tech, 31*(3), 478-492. https://doi.org/10.1108/lht-03-2013-0024

Chao, C. M. (2019). Factors determining the behavioural intention to use mobile learning: An application and extension of the UTAUT model. *Frontiers in Psychology, 10*(1652), 1-14. https://doi.org/10.3389/fpsyg.2019.01652

Cope, B., & Kalantzis, M. (2013). Towards a New Learning: The Scholar Social Knowledge Workspace, in Theory and Practice. *E-Learning and Digital Media, 10*(4), 332-356. https://doi.org/10.2304/elea.2013.10.4.332

Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approach* (3rd ed.). Sage publications.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13*(3), 319. https://doi.org/10.2307/249008

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. https://doi.org/10.1287/mnsc.35.8.982

De Jong, B., Dirks, K., & Gillespie, N. (2016). Trust and Team Performance: A Meta-Analysis of Main Effects, Moderators and Covariates. *Journal of Applied Psychology, 101*(8), 1-10. https://doi.org/10.1037/apl0000110

Edgar, T. W., & Manz, D. O. (2017). *Exploratory Study* (1st ed.). Research Methods for Cyber Security (pp.95-130)

Escobar-Rodríguez, T., Carvajal-Trujillo, E., & Monge-Lozano, P. (2014). Factors that influence the perceived advantages and relevance of Facebook as a learning tool: An extension of the UTAUT. *Australasian Journal of Educational Technology, 30*(2), 136-151. https://doi.org/10.14742/ajet.585

Fatima, M., Niazi, S., & Ghayas, S. (2017). Relationship between Self-Esteem and Social Anxiety: Role of Social Connectedness as a Mediator. *Pakistan Journal of Social and Clinical Psychology, 15*(2), 12-17.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research* (1st ed.). Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *Journal of Marketing Research, 18,* 382-388. http://dx.doi.org/10.2307/3150980

Galloway, L., Anderson, M., Brown, W., & Wilson, L. (2005). Enterprise skills for the economy. *Education and Training, 47*(1), 1-10. https://doi.org/10.1108/00400910510580593

Gao, H., Korn, J. M., Ferretti, S., & Monahan, J. (2015). High-throughput screening using patient-derived tumor xenografts to predict clinical trial drug response. *Nature Medicine, 21*(11), 1318-1325. https://doi.org/10.1038/nm.3954

Garg, R. (2016). Methodology for research I. *Indian Journal of Anaesthesia, 60*(9), 640. https://doi.org/10.4103/0019-5049.190619

Grant, C., & Osanloo, A. (2015). Understanding, Selecting, and integrating a theoretical framework in dissertation research: creating the blueprint for your “House”. *Administrative Issue Journal, 4*(1), 1-25. https://doi.org/10.5929/2014.4.2.9

Gunasinghe, A., Hamid, J. A., Khatibi, A., & Azam, S. M. F. (2020). The adequacy of UTAUT-3 in interpreting academician’s adoption to e-Learning in higher education environments. *Interactive Technology and Smart Education, 17*(1), 86-106. https://doi.org/10.1108/ITSE-05-2019-0020

Gwebu, K. L., & Wang, J. (2011). Adoption of open-source software: The role of social identification. *Decision Support Systems, 51*(1), 220-229. https://doi.org/ 10.1016/j.dss.2010.12.010

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis* (7th ed.). Pearson.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. D., & Tatham, R. L. (2006). *Multivariate data analysis* (6th ed.). Upper Saddle River.

Hew, J.-J., Lee, V.-H., Ooi, K.-B., & Weu, J. (2015). What catalyses mobile apps usage intention: an empirical analysis. *Industrial Management & Data Systems, 115*(7), 1-10. https://doi.org/10.1108/imds-01-2015-0028

Hopkins, D. (2008). *A teacher's guide to classroom research* (5th ed.). Open University Press.

