DETERMINANTS OF STUDENTS' BEHAVIORAL INTENTION TO USE MOBILE LEARNING DURING COVID-19 IN CHENGDU, CHINA

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Abstract

The purpose of this research is to examine the determinants of undergraduate students' behavioral intention to use mobile learning (M-learning) during Covid-19 pandemic. The conceptual framework was based on the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The sampling techniques used were judgmental sampling, quota sampling, and convenience sampling. The target population and sample size were collected by the questionnaire distribution to 500 respondents who are undergraduate students in the three selected universities in Chengdu, China. Confirmatory Factor Analysis (CFA) was applied to test validity and reliability of measurement model. Lastly, Structural Equation Model (SEM) was accounted to measure structural model and hypothesis testing. As a results, there was a significant relationship between perceived usefulness and attitude toward behavioral intention. Effort expectancy, self-efficacy and facilitating condition significantly impacted behavioral intention. Nevertheless, attitude and social influence had no significant impact on behavioral intention. The recommendations for academic practitioners and school management team were to design user's friendly function and promote benefits of a system to build positive attitude and behavior intention to use mobile learning.

Keywords: Mobile Learning, Higher Education, Behavioral Intention, Covid-19, UTAUT

Introduction

Mobile learning (M-learning) derived from Wireless Andrew project implemented by Carnegie Mellon University in 1994, which used wireless network technology to create a mobile learning environment. Since then, several learning programs in Europe had widely adopted as mobile learning or M-education. In the early 21st century, Irish education technology expert, Desmond Keegan, came to China to promote a report entitled "From Distance Learning to E-Learning to Mobile Learning". He was the first person who recommended the concept of M- learning to China (Wei, 2018). There were a variety of mobile learning systems available in the market which learners could not only source a wide variety of functions such as smart phones and tablets, but also adopt learning machines and hand-held computers with wireless communication modules. Learners can also copy learning materials to offline devices such as e-books, MP4 and other learning system (Li, 2020). During Covid-19, in-person classes have been restricted for health security reasons. M-learning had become an ideal way for students to continue their classes and to complete the programs per required by schools and universities. Therefore, it is necessary to consider what factors would affect learners to adopt m-learning more efficiently.

Objectives of the Study

The objectives of this research were clarified in according with the significant relationship between variables as follows;

1. To identify the significant relationship between perceived usefulness and attitude toward using m-learning.

2. To examine the significant relationship among perceived usefulness, attitude, effort expectancy, self-efficacy, facilitating condition, and social influence towards behavioral intention to use m-learning.

Research Framework

The research framework was adopted on the basis of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Seven latent variables used were perceived usefulness, attitude, effort expectancy, self-efficacy, facilitating condition, social influence and behavioral intention as exhibited in Figure 1.

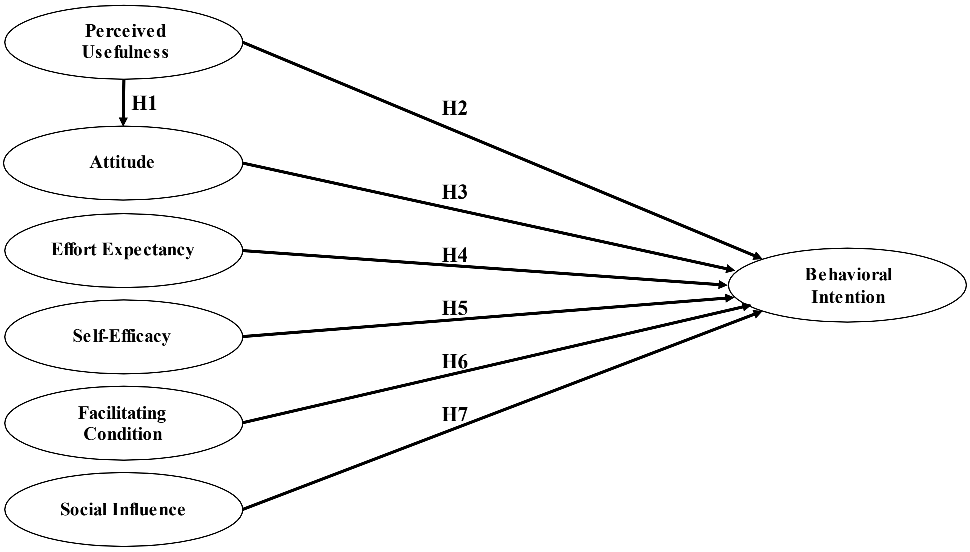

Figure 1 Conceptual Framework

Significance of the Study

This study introduces the importance of influencing factors of behavioral intention to use mobile learning which can provide theoretical contribution for future research. In practice, mobile learning system developers and academic executives can improve their mobile learning system to enhance learning efficiency and performance of students. In returns, the findings and recommendations of this research can greatly contribute to the higher education sector on how they could improve and promote mobile learning as a service quality which can impact institution's image and stay competitive in the education market.

