pISSN: 1906 - 6406 The Scholar: Human Sciences
eISSN: 2586 - 9388 The Scholar: Human Sciences
http://www.assumptionjournal.au.edu/index.php/Scholar

Identifying Factors of Female Students' Behavioral Intention to use 5G for Online Education in Sichuan, China

Wang Xi*

Received: April 11, 2023. Revised: August 15, 2023. Accepted: August 21, 2023.

Abstract

Purpose: The rapid development of higher education in China realizes the importance of 5G in smart education. Hence, this study examines the factors that influence the behavioral intention of female students in Sichuan universities to use the 5G for online education platform. Seven variables and eight hypotheses are constructed regarding previous research, including perceived ease of use, system quality, information quality, service quality, attitude, social influence, perceived usefulness and behavioral intention. **Research design, data, and methodology:** The quantitative study was conducted by distributing a questionnaire to 560 female university students from three universities in Sichuan. Confirmatory factor analysis and structural equation model were applied for data analysis and results. **Results:** The results showed that attitude was the strongest predictor of behavioral change he strongest predictor of behavioral intention to use followed by social influence and perceived usefulness. Compared to perceived usefulness, the perceived ease of use had the strongest effect on attitude. **Conclusions:** The findings of this paper contribute to better understanding of 5G for online education developers, marketers, senior managers in higher education institutions, or related practitioners. Therefore, choice and use and ease of use at university would increase positive feedback and enable students to use the platform system for ongoing learning.

Keywords: Behavioral Intention, System Quality, Information Quality, Online Education Platforms, 5G

JEL Classification Code: E44, F31, F37, G15

1. Introduction

As 5G technology matures and begins to be used commercially, integrating emerging information technologies with education is an important driver for developing online education platforms. E-learning and Online Learning emphasize how information technology is used in education. At the same time, Online Education is more widely used in China's online higher education sector. Online Education is more widely used in online higher education in China.

Zhang et al. (2021) point out that online education can break traditional education's time and space constraints and take full advantage of the various conveniences offered by technological innovations in the Internet to form a new

1 *Wang Xi, Teaching Assistant, Xihua University, China. Email: 476445444@qq.com

educational model. According to the American Society for Training and Development (ASTD), online education relies on the Internet and other related information and communication technologies.

Online education platforms are a vehicle for online teaching and learning. They are an integral part of the online education industry, whose development depends on user acceptance, adoption, and continued use. Zhang et al. (2020) note that 1998 was when online education platforms rose to global prominence and expanded rapidly from North America and Europe to Asia. From 2010 to 2016, online education in China benefited from the rapid development of 4G and 5G technologies and entered the mobile internet era. After 2016, smart education and technologies such as artificial intelligence, big data analytics, and cloud computing became more diversified.

According to Xu and Tian (2020), two main types of online learning platforms exist. One is a commercial online learning platform that provides online courses and charges fees as its main goal. At the same time, the other is an online education platform that mainly aims to carry out online teaching, where teachers can carry out online teaching on the one hand, and students can use the rich learning resources provided by the platform tools to learn online the other. MOOC, Tencent Meeting, and other online learning platforms based on online teaching.

"5G" is the 5th generation mobile network. The foundation of 5G online education is analyzing how college students use current 5G-based online learning environments. The importance of 5G+ Education has been widely recognized by specialists and academics in education domestically and internationally. Chinese universities are now using 5G technology in the education of their students.

The rapid development of education informatization construction in Sichuan province will realize the world's first 5G+VRS process class in 5G+smart education. Especially since 2020, because of the COVID-19, universities in Sichuan province will carry out online education. Sichuan universities mainly rely on 5G online education platforms such as Chinese MOOC, DINGDING, Tencent Meeting, and Rain Classroom to carry out education and teaching. The use of 5G technology will improve data. Using 5G technology will increase data rates, reduce latency, save energy, reduce costs, and meet personalized learning needs. Rodino (1997) pointed out that in the virtual environment, women show stronger social dependence than men. Wang et al. 2007) pointed out gender differences and participation in online learning education. Therefore, considering that gender differences affect behavioral intentions to use 5G for online education platforms, this paper aims to examine the factors that influence the behavioral intentions of female university students in Sichuan Province to use the system.

