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

Assessment of Behavioral Intention to Use Tencent Meeting of First-Year Students for Legal Courses in Chengdu, China

Liren Zhang*

Received: February 14, 2023. Revised: July 10, 2023. Accepted: July 25, 2023.

Abstract

Purpose: This research aims to assess the behavioral intention to use Tencent meetings of students for legal courses in Chengdu, China. The conceptual framework is developed from previous studies, incorporating perceived usefulness, attitude, social influence, perceived behavioral control, subjective norm, behavioral intention, and use behavior**. Research design, data, and methodology:** The target population is 500 first-year students at three selected universities who have experience using the Tencent platform for legal programs. The sample methods are judgmental, stratified random, and convenience sampling. Before the data collection, the Item Objective Congruence (IOC) Index and the pilot test (n=30) by Cronbach's Alpha were assessed to ensure content validity and reliability. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were used as statistical tools to confirm validity, reliability, and hypotheses testing. **Results:** The results show that all hypotheses are supported. Attitude, social influence, perceived behavioral control, and subjective norm significantly impacts behavioral intention and use behavior indirectly. Furthermore, perceived usefulness has a significant impact on attitude. **Conclusions:** The above key variables should be emphasized and strengthened to improve college students' use behavior of Tencent meetings in the learning process. Universities ought to pay attention to enhancing a system to maximize students' learning efficiency.

Keywords: Perceived Usefulness, Social Influence, Perceived Behavioral Control, Subjective Norm, Behavioral Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

As information technology rapidly advances, particularly from the Web to the mobile Web, the method of living, working, and learning across reality has been made, and obtaining information has gone through essential changes. Educating and learning can be unrestricted by time, space, and place, and the channels of obtaining information are adaptable and varied. Because of the pandemic, Dhawan (2020) expressed that internet teaching is no longer a choice. 11 departments of the Ministry of Education guidelines promoted healthy development in online education, put forward to 2020, significantly improve the infrastructure construction of online education, Internet, big data, artificial intelligence, and other modern information technology is more widely applied in the education field, online education pattern to be more perfect, more abundant resources and services. Online education improves the likelihood of gaining from various devices whenever (Pedersen et al., 2017). Online learning benefits give way to the teaching-

1*Liren Zhang, School of Marxism, Chengdu Vocational & Technical College of Industry, China. Email: 52921738@qq.com

learning course to be more student-focused, creative, and adaptable and promote social connection (Dhawan, 2020; Hou, 2015).

The college students who begin their college life in the first year (first-year students) regardless of schools or departments in colleges. Perhaps college's prior year is a difficult one, and students look forward to helping and knowing the new surrounding area and seeing how they may adapt to and struggle to overcome difficulties concerning the new schedule and discipline. It changes a lot in their life (Chavan & Carter, 2018). China's Ministry of Education stipulates that first-year students must take legal courses. It is a compulsory course for them; if they do not take it, they cannot get credit and graduate.

Moreover, they are very clear about the positive significance of legal knowledge to them so that they can find a good job when they graduate from university and enter society. They can protect their legal rights from infringement and harm and ensure that their behavior is legal and will not be punished by law for violating the law. So, the enthusiasm of first-year students to study law courses is quite high. They study law courses very seriously and hard.

With the widespread pandemic of COVID 19 around the world, the usage of the Tencent meeting app had been greatly increased because the student cannot attend school. However, some obstacles in this app's usage (e.g., too many applications of the same type, causing fierce competition, etc.) prevent this application from maximizing the market occupation. Therefore, these problems can lead to an in-depth study of the factors in the behavior intention of Tencent Meeting on the law courses learning of Chinese students in Chengdu. The conceptual framework is developed from previous studies, incorporating perceived usefulness, attitude, social influence, perceived behavioral control, subjective norm, behavioral intention, and use of behavior.

