Unveiling Parental Perspectives: Determinants of Behavioural Intentions and Usage Behaviours in Ubiquitous Learning During Crises

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Abstract
This study aims to investigate the determinants shaping the behavioural intentions and usage patterns of primary school parents within a private school in Samutprakarn, Thailand, specifically in the context of ubiquitous learning (u-learning). Employing a quantitative research design, the study engaged 500 respondents through an online questionnaire, utilising a non-probability sampling technique. Prior to administration, content validity and reliability of the questionnaire were ensured through Item-Objective Congruence and pilot testing. The data underwent analysis via Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM). The results reveal that perceived usefulness significantly influences both attitude and behavioural intention towards u-learning, while effort expectancy directly impacts the intention to embrace technology. Furthermore, behavioural intention emerges as a direct precursor to the actual use behaviour in the context of ubiquitous learning. In contrast, perceived ease of use, performance expectancy, social influence, and attitude were identified as non-significant factors. In conclusion, the study underscores the pivotal role of perceived usefulness, followed by effort expectancy, in shaping the acceptance of technology. This highlights the imperative for technology developers, curriculum designers, and educators to strategically incorporate these elements into the design of effective u-learning systems tailored for primary school learners, particularly during crises.

Keywords: Ubiquitous Learning, TAM, UTAUT2, Primary School Parents, COVID-19

Introduction

The onset of the COVID-19 pandemic brought about a seismic shift in the dynamics of education, compelling parents of school-age children to assume an active role in home-based learning while concurrently managing their daily work responsibilities. As schools transitioned to remote teaching, parents found themselves grappling with concerns over the quality of education, the well-being of their children, and the repercussions of remote learning on family life.

Some parents perceived online learning as less effective than traditional on-site learning, leading to potential repercussions on their children's academic progress (Huang et al., 2017).

In response to the challenges posed by school closures, education officials, school administrators, and teachers explored diverse modes of learning, including digital platforms, TV/radio broadcasts, and traditional paper-based methods, to mitigate the learning gap. Ubiquitous learning (u-learning), as described by Cope and Kalantzis (2013), encompasses traditional classroom elements but distinguishes itself by allowing students to study anywhere and anytime using technology. Haythornthwaite (2019) outlines key features of u-learning, emphasising flexibility in learning location, time, process, output, and the involvement of key individuals managing knowledge flow.

Technology plays a crucial role in u-learning, demanding learners' attention and fostering authentic, instinctive, and unconstrained knowledge acquisition (Li et al., 2005). Various platforms, such as Google Meet, Microsoft Teams, Zoom, and others, enable simultaneous participation, while asynchronous learning is facilitated through Learning Management Systems (LMS) like Google Classroom, Moodle, and others, accommodating different time zones and schedules (Ironsi, 2021; Serdyukov, 2021).

Despite the potential for successful learning experiences, the study recognises the need to consider available resources, including teacher expertise, infrastructure, technology access, and parental support. Concerns raised by parents and guardians in the study locale highlight challenges related to prolonged screen time, limited technical skills, and a lack of understanding of digital learning systems.

As the pandemic persisted, parents faced the inevitability of incorporating technology into their children's education, prompting requests for technical assistance and training on u-learning. The study focuses on the specific use of Google Meet and Google Classroom, where a regular timetable was established, and parents were given the option to choose between live sessions and recorded content for more flexible learning.

The research aims to delve deeper into the behaviour intention and use behaviour of primary school parents as they navigate the role of technology in bridging the gap between teachers and learners during the global health crisis. The study zeros in on the perceptions of parents with practical experience in using u-learning while assisting their children in the context of the pandemic. The results aim to contribute new insights to the intersection of Technology, Education, and Management, particularly in the context of primary school during crises.