2. Literature Review

2.1 Behavioral Intention

Venkatesh et al. (2003) believed that behavioral intention was a person's ability to carry out a certain action in the future. Fishbein and Ajzen (1975) state that behavioral intention governs human behavior. According to research, the social context, performance expectance, perceived utility, cognitive absorption (Mpinganjira, 2019), and other factors significantly influence behavioral intention. Luo et al. (2022) determined that "the cognitive awareness and decision of an individual to use a certain system depends on their level of intention. It also displays a student's willingness to accept a hybrid education."

2.2 System Quality

System quality reflects the response speed and usability of the system (Gao & Bai, 2014), and they signified the accuracy, adaptability, availability, convenience, efficiency, flexibility, reliability, and response time. System quality reflects the stability and reliability of the web services provided to customers, as well as the practical information and layout that allows customers to improve the efficiency of their information search, resulting in high perceived usefulness of the website (Zhou, 2011b). Hence, a hypothesis is proposed:

H1: System quality has a significant influence on perceived usefulness.

2.3 Information Quality

Information quality is the ability to use high-quality features to help users achieve their goals, including accuracy, completeness, relevance, and scope (DeLone & McLean, 2003) and the extent to which users perceive quality and meet their needs and individual needs (Moores, 2012). Cheng (2012b) argues that user usage will increase if e-learning systems are frequently updated with useful and diverse courses and users have access to accurate information and a wealth of knowledge. Zhou (2011a) mentions that the higher the quality that users perceive information systems to provide, the easier they are likely to be, so this study argues that the quality of information systems is related to perceived usefulness is related, as hypothesized below:

H2: Information quality has a significant influence on perceived usefulness.

2.4 Service Quality

Cheng (2012a) states that service quality is a perceived service experience and is the difference between the expected quality and the user's perception. (Saeed et al., 2003) argues that service quality will affect users' perceived usefulness and that a good product will provide timely and professional service. The hypothesis of this study is as follows:

H3: Service quality has a significant influence on perceived usefulness.

2.5 Perceived Usefulness

Perceived usefulness is defined as using a system to improve efficiency (Davis, 1989), and it refers to the benefits derived from using the system (Brömmelstroet, 2017). Many studies have shown that PU positively impacts technology adoption of ATT in terms of new technologies (Bailey et al., 2017). Lee (2006) argues that students' perceived usefulness of information technology affects attitudes toward using new systems and, thus, motivation to learn online. The following assumptions are made in this paper:

H4: Perceived usefulness has a significant influence on attitude.

2.6 Perceived Ease of Use

Cheng et al. (2015) believe that perceived ease of use is more conducive to users' use of the system. Then some researchers found that it covers perceived security (Cho & Fiorito, 2009). If users think that new technology or system learning is easier, they will be more receptive, and their attitude and acceptance will change significantly. In learning tools, Camarero et al. (2010) believe that when a collaborative learning tool is used as a learning tool, online learning tools that consider both PEOU and PU are more likely to show a positive attitude in the study of wireless network technology that the usefulness of the technology would be affected by its ease of use. Hence, hypotheses are suggested:

H5: Perceived ease of use has a significant influence on attitude.

H6: Perceived ease of use has a significant influence on perceived usefulness.

2.7 Social Influence

Venkatesh et al. (2003) mention that social Influence is important in terms of the changes in attitudes or feelings toward you. Social Influence is often measured by subjective norms instead of social pressures, norms, or factors (Lee et al., 2006). Fishbein and Ajzen (1975) used subjective norms to explain social Influence for the first time and proved that they directly affect behavioral Intention.

In addition, it is generally believed that social Influence greatly influences the behavior of technology acceptance (Kesharwani & Tripathy, 2012) and the practicality of perception and further affects the purchase intention of the product. Kucukemiroglu and Kara (2015) studied the use of social networks and found that Social Influence significantly influences Behavioral Intention. Chua and Rezaei (2018) also confirm that social Influence determines users' behavioral Intention when using social network programs. Accordingly, this research hypothesizes the following:

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

2.8 Attitude

Attitude is a dispositional response to an object (Fishbein & Ajzen, 1975). Moreover, attitude reflects a preference for using a particular device or technology (Davis, 1989). Chennamaneni et al. (2012) points out that attitude is the evaluation before people act. Several behavioral research has verified the connection between ATT and BI. (Holsapple & Wu, 2008). In terms of research on technology use, studies on 3D printing (Perry, 2017) and the use of a knowledge system show that ATT has a significant positive effect on BI in the use of the system (Elmorshidy, 2018). The following hypotheses are derived from this study. Therefore, this study provides a hypothesis:

H8: Attitude has a significant influence on behavioral intention.