2. Literature Review

2.1 Perceived Usefulness

Perceived usefulness is how people think that their work will get benefit from the usage of new technologies. (Lee, 2006). Perceived usefulness assesses that the person considers the work performance is decided by the system (Boateng et al., 2016). Perceived usefulness was defined by Davis et al. (1989). People believe that their performance of work would get promoted with the usage of specific techniques (Davis et al., 1989). Taylor and Todd (1995) mentioned that the learning attitude is positively developed by perceived usefulness. Watjatrakul (2016) mentioned using technology and behavioral intention of using a free voluntary service. Furthermore, perceived usefulness has a noticeable effect on the intention to use the online education system through attitude (Bag et al., 2022). Therefore, this study hypothesizes:

H1: Perceived usefulness has a significant impact on attitude.

2.2 Attitude

Attitude describes the person's negative or positive feelings in goal-directed behavior (Fishbein & Ajzen, 1975). Bajaj and Nidumolu (1998) defined attitude as people's curiosity about a particular system. As defined by Kim and Woo (2016), attitudes agreeably or disagreeably differentiate humans, substance, organizations, or the world of others. Ajzen and Fishbein (2005) referred to attitude as the individual's advantageous or disadvantageous valuation or their valuation of the behavior under consideration. Attitude is a tendency to respond in an advantageous or disadvantageous way concerning a referred object (Fishbein & Ajzen, 1975). Foltz et al. (2008) mentioned that attitude influences behavioral intention. Furthermore, attitude straightforwardly impacts behavioral intention to take on e-learning. (Boateng et al., 2016). Besides, Huang et al. (2007) mentioned that attitude is straightforwardly connected with behavioral intention. Based on the discussion of the relationship between attitude and behavioral intention, this research proposes a hypothesis:

H2: Attitude has a significant impact on behavioral intention.

2.3 Social Influence

Venkatesh et al. (2003) explained that social influence is others' views on the necessity of using the technology, which the person himself can perceive. Social influence is people's understanding of the necessity of using technology by people around him or them (Venkatesh et al., 2012). On the condition that specific techniques are adopted, users' cognition will be connected with the social influence. That is the other's response in the group of his social circle. The technical users have their considerations. It is about their opinion on others' necessity of using such technology (Ukut & Krairit, 2018). Social influence impacts behavioral intention to utilize the online learning system. (Shivdas et al., 2020). Thus, social influence fundamentally affects behavioral intention (Ukut & Krairit, 2018). Thus, the effect of social influence on behavioral intention can be hypothesized:

H3: Social influence has a significant impact on behavioral intention.

2.4 Perceived Behavior Control

What individuals think of perceived behavioral control is their capabilities to carry out their actions (Foltz et al., 2008). Based on the planned behavior theory, which was improved by Ajzen (1991), mentioned that the behavioral intention and actions were decided by perceived behavioral control. Perceived behavioral control is the perceived degree of complexity in carrying out the behavior. Foltz et al. (2008) said that what people learned from their past decided their perceived behavior control, and so did the person's assessment of the difficulty degree in performing the actions. Perceived behavioral control will certainly influence behavior (Foltz et al., 2008). Besser et al. (2022) mentioned that Perceived behavior control related to weblog learning would be connected with the student's behavioral intention of using the system. Stockemer (2019) mentioned that perceived behavioral control connected to purchase relates to consumers' behavioral intention. Based on the above discussions, this research hypothesizes that:
H4: Perceived behavior control has a significant impact on behavioral intention.

2.5 Subjective Norm

People perceive who matters to them most and have the idea of whether they should act in consideration of students' will to use mobile learning (Ajzen & Fishbein, 2005). Subjective norm points out the person's cognition of others who matter to them most. It is about their opinion of whether they should carry out the behavior. (Fishbein & Ajzen, 1975). Subjective norm shows the stress outside to carry out the behavior or not and catches the nature of societal impacts (Lee et al., 2006). Subjective norms will decidedly influence behavioral intention (Foltz et al., 2008). Buabeng-Andoh (2018) mentioned that subjective norms would mainly impact behavioral intention. Subjective norms positively affect behavioral intention. (Mytton & Gale, 2012). Thus, a hypothesis is set:
H5: Subjective norm has a significant impact on behavioral intention.