Research Objectives

1. To examine the significant relationship between perceived usefulness and attitude.
2. To analyse the significant relationship between perceived usefulness and behavioural intention.
3. To explore the significant relationship between perceived ease of use and behavioural intention.
4. To discover the significant relationship between performance expectancy and behavioural intention.
5. To inspect the significant relationship between effort expectancy and behavioural intention.
6. To assess the significant relationship between social influence and behavioural intention.
7. To find the significant relationship between attitude and behavioural intention.
8. To scrutinise the significant relationship between behavioural intention and use behaviour.

Research Questions

1. What is the significant relationship of perceived usefulness towards attitude?
2. What is the significant relationship of perceived usefulness toward behavioural intention?
3. What is the significant relationship of perceived ease of use towards behavioural intention?
4. What is the significant relationship of performance expectancy towards behavioural intention?
5. What is the significant relationship of effort expectancy towards behavioural intention?
6. What is the significant relationship of social influence towards behavioural intention?
7. What is the significant relationship of attitude towards behavioural intention?
8. What is the significant relationship of behavioural intention towards use behaviour?

Research Framework

The current research articulates a refined conceptual framework, synthesising fundamental tenets from the Technology Acceptance Model (TAM) and the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) Model. TAM, as elucidated by Davis (1989), provides a lens through which to understand the adoption and utilisation of technology. Core constructs such as perceived usefulness, perceived ease of use, intention, belief, and attitude delineate the trajectory towards technology use. Notably, TAM has demonstrated that perceived usefulness and perceived ease of use, as independent variables, wield a direct influence on behaviour intention and use behaviour—the dependent variables.

In contrast, UTAUT2, posited by Venkatesh et al. (2012), elucidates factors influencing consumer acceptance and use of technology in diverse contexts. Embracing seven key constructs—performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit—UTAUT2 has found application in examining technology acceptance across various domains, including mobile learning, e-commerce, and e-health.

To fortify the foundations of the research model, the study draws upon seven theoretical frameworks. The first is derived from Jaiyeoba and Iloanya's (2019) exploration of perceived usefulness, perceived web-based privacy, e-learning use, perceived ease of use, attitude, and learners' behavioural intentions in predicting technology adoption for e-learning. The second, grounded in Arteaga-Sanchez et al.'s (2013) investigation, explores the impact of technical support, computer self-efficacy, perceived usefulness, ease of use, attitude, and system usage on the adoption of the WebCT system. The third, based on Hu and Zhang's (2016) study, delves into the behavioural intentions of tertiary learners regarding mobile library (m-library), considering constructs like perceived usefulness, service quality, attitude, self-efficacy, system quality, information quality, subjective norm, and behaviour intention.

The fourth framework, from Gunasinghe et al. (2020), investigates the adoption of e-learning in higher education, incorporating nine constructs—performance expectancy, effort expectancy, social influence, hedonic motivation, habit, facilitating conditions, personal innovativeness in IT, behavioural intention to use e-learning, and e-learning adoption behaviour. The fifth framework, drawing on Sitar-Taut and Mican's (2021) research on mobile learning acceptance during social distancing, utilizes the Social Distancing- Unified Theory of Acceptance and Use of Technology (SD-UTAUT2) extended model to explore relations between original constructs and personal innovativeness, information quality, hedonic motivation, and learning value.

The sixth framework, inspired by Paola Torres Maldonado et al.'s (2011) study, probes into e-learning motivation, social influence, facilitating conditions, gender, region, behaviour intention, and use behaviour. The seventh, rooted in McKeown and Anderson's (2016) investigation of an online learning platform, employs the UTAUT framework to scrutinise factors influencing the behaviour intention and use behaviour of undergraduate and postgraduate students.

Synthesising these theoretical frameworks, Figure 1 presents the current conceptual framework, offering a comprehensive depiction of the interplay among various constructs in understanding the behaviour intention and use behaviour of individuals in the context of technology adoption during a global health crisis.