3. Research Methods and Materials

3.1 Research Framework

The model framework for this study uses four core theories, the theory of planned behavior (TPB) by Ajzen (1991), the technology acceptance model (TAM) created by Davis (1989), the unified theory of acceptance and use of technology (UTAUT) by Venkatesh et al. (2003), the information systems success model (ISSM) created by DeLone and McLean (1992), and the theory of planned behavior (TPB) by Ajzen (1991). TPB uses attitudes and behavioral intentions, and TAM uses factors including perceived ease of use, perceived usefulness, attitudes, and behavioral intentions. UTAUT uses behavioral intentions and Social Influence, and the ISSM uses system quality, information quality, service quality, and perceived usefulness.

The framework of this study also draws on previous models. Hu and Zhang (2016) discovered that perceived usefulness, attitude, and behavioral intention were significantly affected by the quality of the information, systems, and services. Wu and Chen (2017) found that perceived usefulness and attitude were critical to a continued willingness to use the system. The third study was conducted by Khan et al. (2018), who found that perceived relevance and perceived competence of social approval significantly positively affected students' behavioral intention to use the system. The fourth study was conducted by Bakhsh et al. (2017), who found that students' attitudes strongly influenced behavioral intentions. The conceptual framework of this study is proposed in Figure 1.

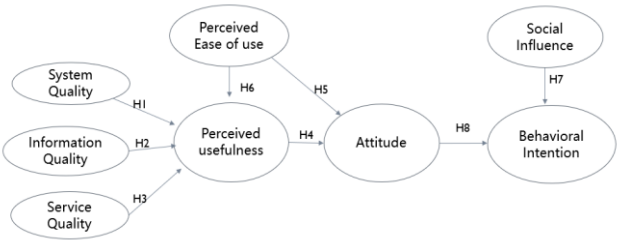

Figure 1: Conceptual Framework

H1: System quality has a significant influence on perceived usefulness.
H2: Information quality has a significant influence on perceived usefulness.
H3: Service quality has a significant influence on perceived usefulness.
H4: Perceived usefulness has a significant influence on attitude.
H5: Perceived ease of use has a significant influence on attitude.
H6: Perceived ease of use has a significant influence on perceived usefulness.
H7: Social influence has a significant influence on behavioral intention.
H8: Attitude has a significant influence on behavioral intention.

3.2 Research Methodology

The researcher applied nonprobability sampling for the quantitative approach with a questionnaire. To analyze all four hypotheses, a 5-point Likert scale was used to measure eight proposed variables, ranging from strong disagreement (1) to strong agreement (5). Three experts' rating of the IOC (index of the item–objective congruence) and pilot test for 30 respondents have been tested, and Cronbach's alpha approach was tested for reliability. The IOC's results are all passes at 0.67 or above. The CA results are acceptable above 0.7. The researcher sent to undergraduates from three universities in Sichuan who had used 5G for online learning, namely Sichuan University, Southwest Jiaotong University, and Xihua University. Following the validity and reliability test, the questionnaire was given to the intended respondents, and 560 approved female responses were obtained.

After the data were collected, CFA was used to measure and test the reliability and validity of the study model. The validity and reliability of the conceptual study model were evaluated using the outcomes of discriminant validity and convergent validity, including composite reliability, factor loading, and average variance extracted analysis. Using structural equation modeling to analyze and explore the factors influencing college students' behavioral intentions to use 5G for online learning. From the eight proposed hypotheses and research questions, seven of which were supported and proven.

3.3 Population and Sample Size

Judging from previous studies, many studies on online learning have attempted to explore gender differences in online learning. Wang et al. (2007) stated gender differences and participation in online learning education. The sample size of the structural equation model suggested that at least 444 respondents should participate in the study (Soper, 2023). In this study, the researcher selected female students at three universities in Sichuan Province to draw the conclusion and represent the target population. A total of 600 respondents eventually took part, and after data screening, 560 valid questionnaires were used in this study.

3.4 Sampling Technique

Judgmental sampling in this study is to select female college students in Sichuan. In order to make the sample more representative, the researchers selected three universities as the sample units. In order to select samples that allow the representation of the population, stratified sampling techniques were applied to calculate several sample sizes, as exhibited in Table 1. The study required a minimum of 500 questionnaires. For convenience sampling, the data collection was completed through online distribution of questionnaires.