2.6 Behavioral Intention

The meaning of behavioral intention shows that people are likely to adopt techniques (Ukut & Krairit, 2018). Behavioral intention shows that individuals mean to adopt the systems of e-learning all the time. (Samsudeen & Mohamed, 2019). Lee (2006) mentioned that behavioral intention is people's clear arrangements to carry out a particular behavior or not (Zhu et al., 2016). Behavioral intention deeply predicts real behavior. Whether people are willing to carry out a particular behavior is assessed by behavioral intention (Fishbein & Ajzen, 1975). Whether people are willing to carry out a specific behavior depends on their intentions (Keong et al., 2012). Awwad and Al-Majali (2015) mentioned that behavioral intention impacts students' use behavior of electronic library services. Hence, behavioral intention essentially affects use behavior. (Ukut & Krairit, 2018). Students' Behavioral intention to utilize e-learning systems emphatically and meaningfully impacts the use behavior of e-learning systems. (Samsudeen & Mohamed, 2019). Accordingly, a final hypothesis is indicated:
H6: Behavioral intention has a significant impact on use behavior.

2.7 Use Behavior

Venkatesh et al. (2003) pointed out that people who use technology are considered to use behavior (Awwad & Al-Majali, 2015). It was usual that how often people use the technology would assess their use behavior (Venkatesh et al., 2012). Celik (2016) studied that both the use behavior of shopping online and behavioral intention is actively affected by promoting factors. Usage intention strongly stimulates the Use behavior. That is how phones aim at shopping (Hubert et al., 2017). Both behavioral intention and contributing factors resulted in active use behavior, including the ERP software (Chauhan & Jaiswal, 2016). De Haan et al. (2018) carried out another research, which found that the rising area on mobile also resulted in active use behavior of such computing devices.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework is developed from three previous studies, incorporating perceived usefulness, attitude, social influence, perceived behavioral control, subjective norm, behavioral intention, and use behavior (Hsiao & Tang, 2014; Hu & Zhang, 2016; Samsudeen & Mohamed, 2019).

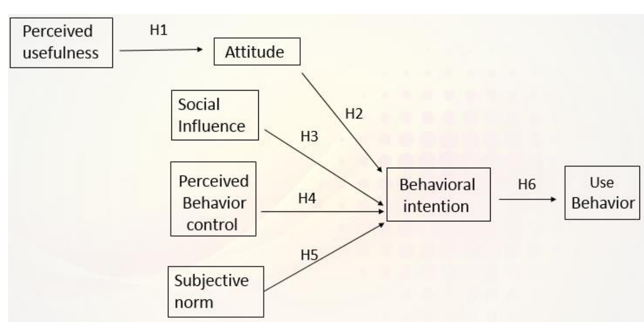

Figure 1: Conceptual Framework

H1: Perceived usefulness has a significant impact on attitude.
H2: Attitude has a significant impact on behavioral intention.
H3: Social influence has a significant impact on behavioral intention.
H4: Perceived behavior control has a significant impact on behavioral intention.
H5: Subjective norm has a significant impact on behavioral intention.
H6: Behavioral intention has a significant impact on use behavior.

3.2 Research Methodology

This study assesses the behavioral intention to use Tencent meetings of students in Chengdu, China. Five hundred first-year students at three selected universities with experience using the Tencent platform for legal programs; Chengdu Vocational & Technical College of Industry, Chengdu Polytechnic, and Sichuan Modern Vocational college. The research applied a quantitative method using a questionnaire as a tool. A survey consists of screening questions, measuring items with a five-point Likert scale, and demographic characteristics. After the data collection, confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were used as statistical tools to confirm validity, reliability, and hypotheses testing.

3.3 Validity and Reliability

Before the data collection, the Item Objective Congruence (IOC) Index and the pilot test (n=30) by Cronbach's Alpha were assessed to ensure content validity and reliability. IOC's results scored by three experts showed that all constructs are approved at equal to 0.6 or above. Cronbach's Alpha's internal consistency values should be equal to or greater than 0.7 (Gable & Wolf, 1993). The results show that perceived usefulness (0.755), attitude (0.785), social influence (0.730), perceived behavior control (0.875), subjective norm (0.909), behavioral intention (0.866), and use behavior (0.800).