Literature Review

1. Technology Acceptance Model (TAM)

Davis (1989) developed TAM model, which was utilized to predict users' behavior of technology acceptance. Devaraj et al. (2002) noted that TAM aims to explore users' adoption of some new technologies, which had been proved theoretically and empirically. TAM has been triumphantly used as one of the most outstanding models for predicting IT usage intentions (Doll et al., 1998). TAM has been broadly applied to determine the probability of technology use in online context. The TAM model stressed two important factors which are perceived usefulness and perceived ease of use to predict behavioral intention (King & He, 2006).

2. Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT borrowed basic elements from the various classic models, such as TRA, TPB, and TAM. Among them, UTAUT was suggested as a theoretical model that has been widely adopted in the technology acceptance research fields. Different results were obtained in according to particular technology and research context (Dwivedi et al., 2011). UTAUT model consists of four core structures, which play an important role in technology context, including performance expectancy, effort expectancy, social influence, and facilitating conditions. These key variables were used to determine users' behavioral intention of various new and complex technologies (Venkatesh et al., 2003).

3. Perceived Usefulness

Perceived usefulness was defined as a user's application in innovation and a new technology which was believed that using particular technology would shorten the time to complete tasks or provide timely information to improve individual work performance (Mathwick et al., 2001). Perceived usefulness was a key factor determining personal attitudes, which further promoted users' behavioral intention (Davis,1989). Ghazali et al. (2018) administrated a study identifying the willingness to use mobile shopping in the Malaysian, which indicated perceived usefulness was a significant predictor to customers' attitude. Castañeda et al. (2007) showed that behavioral intention of customers with more internet experience was strongly impacted by perceived usefulness. Thus, the following hypotheses are proposed:

H1: Perceived usefulness has a significant impact on attitude.

H2: Perceived usefulness has a significant impact on behavioral intention.

4. Attitude

Based on Ajzen and Fishbein(1980), attitude is referred to a person's view and an assessment of a specific information system's application. Attitude is related to how a person would involve or concern of using the system in the future (Bajaj & Nididumolu, 1998). Davis et al. (1989) posited that customers' intention to execute some certain behaviors was functioned by attitude. Individuals' behavioral intention to adopt a technology was impacted by ones' attitude toward using it. Various studies found the impact of attitude upon behavioral intention was significant (Lee et al., 2011). This study pointed that positive attitude of students would encourage their intention to use m-learning. Thereby, H3 is proposed:

H3: Attitude has a significant impact on behavioral intention.

5. Effort Expectancy

Lwoga and Komba (2015) defined effort expectancy as a person's evaluation on whether using a particular technology is difficult or not. According to Yadav et al. (2016), it also considered as the extent of effort that users have to put into a technology, which is the ease use of the system. In most prior researches, the impact of effort expectancy upon behavioral intention was direct and significant (Gupta et al., 2008). Raman and Don (2013) studied preschool teachers learning management system (LMS) adoption which showed effort expectancy had a positive effect on behavioral intention. Accordingly, the next hypothesis is obtained:

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

6. Self-efficacy

Self-efficacy was originally defined as ones' perception of ability to master a skill or use information technology, such as computer (Eom, 2012). Mungania and Reio (2005) stated that self-efficacy in e-learning context referred to an individual capability of searching immediate information, communicating with instructors, and using skills to engage e-learning system, which was regarded as a vital determinant to determine behavioral intention. Tarhin et al. (2017) stated that self-efficacy played a vital role to predict students' behavioral intention to use e-learning. Hence, we hypothesize:

H5: Self-efficacy has a significant impact on behavioral intention.