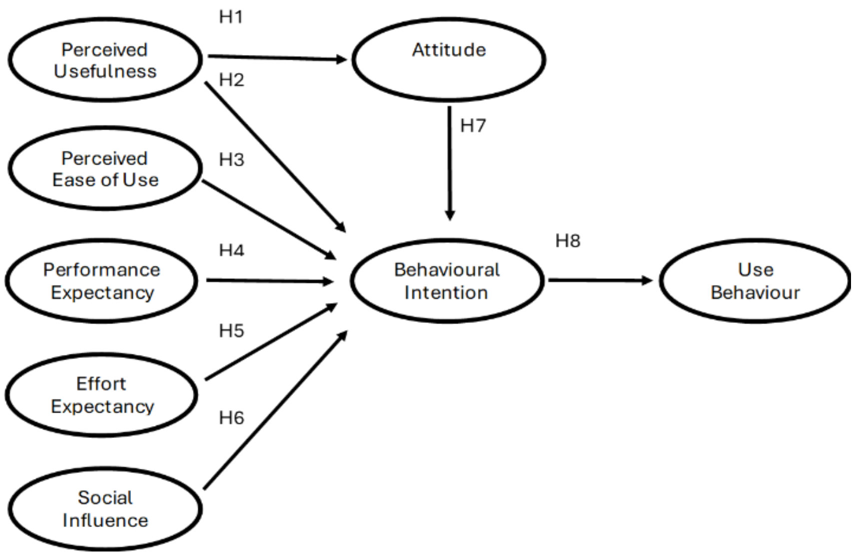


Figure 1: Research Conceptual Framework

Research Hypotheses

Based on the conceptual framework, the following hypotheses were developed.

H1: There is a significant influence between perceived usefulness and attitude.
H2: There is a significant influence between perceived usefulness and behavioural intention.
H3: There is a significant influence between perceived ease of use and behavioural intention.
H4: There is a significant influence between performance expectancy and behavioural intention.
H5: There is a significant influence between effort expectancy and behavioural intention.
H6: There is a significant influence between social influence and behavioural intention.
H7: There is a significant influence between attitude and behavioural intention.
H8: There is a significant influence between behavioural intention and use behaviour.

Research Design

This research employed a quantitative approach, utilising online survey questionnaires administered through the Google survey form platform. A set of 40 scale items, drawn from prior studies investigating technology use in learning, was meticulously crafted and subjected to rigorous evaluation through the Item-Objective Congruence (IOC) test and Cronbach's Alpha test to ensure both relevance and internal consistency. Following the successful completion of reliability testing, the online survey was distributed to a cohort of 500 primary school parents within a private school setting, each having a minimum exposure of one academic term, equivalent to approximately four months, to ubiquitous learning (u-learning).

The analysis of the gathered data involved a two-step process. Firstly, Structural Equation Modelling (SEM) was employed, utilising SPSS and AMOS for Confirmatory Factor Analysis (CFA) to establish convergent validity. Subsequently, SEM was conducted to unveil the causal relationships among all constructs outlined in the conceptual model, scrutinising the significant influences and testing the proposed hypotheses. The application of SEM offers a robust analytical framework, allowing for a comprehensive exploration of the factors shaping technology acceptance and use. This approach not only enhances our understanding of the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT2) but also provides valuable insights into the intricate dynamics influencing these frameworks (Hair et al., 2010).

Results and Discussions

Confirmatory Factor Analysis

The application of Confirmatory Factor Analysis (CFA) stands as a crucial methodological tool within the realm of social and behavioural sciences, playing a pivotal role in bridging the gap between theoretical constructs and observed phenomena (Mueller & Hancock, 2001). In ensuring the comprehensive validation of our model, the researcher conducted assessments of model fit, convergent validity, and discriminant validity.

The outcomes of the CFA unveil the significance of all items within each construct, exhibiting factor loadings that adhere to discriminant validity criteria. Following Stevens' (1992) guidelines, items are considered satisfactory when their loadings exceed 0.40 with a p-value below 0.05.