Table 1: Sample Units and Sample Size

University	Population	Proportional Sample Size
Sichuan University	30908	219
Southwest Jiaotong University	16170	114
Xihua University	23580	167
Total	**70658**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic target for this study of 560 respondents is profiled in Table 2, with over 70 percent of respondents between the ages of 18 and 30. Statistics for the measurement scales included analysis of data concentration trends and variability analysis. The study used means and standard deviations, as shown in Table 3. The standard deviations for each item under the observed variables ranged from 0.789 to 1.051, with none of the standard deviations exceeding the mean, indicating little variability in this data set.

Table 2: Demographic Profile

Demographic and General Data (N=560)		Frequency	Percentage
Age stage	18-30	402	71.79
	30 and over	158	28.21
University	Sichuan University	219	39.11
	Southwest Jiaotong University	114	20.36
	Xihua University	227	40.53

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis was performed in the study to assess the measurement model and gauge how well it suited the data. Construct validity is used in cases where multiple indicators are measured. It is usually measured using both inductive and discriminant validity. Convergent validity may be assessed using the test's reliability indicator, Cronbach's alpha, factor loading, composite reliability, and average variance extracted. As shown in Table 6, if Cronbach's alpha values are more than 0.8, the items' internal consistency is considered dependable. Good internal consistency is indicated by composite reliability (CR) score of more than 0.6 for the model (Wu, 2010).

Factor loading reflects the effect of each latent variable on the measured variable. The factor loading for the second data set (female) ranges from 0.683 to 0.896, so each measurement corresponds to a factor loading greater than 0.5. The data results show that CR range from 0.830 to 0.934, and AVE values range from 0.549 to 0.779. So social influence is the factor with the highest internal consistency.

Table 3: 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
Behavioral Intention (BI)	Fishbein and Ajzen (1975)	4	0.844	0.725-0.783	0.845	0.577
Attitude (ATT)	Fishbein and Ajzen (1975)	4	0.856	0.756-0.784	0.856	0.597
Social Influence (SI)	Rashotte (2007)	4	0.934	0.872-0.896	0.934	0.779
Perceived Ease of Use (PEOU)	Davis (1989)	4	0.829	0.719-0.755	0.830	0.549
Perceived Usefulness (PU)	Davis (1989)	4	0.841	0.683-0.817	0.843	0.574
System Quality (SQ)	Kim et al. (2004)	4	0.839	0.725-0.791	0.840	0.567
Information Quality (IQ)	DeLone and McLean (1992)	4	0.851	0.730-0.798	0.852	0.590
Service Quality (SVQ)	Roca et al. (2006)	3	0.854	0.808-0.820	0.854	0.661

As in Table 4, the model has a good fit, the values of each indicator were CMIN/DF = 1.009, GFI = 0.956, AGFI = 0.946, NFI = 0.956, CFI = 1.000, TLI = 0.999, and RMSEA = 0.004, which is acceptable.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary et al., 2015; Awang, 2012)	409.831/406 or 1.009
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.956
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.946
NFI	≥ 0.80 (Wu & Wang, 2006)	0.956
CFI	≥ 0.80 (Bentler, 1990)	1.000
TLI	≥ 0.80 (Sharma et al., 2005)	0.999
RMSEA	< 0.08 (Pedroso et al., 2016)	0.004
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 = Normed fit index, CFI = Comparative fit index, TLI = Tucker–Lewis index, and RMSEA = Root mean square error of approximation.

When the square root of the AVE of each latent variable on the diagonal is greater than the correlation coefficient between that variable and the other variables, it means that the latent variables are both correlated and differentiated from each other, and the discriminant validity of the scale data is ideal, as shown in Table 5.

Table 5: Discriminant Validity

	BI	ATT	SI	PEOU	PU	SQ	IQ	SVQ
BI	**0.759**							
ATT	0.321	**0.773**						
SI	0.339	0.320	**0.883**					
PEOU	0.288	0.363	0.272	**0.741**				
PU	0.264	0.302	0.240	0.352	**0.758**			
SQ	0.325	0.418	0.248	0.392	0.291	**0.753**		
IQ	0.243	0.417	0.281	0.425	0.251	0.398	**0.768**	
SVQ	0.397	0.353	0.278	0.317	0.230	0.285	0.295	**0.813**