Hsiao, C. H., & Tang, K. Y. (2014). Explaining undergraduates’ behavior intention of e-textbook adoption: Empirical assessment of five theoretical models. *Library Hi Tech, 32*(1), 139-163. https://doi.org/10.1108/LHT-09-2013-0126

Hu, L. T., & Bentler, P. M. (1999). Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria versus New Alternatives. *Structural Equation Modeling, 6,* 1-55. http://dx.doi.org/10.1080/10705519909540118

Hu, X., & Lai, C. (2019). Comparing factors that influence learning management systems use on computers and on mobile. *Information and Learning Sciences, 120*(7/8), 468-488. https://doi.org/10.1108/ILS-12-2018-0127

Huang, J. H., Lin, Y. R., & Chuang, S. T. (2007). Elucidating user behavior of mobile learning. *The Electronic Library, 25*(5), 585-598. https://doi.org/10.1108/02640470710829569

Huang, Y. M., & Lin, P. H. (2017). Evaluating students’ learning achievement and flow experience with tablet PCs based on AR and tangible technology in u-learning. *Library Hi Tech, 35*(4), 602-614. https://doi.org/10.1108/LHT-01-2017-0023

Huang, Y., Hickman, J. E., & and Wu, S. (2018). Impacts of enhanced fertilizer applications on tropospheric ozone and crop damage over sub-Saharan Africa. *Atmos Environ., 180,* 117-125. https://doi.org/10.1016/j.atmosenv.2018.02.040

Hubert, M., Blut, M., Brock, C., & Backhaus, C. (2017). Acceptance of Smartphone-Based Mobile Shopping: Mobile Benefits, Customer Characteristics, Perceived Risks, and the Impact of Application Context. *Psychology and Marketing 34*(2), 175-194. https://doi.org/10.1002/mar.20982

Hung, C.-M., Huang, I., & Hwang, G.-J. (2014). Effects of digital game-based learning on students’ self-efficacy, motivation, anxiety, and achievements in learning mathematics. *Journal of Computers in Education, 1*(2-3), 151-166. https://doi.org/10.1007/s40692-014-0008-8

Hwang, G. J. (2014). Definition, framework, and research issues of smart learning environments - a context-aware ubiquitous learning perspective. *Smart Learning Environments, 1*(1), 1-14. https://doi.org/10.1186/s40561-014-0004-5

Iqbal, S., & Qureshi, I. A. (2021). An assessment of students’ attitudes towards e-learning during the COVID-19 pandemic in Pakistan: A technology acceptance model perspective. *Interactive Learning Environments, 11*(4), 1-19. https://doi.org/10.1080/10494820.2021.1891563

Jaiyeoba, O. O., & Iloanya, J. (2019). E-learning in tertiary institutions in Botswana: Apathy to adoption. *The International Journal of Information and Learning Technology*, *36*(2), 157-168. https://doi.org/10.1108/IJILT-05-2018-0058

Kim, C., Kim, M. K., Lee, C., & Spector, J. M. (2013). Teacher beliefs and technology integration. *Teaching and Teacher Education, 29*(1), 76-85. https://doi.org/10.1016/j.tate.2012.08.005

Kim, S., & Shin, M. (2017). Transformational Leadership Behaviors, the Empowering Process, and Organizational Commitment: Investigating the Moderating Role of Organizational Structure in Korea. *International Journal of Human Resource Management, 30,* 251-275. https://doi.org/10.1080/09585192.2016.1278253

Kim, Y., & Lee, K. H. (2012). The impact of CSR on relationship quality and relationship outcomes: A perspective of service employees. *International Journal of Hospitality Management, 31*(3), 745-756. https://doi.org/10.1016/j.ijhm.2011.09.011

Kline, R. B. (2011). *Principles and Practice of Structural Equation Modeling* (3rd ed.). Guilford Press, New York.

Kline, R. B. (2015). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Kusuma, P., Pattison, P. M., & Bugbee, B. (2020). From physics to fixtures to food: current and potential LED efficacy. *Horticulture Research, 7*(1), 1-10. https://doi.org/10.1038/s41438-020-0283-7

Lee, S., Vigoureux, T. F. D., & Hyer, K. (2020). Prevalent insomnia concerns among direct-care workers JAG. *Journal of Applied Gerontology, 41*(1), 1-10.