To further substantiate the reliability of the model, Composite Reliability (CR) was evaluated against the established threshold of 0.70, as suggested by Fornell and Larcker (1981). The current study attains satisfactory CR values ranging from 0.712 to 0.856, as illustrated in Table 1.

Despite the Average Variance Extracted (AVE) values ranging from 0.369 to 0.576, falling slightly below the recommended threshold of 0.4, the study maintains convergent validity as the Composite Reliability (CR) surpasses 0.6 for all constructs, underscoring the reliability of the instrument.

Cronbach's Alpha, a widely accepted measure of internal consistency reliability, was employed to further validate the instrument's reliability, aligning with established practices in educational research (Tavakol & Dennick, 2011). The reporting of high Cronbach's Alpha values, consistently above 0.7, not only ensures reliability within the current study but also facilitates cross-study comparisons of instrument reliability in the broader field of u-learning research (Nunnally & Bernstein, 1994). As evidenced in Table 1, the reliability analysis values for all constructs in this study range from 0.705 to 0.856, affirming the overall reliability of the instrument.

Variables	**Source of Questionnaire (Measurement Indicator)**	**No. of Items**	**Cronbach's Alpha**	**Factor Loading**	**CR**	**AVE**
Perceived Usefulness (PU)	Arteaga-Sanchez 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 et. al. (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
Behavioural Intention (BI)	Lin (2013)	5	0.739	0.510 – 0.693	0.747	0.374
Use Behaviour (UB)	Sitar-Taut and Mican (2021)	5	0.815	0.534 – 0.862	0.820	0.486

Note: CR = Composite Reliability, AVE = Average Variance Extracted

Table 1: Confirmatory Factor Analysis Result

To confirm discriminant validity and ensure the precise encapsulation of constructs, the square root of each Average Variance Extracted (AVE) was meticulously computed, aligning with established procedures outlined by Fornell and Larcker (1981) and Stevens (1992).

Inspection of Table 2 reveals that the AVE square roots of the variables, listed diagonally, surpass all inter-construct and factor correlations, further affirming the discriminant validity of the measurement tool.

In addition to discriminant validity assessments, several indices were employed to gauge the measurement model's goodness of fit. These indices, including CMIN/DF, GFI, AGFI, NFI, CFI, TLI, IFI, and RMSEA, collectively underscore the alignment between the statistical values and empirical data, attesting to the model's overall goodness of fit. This comprehensive evaluation reinforces the reliability of the measurement model and its apt representation of the underlying constructs.

Variables	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	0.106	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

Table 2: Discriminant Validity

Structural Equation Model (SEM)

The current study employed Structural Equation Modelling (SEM) as the analytical framework for scrutinising the amassed data, offering valuable insights into the intricate factors influencing technology acceptance and use, thereby enriching our comprehension of established models (Hair et al., 2010). SEM's unique capability to simultaneously estimate multiple relationships (Kline, 2015) and account for measurement errors in the estimation of relationships among constructs from Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT2) contributes to the robustness of the analysis (Hair et al., 2010).

Beyond its simultaneous estimation prowess, SEM facilitates the comparison of competing models and the assessment of overall model fit to the data (Hu & Bentler, 1999). Moreover, SEM allows for the exploration of mediation and moderation effects, offering a rigorous statistical approach to testing and validating the theoretical model (Hair et al., 2010; Kline, 2015).

The goodness of fit for the structural model is meticulously evaluated and presented in Table 3, with the following results: 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. These results illustrate values well within the acceptable range for each index, affirming the structural model's appropriateness for elucidating the relationships among the constructs and providing a sound basis for drawing meaningful conclusions.