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

4.3 Structural Equation Model (SEM)

Structural equation modeling was used to assess the fit and the correlation of variables that influence college students' behavioral intentions to utilize the 5G for online education. The researchers used the same fit metrics they used for the CFA to assess the model fit of the structural model. The acceptable fit values in Table 6 were contrasted with the statistical values for each indicator in the CMIN/DF = 2.395, GFI = 0.879, AGFI = 0.860, NFI = 0.889, CFI = 0.932, TLI = 0.926, and RMSEA = 0.050 were the statistical values for the statistical values of the indicators were appropriate and confirmed the applicability of the structural model.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary et al., 2015; Awang, 2012)	1022.202/426 or 2.395
GFI	≥0.85 (Sica & Ghisi, 2007)	0.879
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.860
NFI	≥ 0.80 (Wu & Wang, 2006)	0.889
CFI	≥ 0.80 (Bentler, 1990)	0.932
TLI	≥ 0.80 (Sharma et al., 2005)	0.926
RMSEA	< 0.08 (Pedroso et al., 2016)	0.050
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 = Normed fit index, CFI = Comparative fit index, TLI = Tucker–Lewis index, and RMSEA = Root mean square error of approximation.

4.4 Research Hypothesis Testing Result

There are eight hypotheses proposed for this research, the eight proposed hypotheses were supported, as summarized in Table 7, and behavioral intention to use 5G for online learning was again strongly influenced by attitude, followed by social influence.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SQ→PU	0.190	3.895***	Supported
H2: IQ→PU	0.092	1.930*	Not Supported
H3: SVQ→PU	0.125	2.612**	Supported
H4: PU→ATT	0.242	4.840***	Supported
H5: PEOU→ATT	0.330	6.345***	Supported
H6: PEOU→PU	0.278	5.514	Supported
H7: SI→BI	0.292	6.351***	Supported
H8: ATT→BI	0.303	6.188***	Supported

Note: *** p<0.001, ** p<0.01, * p<0.05
Source: Created by the author

In the hypothesized relationship for **H1**, the set of data was 0.190 with a t-value of 3.895, consistent with the findings of (Fang et al., 2019; Gao & Bai, 2014). In the hypothesized relationship for **H2,** the standardized path coefficient for the second data set was 0.092, with a t-value of 1.930. this indicates that information quality does not affect women's perceived usefulness and therefore does not support H2 and rejects the original hypothesis at the p<0.05 test level.

In the hypothesized relationship for **H3,** the normalized route coefficient was 0.125, and the t-value was 2.612. This is consistent with Roca et al. (2006) and Lee (2010) findings. In the hypothesized relationship for **H4,** the normalized route coefficient was 0.242, and the t-value was 4.84. Thus, the more useful students find 5G for online education, the more likely they will learn it (Hanafizadeh et al., 2014; Venkatesh & Davis, 2000). In the hypothetical relationship for **H5,** the standardized path coefficient was 0.330, and the t-value was 6.345. The influence on attitudes toward 5GOEP use comes primarily from perceived ease of use (Benbunan-Fich & Hiltz, 2003; Camarero et al., 2010; Lee et al., 2007). Perceived ease of use indirectly influences behavioral intentions through attitudes to use and directly contributes to the attitude. In the hypothetical relationship of **H6,** the standardized path coefficient is 0.278, and the t-value is 5.514. It is clear from the results that perceived ease of use has a significant effect on perceived usefulness (Park & Chen, 2007; Wakefield & Whitten, 2006). In the hypothetical relationship for **H7,** the standardized path coefficient is 0.292, and the t-value is 6.351. they indicate that female university students are susceptible to peer, teacher, and social influences affecting the use of 5G for online education. Kucukemiroglu and Kara (2015) and Chua and Rezaei (2018) also came to the same conclusion.

In the hypothetical relationship for **H8,** the standardized path coefficient is 0.303, and the t-value is 6.188. It can be concluded that the strongest factors influencing behavioral intentions are attitudes (Chennamaneni et al., 2012; Elmorshidy, 2018; Holsapple & Wu, 2008; Perry, 2017).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study provides a comprehensive analysis of the important factors influencing the behavioral intention of female university students in Sichuan Province to use 5G for online education. The researcher used four core theories and theoretical frameworks from previous studies and applied seven variables and eight hypotheses for the analysis. A questionnaire was administered, and the target respondents were female university students from three universities in

Sichuan, China, who were all over 18 years old and admitted to using 5G for online education. The researcher received 560 valid questionnaires. The study used Confirmatory Factor Analysis to measure and test the reliability and validity of the research model. The validity and reliability of the conceptual research model were evaluated using the results of discriminant validity, convergent validity, and the structural equation model to analyze and explore the factors influencing female undergraduate students' behavioral intention to use 5G for online education, of which seven hypotheses were supported and proven, One hypothesis was not supported, for female undergraduate students, attitude and social influence significantly influenced female undergraduate students' behavioral intention to use 5G for online education, with attitude being the strongest predictor and indirect factors, perceived ease of use system quality, and service quality, but information quality was not significantly influenced by information quality.