3.4 Population and Sample Size

Target population is characterized as a specific individual that the analyst intends to learn about (Stangor, 2014). The target population of this study is 500 first-year students at three selected universities who have experience using the Tencent platform for legal programs; Chengdu Vocational & Technical College of Industry, Chengdu Polytechnic, and Sichuan Modern Vocational college. According Soper (2022), the recommended sample size is 425 participants. After distributed to over 6,000 freshmen students, 500 responses were received and screened within the data collection timeline to process the analysis.

3.5 Sampling Technique

The study applied both probability and nonprobability sampling, which are judgmental, stratified random, and convenience sampling. Judgmental sampling is to select first-year students at three selected universities who have experience using the Tencent platform for legal programs; Chengdu Vocational & Technical College of Industry, Chengdu Polytechnic, and Sichuan Modern Vocational college. Stratified random sampling is shown in Table 1. Convenience sampling is to distribute the online questionnaire to the target group.

Table 1: Stratified Random Sampling

University	Total Number of Freshmen	Proportionate Sample Size
Chengdu Vocational& Technical College of Industry	2341	180
Chengdu Polytechnic	2018	155
Sichuan modern Vocational College	2158	165
Total	**6517**	**500**

4. Results and Discussion

4.1 Demographic Information

The demographic results of 500 first-year students show that most respondents are females of, 57.6 percent (288), and males of, 42.4 percent (212). For the use frequency of Tencent meetings, 59 percent (295) of students use 4-6 days per week, followed by 27.4 percent (137) of 1-3 days per week, and 13.6 percent (68) of 7 days per week.

Table 2: Demographic Profile

Demographic and General Data (n=500)		Frequency	Percentage
Gender	Male	212	42.4
	Female	288	57.6
Use Frequency of Tencent Meeting	1-3 days/week	137	27.4
	4-6 days/week	295	59.0
	7 days/week	68	13.6

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is a data apparatus increasingly utilized in a wide range of research because of its adaptability and strength. It is usually used to measure validity, reliability, and factor loading (Brown, 2015). As shown in Table 3, CFA's results are verified by factor loading equal to 0.5 or above, Cronbach's Alpha coefficient value at not less than 0.7 (Gable & Wolf, 1993), and the Composite Reliability (CR) at not less than 0.7. In this study, the Composite Reliability (CR) is greater than the cut-off point of 0.6, thus; Average Variance Extracted (AVE) is higher than the cut-off point of 0.4, which can ensure convergent and discriminant validity (Fornell & Larcker, 1981).

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
Perceived Usefulness (PU)	Davis et al. (1989)	4	0.830	0.686-0.796	0.831	0.552
Attitude (AT)	Ajzen (1991)	2	0.843	0.854-0.854	0.843	0.729
Social Influence (SI)	Park (2013)	4	0.844	0.745-0.783	0.844	0.576
Perceived Behavior Control (PBC)	Taylor and Todd (1995)	5	0.833	0.674-0.738	0.833	0.499
Subjective Norm (SN)	Ajzen (1991)	3	0.807	0.744-0.781	0.807	0.582
Behavioral Intention (BI)	Park (2013)	3	0.827	0.757-0.818	0.828	0.616
Use Behavior (UB)	Ajzen (1991)	4	0.859	0.746-0.822	0.860	0.605

The measurement model was tested to confirm the model fit by goodness of fit indices. This study did not require a modification to the measurement model for the original measurement model already provided a model fit. In the Table 4, it approves the measurement model fit, including CMIN/DF = 1.009, GFI = 0.961, AGFI = 0.950, NFI = 0.955, CFI = 1.000, TLI = 1.000, and RMSEA = 0.004.