7. Facilitating Condition

Venkatesh et al. (2003) posted that facilitation condition was the perceived level of use of organization and technological infrastructure to sustain or employ a new system. Samsudeen and Mohamed (2019) pointed out that facilitation condition was an environment supported by technology and organizational infrastructure, which could assist students to use e-learning system. Dwivedi et al. (2011) proposed UTAUT model and signified the influence of facilitating condition on behavioral intention to use a system technology. Based pervious empirical researches, a hypothesis is constructed:

H6: Facilitating condition has a significant impact on behavioral intention.

8. Social Influence

An individual who believes the recommendations of using a certain new system from an influential person was explained as social influence (Venkatesh et al., 2003). Commonly, it refers to opinions of friends, colleagues, or mentors which can have an impact on user's behavioral intention. Gruzd et al.(2012) identified the impact of social influence on individual's behavioral intention to adopt technologies. Fidani and Idrizi (2012) inquired the elements referring to the acceptance of technologies in e-learning context, and found social influence positively impacted users' behavioral intention to use the system. Consequently, a hypothesis is developed.

H7: Social influence has a significant impact on behavioral intention.

9. Behavioral Intention

Behavior intention is conceptualized as the willingness to implement a particular behavioral action (Davis, 1989). It is identified as the probability that a user carries out a certain activity. Many studies indicated that behavioral intention was certified to be the best forecaster of ones' actual behavior (Zhang et al., 2008). Based on e-learning researches, behavioral intention means an individual's intention to change their learning methods from existing teaching ways into online systems in the future. Behavioral intention has been validated to be a predicting factor of the use behavior (Samsudeen & Mohamed, 2019).

Research Methodology

The quantitative method was applied by distributing online questionnaire to the sample group. Questions were set into three parts which include screening questions (3 questions) and demographic profiles (3 questions), applied in multiple choices, and measuring items of Five-point Likert scale questions (30 questions). For ethical concern, researchers contain all data to be anonymous with a conduction of privacy statement. Before data collection, the researcher used Item- Objective Congruence (IOC) to test the content validity, resulting with all items reserved from three experts' rating. The researcher used Cronbach's Alpha to perform an inter-item reliability analysis with the pilot test of 50 participants, resulting with coefficient value at above 0.60 (Nunnally & Bernstein, 1994).

1. Population and Sample Size

The target population is a total set of respondents who meet the set of criteria (Burns & Grove, 1997). The recommended sample size for this study was 425 participants (Soper, n.d.). Based on previous research, 500 sample size was appropriate for this study and applicable for structural equation modeling (SEM) statistical technique. This study purposely chose the second year- to fourth year-undergraduate students who have been experiencing mobile learning in Chengdu during the COVID-19 pandemic.

2. Sampling Technique

Probability and nonprobability sampling were applied in this study. The sampling techniques used were judgmental sampling, quota sampling, and convenience sampling. Firstly, judgmental sampling was accounted to choose second to fourth year of undergraduate students in three universities which are Chengdu University of Technology (CDUT), Chengdu University of Traditional Chinese Medicine (CDUTCM) and Sichuan Normal University (SICNU). Secondly, quota sampling was employed to distribute appropriate percentage as shown in Table 1. Lastly, convenience sampling was to distribute online survey link to students via WeChat application

Table 1 Sample Units and Sample Size

University	Population Size (Total number of undergraduate students)	Proportional Sample Size
Chengdu University of Technology (CDUT)	23100	190
Chengdu University of Traditional Chinese Medicine (CDUTCM)	16000	131
Sichuan Normal University (SICNU)	21750	179
Total	**60850**	**500**

Source: Created by the author

Results and Discussion

1. Demographic Information

The demographic profile was the results from 500 participants, including gender, year of study and residency. The demographic results as of Table 2 showed that males were 45.8% whereas females were 54.2%. For the year of study, there were 39.6% of third year, 31.4% of fourth year and 29.0% of second year students. Most participants were living in Chengdu (57.8%) and participants who live outside Chengdu were 42.2%.

Table 2 Demographic Results

N=500	Demographic Profile	Percentage
Gender	Male	45.8%
	Female	54.2%
Year of Study	Second Year	29.0%
	Third Year	39.6%
	Fourth Year	31.4%
Residency	In Chengdu	57.8%
	Outside Chengdu	42.2%

Source: Created by the author.