Index	Acceptable Values	CFA Value	SEM Value
CMIN/DF	< 3.00 (Hair et al., 2006)	1.333	1.355
GFI	≥ 0.90 (Hair et al., 2006)	0.918	0.915
AGFI	≥ 0.90 (Hair et al., 2006)	0.904	0.901
NFI	≥ 0.85 (Kline, 2011)	0.878	0.874
CFI	≥ 0.85 (Kline, 2011)	0.966	0.963
TLI	≥ 0.85 (Kline, 2011)	0.962	0.960
IFI	≥ 0.85 (Kline, 2011)	0.967	0.964
RMSEA	≤ 0.05 (Browne & Cudeck, 1993)	0.026	0.027

Note: 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 = normalised fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, IFI = Incremental Fit Index, and RMSEA = root mean square error of approximation

Table 3: Goodness of Fit

Research Hypotheses Testing Result

The results of the hypotheses testing for the structural model among primary school parents yield nuanced insights into the factors influencing their acceptance and utilisation of ubiquitous learning (u-learning) during the global health crisis.

H1 establishes a significant influence between perceived usefulness and attitude for primary school parents with an optimistic outlook on technology use in lieu of traditional face-to-face lessons. Their belief in the efficacy of u-learning during the pandemic, aligned with previous studies (Chen & Wu, 2020; Huang et al., 2014), underscores the positive impact of perceived usefulness on fostering favourable attitudes.

H2 confirms that parents' belief in u-learning's potential to enhance their children's academic performance significantly influences their intention to accept it during the health crisis. This relationship, consistent with prior technology acceptance studies (Davis, 1989; Wang & Chen, 2020), emphasises the pivotal role of perceived usefulness in shaping behavioural intentions amid challenging circumstances.

Contrary to expectations, **H3** negates the assumed significant influence between perceived ease of use and behavioural intention among primary school parents. The findings suggest that parents prioritise factors beyond their comfort level when considering u-learning, aligning with studies that highlight diverse considerations in technology adoption (Alzaza & Yaakub, 2018; Kim & Park, 2018).

H4 challenges the assumption that any technology promising improved learning performance would automatically gain support from primary school parents. The results diverge from expectations, echoing similar findings in related literature (Liu, 2015; Ma & Li, 2011), highlighting the need for nuanced considerations beyond performance promises.

In contrast, **H5** upholds the validity of the relationship between effort expectancy and behavioural intention. Parents perceive u-learning as easy and effortless to use, influencing their decision to accept and integrate the system during the pandemic. This aligns with findings in existing literature (Liu et al., 2021; Ma & Li, 2011) emphasising the importance of user-friendly interfaces.

H6, however, fails to gain traction as primary school parents do not consider external opinions and social influence in their intent to allow their children to use u-learning during the crisis. Similar results in other studies (Kim & Park, 2018; Song & Lee, 2020) indicate the insignificance of social influence in this context.

H7 highlights a lack of relationship between attitude and behavioural intention, suggesting that positive feelings may not necessarily drive parents' decisions to allow their children to participate in u-learning. This echoes similar findings in related studies involving primary and university students (Abaido & Al-Rahmi, 2021; Iqbal & Qureshi).

Lastly, **H8** provides evidence of the effect of higher intention on the actual use of technology among primary school parents. Those with a strong purpose and plan to use u-learning exhibit full participation in the system, aligning with conclusions drawn from studies among the same age group or older learners (Hwang et al., 2021; Baturay & Bayir, 2019). These findings collectively offer a comprehensive understanding of the complex dynamics influencing technology acceptance and utilisation in the context of primary school education during a global health crisis.