Table 4: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	256.227/254 or 1.009
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.961
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.950
NFI	≥ 0.80 (Wu & Wang, 2006)	0.955
CFI	≥ 0.80 (Bentler, 1990)	1.000
TLI	≥ 0.80 (Sharma et al., 2005)	1.000
RMSEA	< 0.08 (Pedroso et al., 2016)	0.004
Model summary		**Acceptable Model Fit**

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
Source: Created by the author.

When the square root of the AVE is greater than the coefficient of any intercorrelated construct, discriminant validity is established (Fornell & Larcker, 1981). The square root of AVE for each construct at the diagonal line was greater than the inter-scale correlations, as shown in Table 5. As a result, discriminant validity was ensured.

Table 5: Discriminant Validity

	PU	AT	SI	PBC	SN	BI	UB
PU	**0.743**						
AT	0.495	**0.854**					
SI	0.321	0.332	**0.759**				
PBC	0.313	0.294	0.256	**0.707**			
SN	0.222	0.254	0.237	0.222	**0.763**		
BI	0.306	0.281	0.292	0.235	0.317	**0.785**	
UB	0.445	0.425	0.402	0.466	0.403	0.391	**0.778**

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

4.3 Structural Equation Model (SEM)

The structural model was tested to confirm the model fit by goodness of fit indices. This study did not require a modification to the measurement model for the original measurement model already provided a model fit. In the Table 4, it approves the measurement model fit, including CMIN/DF = 1.795, GFI = 0.931, AGFI = 0.915, NFI = 0.917, CFI = 0.961, TLI = 0.955, and RMSEA = 0.040.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	472.067/263 or 1.795
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.931
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.915
NFI	≥ 0.80 (Wu & Wang, 2006)	0.917
CFI	≥ 0.80 (Bentler, 1990)	0.961
TLI	≥ 0.80 (Sharma et al., 2005)	0.955
RMSEA	< 0.08 (Pedroso et al., 2016)	0.040
Model summary		**Acceptable Model Fit**

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
Source: Created by the author.

4.4 Research Hypothesis Testing Result

Standardized path coefficient value (β) and t-value are used to provide research hypothesis testing result. The significant effect is determined at p-value<0.05. The results show that all hypotheses are supported.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PU→AT	0.617	11.226*	Supported
H2: AT→BI	0.191	3.732*	Supported
H3: SI→BI	0.203	3.760*	Supported
H4: PBC→BI	0.148	2.770*	Supported
H5: SN→BI	0.284	5.176*	Supported
H6: BI→UB	0.531	9.879*	Supported

Note: * p<0.05

Research hypothesis testing results can be discussed below:

H1 reveals that perceived usefulness significantly impacts attitude, resulting in the standardized path coefficient value of 0.617 (t-value = 11.226). The results can be assumed that when students perceive the usefulness of Tencent meetings, they tend to demonstrate a positive attitude toward the use (Lee, 2006).

H2 confirms the relationship between attitude and behavioral intention with a standardized path coefficient value of 0.191 (t-value = 3.732). Many scholars mentioned that attitude influences behavioral intention and explored to confirm whether attitude directly impacts behavioral intention use of e-learning (Boateng et al., 2016; Foltz et al., 2008).

H3 shows that social influence significantly impacts behavioral intention, reflecting the standardized path coefficient value of 0.203 (t-value = 3.760). The results indicate that an e-learning system as an interactive learning tool can socially influence and explain students' views on the necessity of using the Tencent meeting and predict their behavioral intention (Venkatesh et al., 2012).

H4 approves the support relationship between perceived behavioral control and behavioral intention with a standardized path coefficient of 0.148 and a t-value of 2.770. Thus, perceived behavior control impacts behavioral intention (Foltz et al., 2008). Besser et al. (2022) added that behavioral intention is impacted by the perception of the difficulty of carrying out behavior, known as perceived behavior control.

H5 approves the significant relationship between subjective norm and behavioral intention, resulting in a standardized path coefficient of 0.284 (t-value = 5.176). Subjective norms can influence the behavioral intention of students to use Tencent meetings (Mytton & Gale, 2012).