2. Confirmatory Factor Analysis (CFA)

A measurement model was tested in CFA using SPSS AMOS program. The results of fit model were Chi–Square (χ^2/df) = 1.428, goodness-of-fit index (GFI) = 0.934, adjusted goodness-of-fit index (AGFI) = 0.920, normalized fit index (NFI) = 0.923, comparative fit index (CFI) = 0.975, Tucker-Lewis index (TLI) = 0.972, incremental fit index (IFI) = 0.975, and root mean square error of approximation (RMSEA) = 0.029. The measurement model resulted a good fit with no adjustment required. Furthermore, the convergent and discriminant validity were approved as exhibited in Table 3

Table 3 Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	548.372/384 = 1.428
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.934
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.920
NFI	≥ 0.80 (Forza & Filippini, 1998; Al-Mamary & Shamsuddin, 2015)	0.923
CFI	≥ 0.85 (Kline, 2011)	0.975
TLI	≥ 0.85 (Kline, 2011)	0.972
IFI	≥ 0.85 (Kline, 2011)	0.975
RMSEA	< 0.08 (Pedroso et al., 2016)	0.029
Model summary		**In harmony with empirical data**

Table 4 shows results of CFA including Cronbach's Alpha coefficient value at above 0.60 (Nunnally & Bernstein, 1994), Factor loadings are higher than 0.50 and p-value of lower than 0.05. Aligning with the recommendation from Fornell and Larcker (1981), Average Variance Extracted (AVE) is less than 0.5, but Composite Reliability (CR) is greater than 0.6, the convergent validity of the construct is still sufficient.

Table 4 Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Latent Variables	Source of Questionnaire	No. of Items	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Usefulness (PU)	Andoh (2018)	4	0.780	0.650-0.704	0.781	0.472
Attitude (ATT)	Andoh (2018)	3	0.884	0.827-0.876	0.885	0.720
Effort expectancy (EE)	Samsudeen and Mohamed (2019)	4	0.804	0.679-0.745	0.804	0.507
Self-efficacy (SE)	Lwoga and Komba (2015)	6	0.856	0.677-0.740	0.857	0.500
Facilitating Conditions (FC)	Al-Hujran et al. (2014)	4	0.795	0.648-0.743	0.797	0.495
Social influence (SI)	Lwoga and Komba (2015)	4	0.881	0.750-0.861	0.884	0.656
Behavioral intention (BI)	Samsudeen and Mohamed (2019)	5	0.822	0.625-0.765	0.825	0.486

Source: Created by the author

According to Fornell and Larcker (1981), discriminant validity was measured by computing the square root of each AVE. The value of discriminant validity in this study is greater than all inter-construct/factor correlations, thus, the discriminant validity is supportive. Additionally, multicollinearity is not an issue through correlation coefficient as of Table 5 (Studenmund, 1992).

Table 5 Discriminant Validity

	SI	PU	ATT	EE	SE	FC	BI
SI	**0.810**						
PU	0.206	**0.687**					
ATT	0.300	0.668	**0.848**				
EE	0.197	0.282	0.354	**0.712**			
SE	0.215	0.615	0.534	0.196	**0.707**		
FC	0.289	0.624	0.693	0.513	0.518	**0.704**	
BI	0.241	0.677	0.538	0.413	0.553	0.652	**0.697**

Note: The diagonally listed value is the AVE square roots of the variables

Source: Created by the author

3. Structural Equation Model (SEM)

SEM was used to test the structural model. The goodness of fit results was Chi–Square ($\chi2$/df) = 2.821, goodness-of-fit index (GFI) = 0.862, adjusted goodness-of-fit index (AGFI) = 0.839, normalized fit index (NFI) = 0.842, comparative fit index (CFI) = 0.891, Tucker-Lewis index (TLI) = 0.881, incremental fit index (IFI) = 0.892, and root mean square error of approximation (RMSEA) = 0.060. The structural model resulted a good fit with no modification required per shown in Table 6.

Table 6: Goodness of Fit for Structural Model

Index	**Acceptable Values**	**Statistical Values**
CMIN/DF	< 3.00 (Hair et al., 2006)	1122.670/398 = 2.821
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.862
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.839
NFI	≥ 0.80 (Forza & Filippini, 1998; Al-Mamary & Shamsuddin, 2015)	0.842
CFI	≥ 0.85 (Kline, 2011)	0.891
TLI	≥ 0.85 (Kline, 2011)	0.881
IFI	≥ 0.85 (Kline, 2011)	0.892
RMSEA	< 0.08 (Pedroso et al., 2016)	0.060
Model summary		**In harmony with empirical data**

4. Hypothesis Testing Result

Table 7 presents the results of SEM including significant relationships and hypothesis testing. The standardized path coefficient (β) and t-value were examined to ensure the significant value of $p<0.05$. The results were that H1, H2, H4, H5 and H6 were supported, whereas H3 and H7 were not significant.