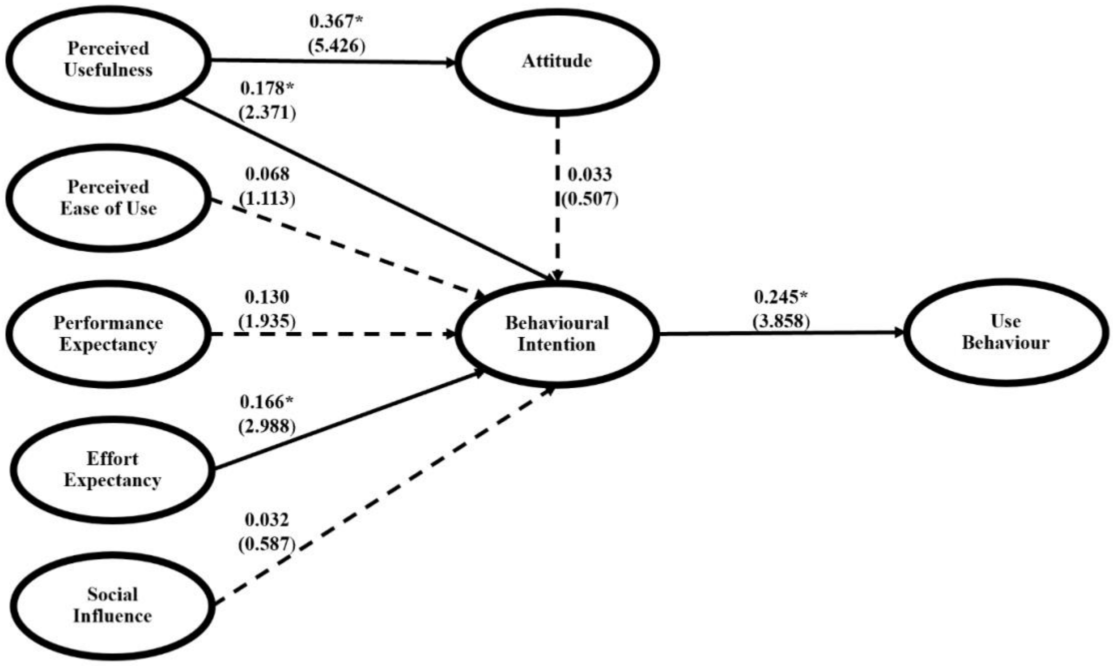
Summary of the Hypotheses Testing Result

Table 4 presents the statistical significance of each variable, elucidated through its standardised path coefficient (ß) and corresponding t-value. The relationships between the constructs are visually represented in Figure 2, where a p-value of <0.05 is essential to substantiate each hypothesis. In the graphical depiction, a solid line denotes support for the hypothesis, while a dashed line signifies a lack of validation for the proposed premise.

Hypothesis	**Standardised path coefficient (β)**	**t-value**	**Testing 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: *Significant at p-value, $p<0.05$

Table 4: Hypotheses Testing Result of the Structural Model



Note: Solid line reported the Standardised Coefficient with * as p<0.05, and t-value in Parentheses; Dash line reports Not Significant

Figure 2: The Result of Structural Model

Conclusion

In accordance with the study's findings, significant relationships emerged between perceived usefulness and attitude, perceived usefulness and behavioural intention, effort expectancy and behavioural intention, as well as behavioural intention and use behaviour. These observed associations align with established frameworks such as TAM and UTAUT2.

Existing research consistently emphasises a positive relationship between perceived usefulness and attitude, where users perceiving a technology as useful develop a favourable attitude, enhancing the likelihood of technology adoption and usage (Davis, 1989; Venkatesh & Davis, 2000). Furthermore, literature on technology adoption consistently supports perceived usefulness as a significant predictor of both behavioural intention and use behaviour in the context of u-learning (Al-Fraihat et al., 2020; Hung et al., 2014). This underlines the pivotal role of users' perception that u-learning aligns with their learning goals and enhances academic performance.

Additionally, the study affirms the critical predictive role of effort expectancy in behavioural intention and use behaviour, suggesting that users are more inclined to adopt and use u-learning when it is perceived as easy and requires minimal effort (Al-Fraihat et al., 2020; Lee et al., 2020). These findings confirm that factors highlighted in TAM and UTAUT2, specifically perceived usefulness and effort expectancy, significantly influence behavioural intention and use behaviour. Consequently, designers and educators should prioritise the development and promotion of u-learning technologies perceived as useful, user-friendly, and positively evaluated by users.