H6 results that behavioral intention significantly impacts user behavior with a standardized path coefficient of 0.531 (t-value = 9.879). This study assumes whether students are willing to carry out a specific behavior depends on their intentions to use Tencent meetings (Keong et al., 2012).

5. Conclusions and Recommendation

5.1 Conclusion and Discussion

The conclusion and discussion are based on the accomplishment of the research objectives. This research aims to assess the significant impact of perceived usefulness, attitude, social influence, perceived behavioral control, and subjective norm on behavioral intention to use Tencent meetings of students for legal courses in Chengdu, China. The data results show that all hypotheses are supported. Attitude, social influence, perceived behavioral control, and subjective norm significantly impacts behavioral intention and use behavior indirectly. Furthermore, perceived usefulness has a significant impact on attitude.

In discussions, the behavioral intention to analyze users' technical acceptability was another UTAUT-adopted variable. Finally, social influence, behavioral intention, and use behavior were incorporated into the framework to evaluate online learning adoption. In order to define the significant factors, the study's determinants were also formulated from previous literature reviews. Samsudeen and Mohamed (2019) conducted the first study, which examined university students' intentions to use e-learning systems. The findings revealed that Use Behavior is greatly influenced by external UTAUT variables, specifically social influence and behavioral intention.

Hsiao and Tang (2014) studied the second study, which examined undergraduates' behavioral intention to adopt e-textbooks. The findings revealed that Behavioral Intention is greatly influenced by external TAM variables, specifically Subjective Norms and Perceived Behavior Control. The behavior intention of Chinese students using mobile library apps was the subject of the third study, which was carried out by Hsiao and Tang (2014). The findings revealed that external TPB variables, specifically attitude, greatly influence Behavioral intention.

The significant factors identified from the research findings serve as the foundation for the recommendations discussed in the subsequent section on implications for practice. In order to encourage students' behavioral intention to use Tencent Meeting for their education, this could benefit the developer of Tencent Meeting, its top management, and college instructors in developing course materials and teaching-learning processes tailored to their needs.

5.2 Recommendation

The findings of this study indicate that several factors have a significant influence on use behavior. The strongest predictor of use behavior for undergraduate students was the behavioral intention to use. Other significant predictors indirectly impacted perceived usefulness, attitude, social influence, perceived behavior control, and subjective norm. These can help determine the most important aspects that Tencent meeting developers, college administrators, or practitioners should focus on to improve students' Tencent meeting use behavior. The developer of Tencent Meeting and the college's top management ought to concentrate on making students' perceptions of the app's usefulness, influence, and service attitude more positive. Promoting online learning tools like Tencent Meeting in the teaching-learning process is essential. Not only for the digital age but also as a backup to guarantee ongoing learning in any circumstance that could disrupt learning, like the COVID-19 pandemic.

In order to improve college students' Use Behavior of Tencent meeting in the learning process, the above key variables should be emphasized and strengthened. In the study, behavioral intention is the strongest variable influencing college students' use behavior of Tencent meetings in the learning process. Therefore, it is necessary to emphasize the utility of the variable. This means that college students are inclined to use Tencent Meeting if they think it is useful to improve their academic performance. Therefore, on the one hand, it is necessary to improve the technical skills of Tencent Meeting software developers; on the other hand, it is necessary to provide adequate training to teachers and students, thus helping them to use Tencent Meeting more effectively to study online courses and to improve teachers' and students' use behavior of Tencent Meeting.

5.3 Limitation and Further Study

This study has some limitations that need to be pointed out. First, this study's scope and sample size is limited due to its initial focus solely on higher education and data collection from three selected Chengdu higher education institutions. Second, Tencent meetings served as a basis for this study. Other online learning systems, such as Massive Open Online Courses (MOOCs), Ubiquitous Learning (U-Learning), and online learning for business organizations, may be the subject of further research. Third, the research only includes students as respondents. Teachers may be included as respondents in subsequent research to obtain their perspectives on Tencent meeting use behavior.