Table 7: Hypothesis Result of the Structural Equation Model

Hypothesis	Standardized path coefficient (β)	t-value	Testing result
H1: PU → ATT	0.668	10.989*	Supported
H2: PU → BI	0.534	5.935*	Supported
H3: ATT → BI	-0.079	-1.085	Not Supported
H4: EE → BI	0.190	3.737*	Supported
H5: SE → BI	0.240	4.730*	Supported
H6: FC → BI	0.323	5.666*	Supported
H7: SI → BI	0.051	1.104	Not Supported

Note: * $p<0.05$

Source: Created by the author.

The hypothesis testing results from Table 7 can be described per below:

H1 showed that the relationship between perceived usefulness and attitude was significant at standard coefficient value of 0.668 (t-value = 10.989).

H2 supported relationship of perceived usefulness and behavioral intention to use mobile learning, representing the value of standard coefficient value at 0.534 (t-value = 5.935).

H3 resulted that attitude had no significant impact on attitude of students toward the use of online learning system with standard coefficient value of -0.079 (t-value = -1.085).

H4 verified the support relationship between effort expectancy and behavioral intention to use mobile learning per the standard coefficient value at 0.190 (t-value = 9.665).

H5 was confirmed with the standard coefficient value at 0.240 (t-value = 4.730), showing the significant relationship between self-efficacy and behavioral intention.

H6 was tested that facilitating condition significantly impacted behavioral intention to use mobile learning among students at standard coefficient value of 0.323 (t-value = 5.666).

H7 was contradicted with previous studies (Venkatesh et al., 2003; Gruzd et al., 2012; Fidani & Idrizi, 2012) The result showed social influence had no significant impact on behavioral intention, reflecting the standard coefficient value at 0.051 (t-value = 1.104).

Conclusions, Recommendations and Limitations

1. Conclusions

Mobile learning has been viewed as a powerful tool to organize virtual classes during the COVID-19 pandemic because it is accessible, efficient and convenient. TAM and UTAUT were key theories for this research to investigate the determinants of behavioral intention to use mobile learning among undergraduate students in Chengdu, China. Firstly, the result implied that perceived usefulness had the strongest impact on attitude toward using mobile learning as confirmed by numerous scholars ((Mathwick et al., 2001; Davis,1989). Mobile learning can be perceived as convenient, efficient and accessible anytime and anywhere, especially during Covid-19 pandemic. Therefore, students tend to have a positive attitude toward using it. Secondly, Ghazali et al. (2018) and Castañeda et al. (2007) previously confirmed that behavioral intention to use m-learning was strongly impacted by perceived usefulness among users. Mobile learning can provide various benefits to students to continue and complete their courses during the pandemic. Thirdly, favorable attitude of students cannot determine the willingness to use mobile learning which opposed to many studies (Ajzen & Fishbein, 1980; Bajaj & Nididumolu, 1998; Davis et al., 1989; Lee et al., 2011). The reason could be that mobile learning was the only choice during the pandemic as in-person class has been prohibited during the lockdown.

Fourthly, previous literatures also agreed the significant relationship and explained that ease-of-use mobile learning system would encourage the intention to use among students (Lwoga & Komba, 2015; Yadav et al., 2016; Gupta et al., 2008; Raman & Don, 2013). Students who found no complication in using mobile system for learning would accelerate their intention to use. Fifthly, there was a significant relationship between self-efficacy and behavioral intention. It implied that self-efficacy in m-learning context due to students believe in their own capability to source usage information as well as to develop skills in using the system, hence, they are more likely to use it during the pandemic period (Eom, 2012; Mungania & Reio, 2005; Tarhin et al., 2017).

