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

An Examination on Online Learning Adoption of Postgraduate Students in Chengdu, China During COVID-19

Yaze Lyu*

Received: February 7, 2023. Revised: May 22, 2023. Accepted: June 6, 2023.

Abstract

Purpose: Online learning has dramatically increased adoption in the educational sector during the COVID-19 pandemic. This study examines the online learning adoption of college students in Chengdu, China. Technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) incorporates perceived ease of use, perceived usefulness, attitude, social influence, facilitating conditions, behavioral intention, and use behavior. **Research design, data, and methodology:** The target population is 500 postgraduate students in the top three universities in Chengdu. The sample techniques are purposive, stratified random, convenience, and snowball samplings. The Item Objective Congruence (IOC) Index and the pilot test (n=50) by Cronbach's Alpha were used to ensure content and construct validity. The data analysis was conducted by Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). **Results:** The findings show that perceived ease of use significantly impacts perceived usefulness. Behavioral intention strongly and significantly impacts use behavior. Behavioral intention is significantly impacted by perceived ease of use, usefulness, attitude, social influence, and facilitating conditions. **Conclusions:** The virtual classroom has continued in China due to China's "Zero-COVID" Policy after the decline of health and safety restrictions. Therefore, this study addresses the factors to improve the online learning adoption rate.

Keywords: Online Learning, Technology Acceptance Model, Unified Theory Of Acceptance And Use Of Technology, Behavioral Intention, Use Behavior

JEL Classification Code: E44, F31, F37, G15

1. Introduction

According to UNESCO (2022), the outbreak has embarked China to exercise large-scale online learning adoption. UNESCO, with the Ministry of Education of the People's Republic of China, has discussed leveraging new technology, such as artificial intelligence (AI) and Cloud, to ensure the learning continuity of students. The school management has been encouraged to maximize the efficiency of online learning platforms. The course and telecom providers are the key stakeholders in forcing rapid and efficient online learning adoption in China. For online learning purposes, the collaboration between the Ministry of

1 *Yaze Lyu, Ph.D. Candidate in Technology, Education and Management, Graduate School of Business and Advanced Technology Management, Assumption University. Email: yazelyu@outlook.com

Education with the Ministry of Industry and Information Technology in China aims to boost internet connectivity, upgrade the bandwidth of major online education service platforms, provide accessibility to over 24,000 online courses, digitalize TVs or mobile Apps, strengthen online security and provide psycho-social support to instructors and learners.

According to Chang (2020), China's online education market already numbered 200 million users in 2018, seeing year-on-year growth of 25.7% to reach revenues of RMB 251.7 billion ($35.9 billion). The sector was expected to grow 12.3% to RMB 435.8 billion ($61.5 billion) in 2020. The wake of COVID-19 has accelerated the online education growth in China, expected to reach RMB 500 billion ($70.6 billion) in 2022. Online education in China was inefficient and has taken major improvements as a reception of the COVID-19 pandemic. Even though the pandemic has accelerated the online experience experiences of Chinese students, the degree of online learning system adoption still needs to be determined. A growing online education acceptance remains a key challenge for online educators to overcome to gain true acceptability in China's higher education sector (Swanson & Valdois, 2022).

The researcher can exploit the findings of this study to make a comparison in a different situation. Online education has been continued as it offers flexibility, a variety of program selections, accessibility, customized experience for users, and cost-effectiveness for educators. Therefore, online learning adoption can open the opportunity for educators and learners to exploit benefits in the future. Singh (2022) pointed out that online learning will continue transforming education post-COVID-19. Digital learning, or video-based learning, has been growing exponentially worldwide since the wake of COVID-19. The evidence is that 3 trillion minutes of video content were streamed monthly in 2021. It proves that most people access different types of learning content on online platforms via smartphones. Consequently, online learning continues to rise and still be the fastest emerging segment, gaining wide attention among researchers on online learning adoption.

Furthermore, due to China's "Zero-COVID" Policy, online learning adoption has continued to gain traction among researchers in China. Therefore, as Chengdu is one of the top cities in China as higher education hub of the country, the researcher has adopted the research model stimulated by earlier literature and employed it to contribute to understanding user perceptions and adopting online learning in higher education. Therefore, this study aims to examine the online learning adoption of college students in Chengdu, China. The main variables constructed in a conceptual framework based on the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) are perceived ease of use, perceived usefulness, attitude, social influence, facilitating conditions, behavioral intention, and use behavior.

2. Literature Review

2.1 Technology Acceptance Model (TAM)

This research pointed out that TAM is "how a student believes and has a psychological state concerning their voluntary or intended use of online learning." The key variables of the original TAM are perceived ease of use, perceived usefulness, attitude, behavioral intention, and use behavior. The extended model of TAM has additional variables, such as subjective norms, trust, and satisfaction, which can be modified according to the relevant factors and topics (Venkatesh et al., 2003). Patel and Patel (2018) indicated that various empirical studies had adopted the TAM as the foundation with two main determinants of intentions: perceived ease of use and perceived usefulness. Attitude is also a key predictor in the model.