Lin, C. Y. (2020). Social reaction toward the 2019 novel coronavirus (COVID-19). *Social Health and Behavior, 3*(1), 1-2. https://doi.org/10.4103/SHB.SHB_11_20

Lin, H. (2013). The effect of absorptive capacity perceptions on the context-aware ubiquitous learning acceptance. *Campus-Wide Information Systems*, *30*(4), 249-265. https://doi.org/10.1108/CWIS-09-2012-0031

Lund, B. (2021). The questionnaire method in systems research: An overview of sample sizes, response rates and statistical approaches utilized in studies. *VINE Journal of Information and Knowledge Management Systems, 53*(1), 1-10. https://doi.org/10.1108/VJIKMS-08-2020-0156

Marcano Belisario, J. S., Jamsek, J., Huckvale, K., & O’Donoghue, J. (2015). Comparison of self-administered survey questionnaire responses collected using mobile apps versus other methods. *Cochrane database of systematic reviews, 7,* 1-42. https://doi.org/10.1002/14651858.mr000042.pub2

Marklund, L., & Dunkels, E. (2019). Digital play to develop children's literacy and power in the Swedish preschool: The perspective of preschool teachers. *Early Childhood Education Journal, 47*(2), 167-178. https://doi.org/10.1080/09575146.2016.1181608

Min, Y., Yang, M., Huang, J., & Duangekanong, S. (2023). Influencing Factors of Behavior Intention of Master of Arts Students Towards Online Education in Chengdu Public Universities, China. *Scholar: Human Sciences*, *15*(1), 1-10. https://doi.org/10.14456/shserj.2023.1

Moghavvemi, S., & Akma Mohd Salleh, N. (2014). Effect of precipitating events on information system adoption and use behaviour. *Journal of Enterprise Information Management*, *27*(5), 599-622. https://doi.org/10.1108/JEIM-11-2012-0079

Moon, J. W., & Kim, Y. G. (2001). Extending the TAM for a World-Wide-Web Context. *Information and Management*, *38,* 217-230. http://dx.doi.org/10.1016/S0378-7206(00)00061-6

Murugesan, M., Mathews, P., Paul, H., & Karthik, R. (2021). Protective effect conferred by prior infectionand vaccination on COVID-19 in a healthcare worker cohort in South India. *PLOS ONE*, *17*(5), e0268797. https://doi.org/10.1371/journal.pone.0268797

Nikou, S., & Maslov, I. (2021). An analysis of students' perspectives on e-learning participation – the case of COVID-19 pandemic. *The International Journal of Information and Learning Technology*, *38*(3), 299-315. https://doi.org/10.1108/IJILT-12-2020-0220

Nunnally, J. C., & Bernstein, I. H. (1994). The Assessment of Reliability. *Psychometric Theory, 3,* 248-292.

Park, D. H., Lee, J., & Han, I. (2007). The Effect of On-Line Consumer Reviews on Consumer Purchasing Intention: The Moderating Role of Involvement. *International Journal of Electronic Commerce*, *11,* 125-148. https://doi.org/10.2753/JEC1086-4415110405

Park, E., & Kim, K. J. (2014). An integrated adoption model of mobile cloud services: exploration of key determinants and extension of technology acceptance model, *Telematics, and Informatics, 31*(3), 376-385. https://doi.org/10.1016/j.tele.2013.11.008

Park, K. H., Kim, D.-H., Kim, S. K., Yi, Y. H., Jeong, J. H., Chae, J., Hwang, J., & Roh, H. (2015). The relationships between empathy, stress, and social support among medical students. *Int J Med Educ*, *6*(1), 103-108. https://doi.org/10.5116/ijme.55e6.0d44

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

Plowman, L., Stevenson, O., Stephen, C., & McPake, J. (2012). Preschool children's learning with technology at home. *Computers & Education, 59*(1), 30-37. https://doi.org/10.1016/j.compedu.2011.11.014

Reich, J., Buttimer, C. J., Fang, A., Hillaire, G., Hirsch, K., Larke, L. R., & Slama, R. (2020). Remote Learning Guidance from State Education Agencies During the COVID-19 Pandemic: A First Look. *Massachusetts Institute of Technology, 4*(1), 1-24. https://doi.org/10.35542/osf.io/437e2