Next, the finding was also supported by many scholars that facilitating condition significantly impacted behavioral intention (Venkatesh et al., 2003; Samsudeen & Mohamed, 2019; Dwivedi et al., 2011). The researchers assumed from the results that most universities have been forced to provide effective infrastructure to encourage behavioral intention to use mobile learning as it is a practical and only option to continue teaching and learning during epidemic. Lastly, the result showed social influence had no significant impact on behavioral intention. It can be interpreted that the influence of family and peers did not impact the decision to use mobile learning during the Covid-19 pandemic because it has been forced by universities as attendance's requirement and course completion.

2. Recommendations

The results pointed that perceived usefulness had a strongest impact on attitude of students, the academic practitioners and school management should communicate to the benefits of mobile learning and its features such as recording classes, group activities, learning hours tracking to serve as an effective tool to enhance their learning performance which contribute to behavioral intention to use. Effort expectancy, self-efficacy and facilitating condition were found to determine behavioral intention. Consequently, mobile learning platform is required to carefully selected to be user friendly and self-control. Facilitating conditions could serve in the form of software license, 24-hours service support and video training on how to use it.

On the other hand, attitude and social influence had no significant impact on behavioral intention because an online class was the only way to provide the learning service for students during Covid-19. Therefore, the negative or positive attitude and influence by others cannot motivate students to use mobile learning. However, it is important to ensure the successful adoption of mobile learning. By verifying the pragmatic factors impacting the use of mobile learning, academic practitioners and school management team were recommended to ensure ease of use of the system as well as to promote benefits of such system for favorable attitude of students which can bring greatly return in terms of student's performance and university image.

3. Limitations and Future Research

Researchers only focused on certain constructs from TAM and UTAUT models. The actual usage behavior was not tested to explain whether or not students actually use mobile learning. Therefore, the conceptual model can be modified or extended in accordance with the results of this study. In addition, future researchers can further examine some other sample group such as high school or post graduate students. For deeper insights, qualitative research is suggested to be conducted for better articulation of the findings.

References

Ajzen, I., & Fishbein, M. (1980). *Understanding Attitudes and Predicting Social Behavior*. NY: Prentice-Hall.

Al-Hujran, O., Al-Lozi, E., & Al-Debei, M. M. (2014). Get ready to mobile learning": Examining factors affecting college students' behavioral intentions to use m-learning in Saudi Arabia. *Jordan Journal of Business Administration, 10*(1), 1-18. Retrieved from https://doi.org/10.12816/0026186

Al-Mamary, Y. H., & Shamsuddin, A. (2015) Testing of The Technology Acceptance Model in Context of Yemen. *Mediterranean Journal of Social Sciences, 6*(4). 268-273.

Andoh, B.(2018). Predicting students' intention to adopt mobile learning. *Journal of Research in Innovative Teaching & Learning, 11(2),* 178-191.

Bajaj, A., & Nidumolu, S. R. (1998) A Feedback Model to Understand Information System Usage. *Information & Management, 33,* 213-224. Retrieved from https://doi.org/10.1016/S0378-7206(98)00026-3

Burns, N., & Grove, S. K. (1997). *The Practice of Nursing Research: Conduct, Critique and Utilization* (3rd ed.). St. Louis: Saunders.

Castañeda, A., Ríos, F., & Luque Martínez, T. (2007). The dimensionality of customer privacy concern on the internet. *Online Information Review, 31*(4), 420-439. Retrieved from https://doi.org/10.1108/14684520710780395

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Management Science, 35(8),* 982-1003. Retrieved from https://doi.org/10.1287/mnsc.35.8.982.

Devaraj, S., Fan, M., & Kohli, R. (2002). Antecedents of b2C channel satisfaction and preference: validating e-commerce metrics, *Information Systems Research, 13(3),* 316-333.

Doll, W. J., Hendrickson, A. & Deng, X. (1998). Using Davis's perceived usefulness and ease-of-use instruments for decision making: a confirmatory and multi-group invariance analysis, *Decision Sciences, 29(4),* 839-69.

Dwivedi, K., Rana, P., Chen, H., & Williams, D. (2011). A meta-analysis of the unified theory of acceptance and use of technology (UTAUT). *Proceedings of the International Conference on Governance and Sustainability in Information Systems.*

Eom, S. B. (2012). Effects of LMS, self-efficacy, and self-regulated learning on LMS effectiveness in business education. *Journal of International Education in Business, 5*(2), 129-144. Retrieved from https://doi.org/10.1108/18363261211281744

Fidani, A., & Idrizi, F. (2012). Investigating students' acceptance of a learning management system in university education: a structural equation modeling approach. *ICT Innovations,* 311.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. Retrieved from https://doi.org/10.2307/3151312

Forza, C. & Filippini, R. (1998) TQM impact on quality conformance and customer satisfaction: a causal model. *International Journal of Production Economics, 55*(1), 1-20.