On the contrary, the study delves into the implications for TAM and UTAUT2 theories arising from the insignificant influences between perceived ease of use and behavioural intention, performance expectancy and behavioural intention, social influence and behavioural intention, and attitude toward behavioural intention. Discrepant findings across various studies indicate the complex nature of these relationships in the context of u-learning adoption. Some studies negate the relevance of perceived ease of use, performance expectancy, and social influence in u-learning adoption (Al-Fraihat et al., 2020; Hung et al., 2014), while others identify their significance (Lee et al., 2020; Kim and Park, 2018).

While attitude traditionally holds a strong association with technology adoption, instances exist where it does not significantly impact behavioural intention, as evidenced by Kim and Kankanhalli's (2009) study on web-based learning. This underscores the intricate nature of the attitude-behavioural intention relationship, dependent on various factors such as technology specificity, user characteristics, and contextual considerations. Users may harbour positive attitudes but refrain from using a technology due to factors like cost, time constraints, or social norms.

In summary, despite the importance of perceived ease of use, performance expectancy, social influence, and attitude in TAM and UTAUT2, the study emphasises the need for further research specific to the primary school context during a crisis. Gaining a comprehensive understanding of the factors influencing the adoption and use of u-learning necessitates exploration beyond traditional constructs, considering the unique challenges and dynamics present in this specific educational setting.

Implications

The outcomes of this study offer valuable insights into enhancing technology acceptance and usage, particularly among primary school parents during the COVID-19 pandemic or any natural or unnatural crises. In recognizing the factors with either weak or no influence on the adoption and use of u-learning, the following recommendations are proposed.

Firstly, given the insignificance of perceived ease of use, designers should prioritise simplifying the user interface through streamlined navigation and clear language, complemented by online tutorials and helpdesk support.

Secondly, as performance expectancy was found to have no influence, it is essential to enhance the perceived value by ensuring learning content is relevant, up-to-date, and engaging, incorporating gamification elements for a more enjoyable learning experience.

Thirdly, addressing the lack of impact of social influence involves promoting collaborative and social learning, encouraging peer feedback and integrating social media tools for enhanced connectivity.

Lastly, the insignificance of attitude calls for emphasising the benefits of u-learning, highlighting its convenience, flexibility, cost-effectiveness, and potential for personalised learning, alongside user support mechanisms such as tutorials and online help desks. By comprehensively addressing these aspects, educators and researchers can develop effective strategies to promote the adoption and use of u-learning platforms, catering to the specific needs of primary school learners in the context of the pandemic.

Limitations

It has to be noted that this study delves mainly into the determinants influencing the behaviour intention and use behaviour of u-learning among primary school parents in a private school in Samutprakarn, Thailand. To enhance the comprehensiveness and applicability of the research, a suggestion is made to augment the research methodology beyond the current quantitative approach. Integrating a qualitative dimension, such as Key Informant Interviews (KIIs) involving parents, educators, and students, can bring depth to the investigation and mitigate potential limitations. Additionally, conducting Focus Group Discussions (FGDs) with parents from both pre-school and primary school levels can yield a richer analysis of responses, allowing for a nuanced understanding of the phenomena. This mixed-methods approach would prove valuable in identifying any disparities between quantitative and qualitative findings.

Furthermore, in advancing the study's breadth, future research could incorporate a diverse array of participants, encompassing teachers, students, administrators, and technology designers. Expanding the study to include various school types, both government and private, in urban and rural areas would contribute to a more comprehensive exploration. Moreover, involving participants from different economic backgrounds would offer insights into the varying degrees of acceptance and utilisation of u-learning, considering potential discrepancies in technology access.

Finally, a prospective study could investigate the inclusivity of the u-learning system, specifically examining how learners with physical impairments and learning difficulties engage with and respond to u-learning. This examination could yield valuable insights guiding platform refinement, content adaptation, or system adjustments tailored to the diverse needs of these learners. Such enhancements would contribute to the overall effectiveness and accessibility of u-learning in diverse educational settings.

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