5.2 Recommendation

The findings of this paper can be used by 5G for online education developers, marketers, senior managers in higher education institutions, or related practitioners as an important reference factor when considering increasing student usage. There are three main recommendations. First, attitudes were the strongest predictor of behavioral intention to use compared to social influence. Second, female students were more concerned about the impact of service quality, system quality, and ease of use on perceived usefulness than information quality. Second, female students are more concerned about the impact of service quality, system quality, and ease of use on perceived usefulness than information quality. Compared to traditional learning methods, e-learning platforms provide richer and more up-to-date information, which makes it perceived as effective by learners and arouses students' interest in learning (Al-Omairi et al., 2021). Third, when selecting and using 5G for online education in universities, it is important to ensure that the interest of students in learning is aroused as much as possible and to improve the quality and ease of use of the system in order to facilitate female students to make better use of the platform system and create a positive learning experience.

5.3 Limitation and Further Study

The limitations of this study are that the scope of the target population is three universities in Sichuan, not all regions and all students are currently covered, and only online education platforms using 5G technology support have been studied. Quantitative analysis could provide a significance of the data results, but not yet clear interpretation of the motives behind respondents. Therefore, future scholars should consider to conduct qualitative method.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-t

Al-Mamary, Y. H., Shamsuddin, A., Hamid, N. A., & Al-Maamari, M. H. (2015). Adoption of management information systems in context of Yemeni organizations: A structural equation modeling approach. *Journal of Digital Information Management, 13*(6), 429-444.

Al-Omairi, L., Al-Samarraie, H., Alzahrani, A. I., & Alalwan, N. (2021). Students' intention to adopt e-government learning services: A developing country perspective. *Library Hi Tech, 39*(1), 308-334. https://doi.org/10.1108/LHT-02-2020-0034.

Awang, Z. (2012). *Structural equation modeling using AMOS graphic* (5th ed.). Penerbit Universiti Teknologi MARA

Bailey, A. A., Pentina, I., Mishra, A. S., & Ben Mimoun, M. S. (2017). Mobile payments adoption by US consumers: an extended TAM. *International Journal of Retail and Distribution Management*, *45*(6), 626-640. https://doi.org/10.1108/ijrdm-08-2016-0144

Bakhsh, M., Mahmood, A., & Sangi, N. (2017). Examination of factors influencing students and faculty behavior towards m-learning acceptance: an empirical study. *The International Journal of Information and Learning Technology, 34*(3), 166-188. https://doi.org/10.1108/ijilt-08-2016-0028

Benbunan-Fich, R., & Hiltz, S. R. (2003). Mediators of the effectiveness of online courses. *IEEE Transactions on Professional Communication*, *46*(4), 298-312. https://doi.org/10.1109/tpc.2003.819639.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238-246. https://doi.org/10.1037/0033-2909.107.2.238

Brömmelstroet, M. (2017). PSS are more user-friendly, but are they also increasingly useful. *Transportation Research Part A: Policy and Practice*, *91*(7), 166-177.

Camarero, C., Rodríguez, J., & San José, R. (2010). An exploratory study of online forums as a collaborative learning tool. *Online Information Review, 36*(4), 568-586. https://doi.org/10.1108/14684521211254077

Cheng, S. I., Chen, S. C., & Yen, D. C. (2015). Continuance intention of E-portfolio system: a confirmatory and multigroup invariance analysis of technology acceptance model. *Computer Standards & Interfaces, 42*, 17-23. https://doi.org/10.1016/j.csi.2015.03.002

Cheng, Y. M. (2012a). Effects of quality antecedents on e-learning acceptance. *Internet Research, 22*(3), 361-390. https://doi.org/10.1108/10662241211235699

Cheng, Y. M. (2012b). The effects of information systems quality on nurses' acceptance of the electronic learning system. *Journal of Nursing Research*, *20*(1), 19-30. https://doi.org/10.1097/jnr.0b013e31824777aa

Chennamaneni, A., Teng, J. T. C., & Raja, M. K. (2012). A unified model of knowledge sharing behaviors: theoretical development and empirical test. *Behavior & Information Technology*, *31*(11), 1097-1115. https://doi.org/10.1080/0144929x.2011.624637

Cho, H., & Fiorito, S. S. (2009). Acceptance of online customization for apparel shopping. *International Journal of Retail & Distribution Management, 37*(5), 389-407. https://doi.org/10.1108/09590550910954892

Chua, P. Y., & Rezaei, S. (2018). Elucidating social networking apps decisions Performance expectancy, effort expectancy and social influence. *Nankai Business Review International*, *9*(2), 118-142. https://doi.org/10.1108/nbri-01-2017-0003

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-40. https://doi.org/10.2307/249008

DeLone, W. H., & McLean, E. R. (1992). Information systems success: the quest for the dependent variable. *Information Systems Research, 3*(1), 60-95. https://doi.org/10.1287/isre.3.1.60

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: a ten -year update. *Journal of Management Information Systems, 9*(4), 9-30.