Ghazali, E. M., Mutum, D. S., Chong, J .H., & Nguyen, B. (2018). Do consumers want mobile commerce? A closer look at M-shopping and technology adoption in Malaysia. *Asia Pacific Journal of Marketing and Logistics, 30*(4), 1064-1086.

Gruzd, A., Staves, K., & Wilk, A. (2012). Connected scholars: Examining the role of social media in research practices of faculty using the UTAUT model. *Computers in Human Behavior, 28*(6), 2340-2350.

Gupta, B., Dasgupta, S., & Gupta, A. (2008). Adoption of ICT in a government organization in a developing country: an empirical study. *Journal of Strategic Information Systems, 17*(2), 140-154.

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate Data Analysis* (6th ed.). NY: Pearson.

King, W., & He, J. (2006). A meta-analysis of the Technology Acceptance Model. *Information & Management, 43*(6), 740-755. Retrieved from https://doi.org/10.1016/j.im.2006.05.003

Kline, R. B. (2011). *Principles and practice of structural equation modeling* (3rd ed.). NY: The Guilford Press.

Lee, L., Petter, S., Fayard, D., & Robinson, S. (2011). On the use of partial least squares path modeling in accounting research. *International Journal of Accounting Information Systems, 12*(4), 305-328. Retrieved from https://doi.org/10.1016/j.accinf.2011.05.002

Li, A. Q. (2020). *Research on the development of college students' mobile learning power.* Dalian University of Technology press.

Lwoga, E. T., & Komba, M. (2015). Antecedents of continued usage intentions of web-based learning management system in Tanzania. *Education + Training, 57(7), 738*-756.

Mathwick, C., Malhotra, N., & Rigdon, E. (2001). Experiential value: conceptualization, measurement and application in the catalog and Internet shopping environment. *Journal of Retailing, 77*(1), 39-56.

Mungania, P., & Reio, T. G. (2005, February 24-27). *If e-learners get there, will they stay? the role of e-learning self-efficacy* [Paper Presentation]. Academy of Human Resource Development International Conference (AHRD), Estes Park, CO. Retrieved from http://www.eric.ed.gov/PDFS/ED492287.pdf

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

Pedroso, R., Zanetello, L., Guimaraes, L., Pettenon, M., Goncalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor anlaysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry, 43*(3), 37-40.

Raman, A., & Don, Y. (2013). Preservice Teachers’ Acceptance of Learning Management Software: An Application of the UTAUT2 Model. *International Education Studies, 6*(7), Retrieved from https://doi.org/10.5539/ies.v6n7p157

Samsudeen, S. N., & Mohamed, R. (2019). University students’ intention to use e-learning systems. *Interactive Technology and Smart Education, 16(3),* 219-238.

Sica, C. & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. In M.A. Lange (Ed.), *Leading - Edge Psychological Tests and Testing Research* (pp. 27-50). Nova.

Soper, D. S. (n.d.). *A-priori Sample Size Calculator for Structural Equation Models* [Software]. Retrieved from www.danielsoper.com/statcalc/default.aspx

Studenmund, A. H. (1992). *Using Econometrics: A Practical Guide.* NY: Harper Collins.

Tarhini, A., Masa'deh, R., Al-Busaidi, K. A., Mohammed, A. B., & Maqableh, M. (2017). Factors influencing students' adoption of e-learning: a structural equation modeling approach. *Journal of International Education in Business, 10*(2), 164-182. Retrieved from https://doi.org/10.1108/JIEB-09-2016-0032

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.

Wei, M. (2018). *Research on influencing factors model of college students' willingness to use mobile learning.* Minzu university of China.

Yadav, R., Sharma, S.K., & Tarhini, A. (2016). A multi-analytical approach to understand and predict the mobile commerce adoption. *Journal of Enterprise Information Management, 29*(2), 222-237.

Zhang, S., Zhao, J., & Tan, W. (2008) Extending TAM for online learning systems: An intrinsic motivation perspective. *Tsinghua Science & Technology, 13*(3), 312-317.