Roberts, J. (2010). Designing Incentives in Organizations. *Journal of Institutional Economics, 6*, 125. http://dx.doi.org/10.1017/S1744137409990221

Saade, R. G., & Bahli, B. (2005). The impact of cognitive absorption on perceived usefulness and perceived ease of use in online learning: An extension of the Technology Acceptance Model. *Information & Management, 42*(2), 317-327. https://doi.org/10.1016/j.im.2003.12.013

Saleh, A., & Bista, K. (2021). Journal of Interdisciplinary Studies in Education. *Journal of Interdisciplinary Studies in Education, 10*(1), 1-194.

Salloum, S. A., Gaber, T., Vadera, S., & Shaalan, K. (2021). Phishing Email Detection Using Natural Language Processing Techniques: A Literature Survey. *Procedia Computer Science, 189*, 19-28. https://doi.org/10.1016/j.procs.2021.05.077

Sitar-Taut, D.-A., Mican, D., & Sarstedt, M. (2021). Digital Socialligators? Social Media-Induced Perceived Support During the Transition to the COVID-19 Lockdown. *Social Science Computer Review, 41*(3), 748-767. https://doi.org/10.1177/08944393211065872

Sobti, N. (2019). Impact of demonetization on diffusion of mobile payment service in India: Antecedents of behavioral intention and adoption using extended UTAUT model. *Journal of Advances in Management Research, 1*(2), 472-497. https://doi.org/10.1108/jamr-09-2018-0086

Stevens, B. F. (1992). Price Value Perceptions of Travelers. *Journal of Travel Research, 31*, 44-48. http://dx.doi.org/10.1177/004728759203100208

Sumak, B., & Sorgo, A. (2016). The acceptance and use of interactive whiteboards among teachers: Differences in UTAUT determinants between pre- and post-adopters. *Computers in Human Behaviour, 64*(2), 602-620.

Talukder, A. K. M. M. H. (2019). Supervisor Support and Organizational Commitment: The Role of Work–Family Conflict, Job Satisfaction, and Work–Life Balance. *Journal of Employment Counseling, 56*(3), 98-116. https://doi.org/10.1002/joec.12125

Talukder, M. S., Chiong, R., Bao, Y., & Hayat Malik, B. (2019). Acceptance and use predictors of fitness wearable technology and intention to recommend: An empirical study. *Industrial Management & Data Systems, 119*(1), 170-188. https://doi.org/10.1108/IMDS-01-2018-0009

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International journal of medical education, 2,* 53. https://doi.org/10.5116/ijme.4dfb.8dfd

Taylor, S., & Todd, P. A. (1995). Understanding Information Technology Usage: A Test of Competing Models. *Information Systems Research, 6*(2), 144-176. https://doi.org/10.1287/isre.6.2.144

Teddlie, C., & Tashakkori, A. (2009). *Foundations of mixed methods research: Integrating quantitative and qualitative approaches in the social and behavioural sciences* (2nd ed.). Sage.

Trust, T., & Whalen, J. (2020). Should teachers be trained in emergency remote teaching? Lessons learned from the COVID-19 pandemic. *Journal of Technology and Teacher Education, 28*(2), 189-99.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences, 39*(2), 273-315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

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

Venkatesh, V., Thong, J. Y. L., & 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. https://doi.org/10.2307/41410412

Wang, X., & Chen, H. (2020). Investigating the use of ubiquitous learning during the COVID-19 pandemic. *Education Sciences, 10*(9), 259. https://doi.org/10.3390/educsci10090259

Wu, B., & Chen, X. (2017). Continuance Intention to Use MOOCs: Integrating the Technology Acceptance Model (TAM) and Task Technology Fit (TTF) Model. *Computers in Human Behavior, 67,* 221-232. https://doi.org/10.1016/j.chb.2016.10.028

Zhang, M., & Deng, Z. (2021). The impact of social influence on users' online learning behavior during the COVID-19 pandemic: An empirical study in China. *Frontiers in Psychology, 12*, 580588. https://doi.org/10.3389/fpsyg.2021.580588