Elmorshidy, A. (2018). The impact of knowledge management systems on innovation-An empirical investigation in Kuwait. *Journal of Information and Knowledge Management Systems, 48*(3), 388-403. https://doi.org/10.1108/vjikms-12-2017-0089

Fang, J. W., Hwang, G. J., & Chang, C. Y. (2019). *Advancement and the foci of investigation of MOOCs and open online courses for language learning: a review of journal publications from 2009 to 2018* (1st ed.). Interactive Learning Environments.

Fishbein, M. A., & Ajzen, I. (1975). *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research* (1st ed.). Addison Wesley.

Gao, L. L., & Bai, X. S. (2014). An empirical study on continuance intention of mobile social networking services Integrating the IS success model, network externalities and flow theory. *Asia Pacific Journal of Marketing and Logistics, 26*(2), 168-189. https://doi.org/10.1108/apjml-07-2013-0086

Hanafizadeh, P., Behboudi, M., Khoshksaray, A., & Shirkhani Tabar, M. (2014). Mobile-banking adoption by Iranian bank clients. *Telematics and Informatics, 31*(1), 62-78. https://doi.org/10.1016/j.tele.2012.11.001

Holsapple, C., & Wu, J. (2008). Building effective online game websites with knowledge-based trust. *Information Systems Frontiers*, *10*(1), 47-60. https://doi.org/10.1007/s10796-007-9060-5

Hu, J., & Zhang, Y. (2016). Chinese students' behavior intention to use mobile library apps and effects of education level and discipline. *Library Hi Tech*, *34*(4), 639-656. https://doi.org/10.1108/lht-06-2016-0061

Kesharwani, A., & Tripathy, T. (2012). Dimensionality of perceived risk and its impact on Internet banking adoption: an empirical investigation. *Services Marketing Quarterly*, *33*(2), 177-193. https://doi.org/10.1080/15332969.2012.662461

Khan, I. U., Hameed, Z., Yu, Y., Islam, T., Sheikh, Z., & Khan, S. U. (2018). Predicting the acceptance of MOOCs in a developing country: Application of task-technology fit model, social motivation, and self-determination theory. *Telematics and Informatics*, *35*(4), 964-978. https://doi.org/10.1016/j.tele.2017.09.009

Kim, H. W., Xu, Y., & Koh, J. (2004). A comparison of online trust building factors between potential customers & repeats customers. *Journal of the Association for Information Systems*, *5*(10), 392-420. https://doi.org/10.17705/1jais.00056

Kucukemiroglu, S., & Kara, A. (2015). Online word-of-mouth communication on social networking sites. *International Journal of Commerce and Management*, *25*(1), 2-20. https://doi.org/10.1108/ijcoma-11-2012-0070

Lee, J. W. (2010). Online support service quality, online learning acceptance, and student satisfaction. *The Internet and Higher Education, 13*(4), 277-283. https://doi.org/10.1016/j.iheduc.2010.08.002

Lee, Y. C. (2006). An empirical investigation into factors influencing the adoption of an e-learning system. *Online Information Review*, *30*(5), 517-541. https://doi.org/10.1108/14684520610706406

Lee, Y., Lee, J., & Lee, Z. (2006). Social influence on technology acceptance behavior: self-identity theory perspective. *The Data Base for Advances in Information Systems*, *37*(2-3), 60-75. https://doi.org/10.1145/1161345.1161355

Lee, Y., Shih-Pang, T., & Liu, F. (2007). Antecedents of learner satisfaction towards e-learning. *Journal of American Academy of Business*, *11*(2), 161-168. https://doi.org/10.4018/978-1-60960-762-3.ch029

Luo, L., Pibulcharoensit, S., Kitcharoen, K., & Feng, D. (2022). Exploring Behavioral Intention Towards Hybrid Education of Undergraduate Students in Public Universities in Chongqing, China. *AU-GSB E-JOURNAL*, *15*(2), 178-186. https://doi.org/10.14456/augsbejr.2022.83