References

Ajzen, I. (1991). Theory of planned behavior. *Organization Behavior and Human Decision Process, 50*(2), 179-211.

Ajzen, I., & Fishbein, M. (2005). The Influence of Attitudes on Behavior. In D. Albarracín, B. T. Johnson, & M. P. Zanna (Eds.), *The handbook of attitudes* (pp. 173-221). Lawrence Erlbaum Associates Publishers.

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.

Awang, Z. (2012). *A Handbook on SEM Structural Equation Modelling: SEM Using AMOS Graphic* (5th ed.). Universiti Teknologi Mara Kelantan.

Awwad, M. S., & Al-Majali, S. M. (2015). Electronic library services acceptance and use. *The Electronic Library, 33*(6),1100-1120. https://doi.org/10.1108/el-03-2014-0057

Bag, S., Aich, P., & Islam, M. A. (2022). Behavioral intention of "digital natives" toward adapting the online education system in higher education. *Journal of Applied Research in Higher Education, 14*(1), 16-40. https://doi.org/10.1108/JARHE-08-2020-0278.

Bajaj, A., & Nidumolu, S. R. (1998). A feedback model to understand information system usage. *Information & Management, 33*(4), 213-224.

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

Besser, A., Flett, G. L., & Zeigler-Hill, V. (2022). Adaptability to a sudden transition to online learning during the COVID-19 pandemic: Understanding the challenges for students. *Scholarship of Teaching and Learning in Psychology, 8*(2), 85-105. https://doi.org/10.1037/stl0000198

Boateng, R., Mbrokoh, A. S., Boateng, L., Senyo, K., & Ansong, E. (2016). Determinants of e-learning adoption among students of developing countries. *The International Journal of Information and Learning Technology, 33*(4), 248-262. https://doi.org/10.1108/ijilt-02-2016-0008

Brown, T. A. (2015). *Confirmatory factor analysis for applied research* (2nd ed.). The Guilford Press.

Buabeng-Andoh, C. (2018). Predicting students' intention to adopt mobile learning: A combination of theory of reasoned action and technology acceptance model. *Journal of Research in Innovative Teaching & Learning, 11*(2), 178-191. https://doi.org/10.1108/JRIT-03-2017-0004

Celik, H. (2016). Customer online shopping anxiety within the unified theory of acceptance and use technology (UTAUT) framework. *Asia Pacific Journal of Marketing and Logistics, 28(*2), 278-307. https://doi.org/10.1108/apjml-05-2015-0077

Chauhan, S., & Jaiswal, M. (2016). Determinants of acceptance of ERP software training in business schools: empirical investigation using UTAUT model. *The International Journal of Management Education, 14*(3), 248-262. https://doi.org/10.1016/j.ijme.2016.05.005

Chavan, M., & Carter, L. (2018). Management students – expectations and perceptions on work readiness. International *Journal of Educational Management, 32*(5), 825-850.

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.

De Haan, E., Kannan, P. K., Verhoef, P. C., & Wiesel, T. (2018). Device switching in online purchasing: examining the strategic contingencies. *Journal of Marketing, 82*(5), 1-19. https://doi.org/10.1509/jm.17.0113

Dhawan, S. (2020). Online learning: a panacea in the time of COVID-19 crisis. *Journal of Educational Technology Systems, 49*(1), 5-22. https://doi.org/10.1177/0047239520934018

Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research* (1st ed.). Addison-Wesley. https://doi.org/10.2307/2065853

Foltz, C. B., Schwager, P. H., & Anderson, J. E. (2008). Why users (fail to) read computer usage policies. *Industrial Management & Data Systems, 108*(6), 701-712. https://doi.org/10.1108/02635570810883969

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

Gable, R., & Wolf, M. (1993). *Instrument Development in the Affective Domain: Measuring Attitudes and Values in Corporate and School Settings* (2nd ed.). Kluwer Academic Publishers. https://doi.org/10.1007/978-94-011-1400-4_1

Hou, H. (2015). What makes an online community of practice work? A situated study of Chinese student teachers' perceptions of online professional learning. *Teaching and Teacher Education, 46*(2), 6-16. https://doi.org/10.1016/j.tate.2014.10.005