Moores, T. T. (2012). Towards an integrated model of IT acceptance in healthcare. *Decision Support Systems*, *53*(3), 507-516. https://doi.org/10.1016/j.dss.2012.04.014

Mpinganjira, M. (2019). Cognitive absorption and behavioral intentions in virtual health communities: A focus on content posters. *Journal of Systems and Information Technology*, *21*(1), 122-145. https://doi.org/10.1108/jsit-06-2017-0044

Park, Y., & Chen, J. V. (2007). Acceptance and adoption of the innovative use of Smartphone. *Industrial Management & Data Systems*, *107*(9), 1349-1365. https://doi.org/10.1108/02635570710834009

Pedroso, R., Zanetello, L., Guimaraes, L., Pettenon, M., Goncalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry, 43*(3), 37-40. https://doi.org/10.1590/0101-60830000000081

Perry, A. (2017). Factors comprehensively influencing acceptance of 3D-printed apparel. *Journal of Fashion Marketing and Management, Bradford*, *21*(2), 219-234. https://doi.org/10.1108/jfmm-03-2016-0028

Rashotte, L. S. (2007). Social influence. In G. Ritzer (Ed.), *Blackwell Encyclopedia of Sociology, Blackwell,* (pp. 4426-4429). Oxford. https://doi.org/10.1002/9781405165518.wbeoss154

Roca, J. C., Chiu, C. M., & Martinez, F. J. (2006). Understanding e-learning continuance intention: an extension of the technology acceptance model. *International Journal of Human-Computer Studies, 64*(8), 683-696. https://doi.org/10.1016/j.ijhcs.2006.01.003

Rodino, M. (1997). Breaking out of binaries: Reconceptualizing gender and its relationship to language in computer - mediated communication. *Journal of Computer - Mediated Communication*, *3*(3). https://doi.org/10.1111/j.1083-6101.1997.tb00074.x

Saeed, K. A., Hwang, Y., & Yi, M. Y. (2003). Toward an Integrative Framework for Online Consumer Behavior Research: A Meta-Analysis Approach. *Journal of Organizational and End User Computing, 15*(4), 1-26. https://doi.org/10.4018/joeuc.2003100101

Sharma, G. P., Verma, R. C., & Pathare, P. (2005). Mathematical modeling of infrared radiation thin layer drying of onion slices. *Journal of Food Engineering, 71*(3), 282-286. https://doi.org/10.1016/j.jfoodeng.2005.02.010

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. (2023, March 13). *A-Priori Sample Size Calculator for Structural Equation Models [Software]*. http://wwwdanielsopercom/statcalc

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*, 186-204.

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

Wakefield, R. L., & Whitten, D. (2006). Mobile computing: a user study on hedonic/utilitarian mobile device usage. *European Journal of Information Systems*, *15*(3), 292-300. https://doi.org/10.1057/palgrave.ejis.3000619

Wang, M. J., Zhao, X. L., & Serra, C. (2007). Gender differences, dialogue styles and equal participation in online learning. *Distance Education in China*, *2*, 25-29.

Wu, B., & Chen, X. H. (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

Wu, J. H., & Wang, Y. M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information and Management, 43*(6), 728-739. https://doi.org/10.1016/j.im.2006.05.002

Wu, M. L. (2010). *Structural equation model -Operation and application of amos* (2nd ed.). Chongqing University Press.

Xu, S., & Tian, X. X. (2020). Research on Influencing Factors of User Intention to Use of Online Learning Platform Based on TAM (8). *The Chinese Journal of ICT in Education*, *15*(3), 1-10.

Zhang, M., Zhu, A., & Zhang, F. (2020). Research on Influencing Factors of Online Education Platform Users' Continuous Use Behavior. *Library Forum*, *40*(5), 1-10.

Zhang, N. X., Sun, J. H., Wang, C. C., & Gui, Q. P. (2021). The Status Quo and Further Development Strategy of China's Online Higher Education in the Perspective of International Comparison. *China Higher Education Research*, *1*, 48-55.

Zhou, T. (2011a). An empirical examination of initial trust in mobile banking. *Internet Research*, *21*(5), 527-540. https://doi.org/10.1108/10662241111176353

Zhou, T. (2011b). Examining the critical success factors of mobile website adoption. *Online Information Review*, *35*(4), 636-655. https://doi.org/10.1108/14684521111161972