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

Hu, 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

Huang, J., Lin, Y., & Chuang, S. (2007). Elucidating user behavior of mobile learning: A perspective of the extended technology acceptance model. *The Electronic Library, 25*(5), 585-598. https://doi.org/10.1108/02640470710829569

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

Keong, M. L., Thurasamy, R., Sherah, K., & Chiun, L. M. (2012). Explaining intention to use an enterprise resource planning (ERP) system: an extension of the UTAUT model. *Business Strategy Series, 13*(4), 108-120. https://doi.org/10.1108/17515631211246249

Kim, Y. G., & Woo, E. (2016). Consumer acceptance of a quick response (QR) code for the food traceability system: Application of an extended technology acceptance model (TAM). *Food Research International, 85,* 266-272. https://doi.org/10.1016/j.foodres.2016.05.002

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

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), 60-75. https://doi.org/10.1145/1161345.1161355

Mytton, E., & Gale, C. (2012). Prevailing issues in legal education within management and business environments. *International Journal of Law and Management, 54*(4), 311-321.

Park, E. (2013). The adoption of tele-presence systems: Factors affecting intention to use tele-presence systems. *Kybernetes, 42*(6), 869-887. https://doi.org/10.1108/k-01-2013-0013

Pedersen, S., Cooley, P., & Cruickshank, V. (2017). Caution regarding exergames: a skill acquisition perspective. *Physical Education and Sport Pedagogy, 22*(3), 246-256. https://doi.org/10.1080/17408989.2016.1176131

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.

Samsudeen, S. N., & Mohamed, R. (2019). University students' intention to use e-learning systems A study of higher educational institutions in Sri Lanka. *Interactive Technology and Smart Education, 16*(3), 219-238. https://doi.org/10.1108/itse-11-2018-0092

Sharma, S., Mukherjee, S., Kumar, A., & Dillon, W. (2005). A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models. *Journal of Business Research, 58*(7), 935-943. https://doi.org/10.1016/j.jbusres.2003.10.007

Shivdas, A., Menon, D. G., & Nair, C. S. (2020). Antecedents of acceptance and use of a digital library system: Experience from a Tier 3 Indian city. *The Electronic Library, 38*(1), 170-185. https://doi.org/10.1108/EL-03-2019-0074

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 Science Publishers.

Soper, D. S. (2022, May 24). *A-priori Sample Size Calculator for Structural Equation Models*. Danielsoper. www.danielsoper.com/statcalc/default.aspx

Stangor, C. (2014). *Research methods for the behavioral sciences* (5th ed.). Cengage Learning.

Stockemer, D. (2019). *Quantitative Methods for the Social Sciences: A Practical Introduction with Examples in SPSS and Stata* (1st ed.). Springer.

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: a test of competing models. *Information Systems Research, 6*(2), 144-176. https://doi.org/10.1287/isre.6.2.144

Ukut, I. I. T., & Krairit, D. (2018). Justifying students' performance, A comparative study of both ICT students' and instructors' perspective. *Interactive Technology and Smart Education, 16*(1), 18-35. https://doi.org/10.1108/itse-05-2018-0028

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

Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 156-178. https://doi.org/10.2307/41410412

Watjatrakul, B. (2016). Online learning adoption: effects of neuroticism, openness to experience, and perceived values. *Interactive Technology and Smart Education, 13*(3), 229-243. https://doi.org/10.1108/ITSE-06-2016-0017

Wu, J. H., & Wang, Y. M. (2006). Measuring KMS Success: A Respecification of the DeLone and McLean's Model. *Journal of Information & Management, 43*(6), 728-739. http://dx.doi.org/10.1016/j.im.2006.05.002

Zhu, W., Wei, J., & Zhao, D. (2016). Anti-nuclear behavioral intentions: the role of perceived knowledge, information processing, and risk perception. *Energy Policy, 88*, 168-177. https://doi.org/10.1016/j.enpol.2015.10.009