2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT focuses on key factors affecting technology adoption: performance expectancy, effort expectancy, facilitating conditions, social influence, behavioral intention, and actual use behavior (Venkatesh et al., 2012). Many studies determine the mediators, including gender, age, experience, and voluntariness of use. Scholars have applied both TAM and UTAUT in the online learning adoption topic, which has commonly examined the behavioral intention and use behavior (Feng et al., 2022; Luo et al., 2022; Min et al., 2022; Xie et al., 2022; Zhong et al., 2022). According to Venkatesh et al. (2003), the Unified Theory of Acceptance and Use of Technology (UTAUT) has been applied to investigate new technology adoption and has been widely used among researchers.

2.3 Perceived Ease of Use

The definition of perceived ease of use is "to what extent people considered applying some techniques such as a certain platform was easy." Davis (1989) primarily stated that perceived ease of use is defined as "the degree to which a person believes that using a particular system would be free of effort, and the degree to which the prospective user expects the target system to be easy to use." Lin (2013) examined ubiquitous learning and implied perceived ease of use that learners feel online learning is free of effort to engage. Perceived ease of use is a predictor of perceived usefulness due to students' awareness that ease of use relates to the benefit they expect. Online learning can provide convenience and improve student performance (Lin, 2013). Some studies during the COVID-19 situation found a strong correlation between perceived ease of use and perceived usefulness among students' behavioral intention to use online learning (Lan et al., 2022; Min et al., 2022; Zhong et al., 2022). Effective online learning systems and their facilitators can enhance the behavioral intention to use such systems (Bashir & Madhavaiah, 2015). Perceived ease of use is "an intrinsic motivation and behavioral intention" (Zeithaml et al., 2002). Based on the previous research, this study assumes a hypothesis:

H1: Perceived ease of use has a significant impact on perceived usefulness.

H2: Perceived ease of use has a significant impact on behavioral intention.

2.4 Perceived Usefulness

This study assumed that perceived usefulness describes "the degree to which a student believes the benefits of using an online learning system would enhance his or her learning performance" (Cao & Jittawiriyanukoon, 2022). Feng et al. (2022) also addressed that perceived usefulness determines "how online learning methods are more beneficial and effective for students and refers to the degree to which a student trusts a system and believes that it will improve his/her learning performance" Zhong et al. (2022) claimed that "students believe that using an online learning would improve their outcomes, which impact the behavioral intention." Consequently, this study proposes the following hypothesis predicting perceived usefulness to impact behavioral intention significantly.

H3: Perceived usefulness has a significant impact on behavioral intention.

2.5 Attitude

This study implies that attitude is "student's intentions in using the online system and refers to their evaluation, which can be a positive or negative emotion towards, which determines behavioral intention to the use of online learning" (Zhong et al., 2022). Cao and Jittawiriyanukoon (2022) posited that attitude toward the use of online learning of learners is "the favorably or unfavorably respond to such system, which leads to a successful adoption." Hsiao and Tang (2014) stressed that attitude represents a student's positive or negative feelings about using online learning mode. Zhong et al. (2022) discovered a strong association between attitude and behavioral intention. Many scholars are in consensus that attitude is an influential driver of intentional behavior to engage in online learning among students (Lan et al., 2022; Min et al., 2022; Zhong et al., 2022). Thereby, the researcher addressed a correlation between attitude and behavioral intention to use online learning among Chinese students per below:

H4: Attitude has a significant impact on behavioral intention.

2.6 Social Influence

This study implies that the social influence of students is their peers, teachers, and parents who impact their decision to adopt an online learning system (Luo et al., 2022). Pham and Dau (2022) also defined social influence in the online learning perspective that it is "the degree to which learners perceive social pressure or expect to engage in some behavior, and they feel the need to conform to that pressure" Chiu and Tsai (2014) cited that "the social environment is learners' motivation to employ online learning." Venkatesh et al. (2003) demonstrated in the UTAUT model that "an individual behavior is influenced by how others expect them to use a technology, and how possible an individual will consider other beliefs and expectation that he or she should use the new system technology." Vululleh (2018) attested that social influence is "the connection between students and other influencers such as peers or instructors who encourage them to use online learning." Accordingly, a developed assumption is indicated:

H5: Social influence has a significant impact on behavioral intention.

2.7 Facilitating Conditions

Xie et al. (2022) postulated that facilitating conditions are "the extent to which a student believes that educational institutions provide infrastructure and equipment to facilitate the use of the hybrid learning system." Rienties et al. (2016) interpreted that when users engage with new and unfamiliar technology, such as a new online learning system, facilitating conditions are hardware, software, manual, and learning content, which encourage them to use it. Students' adoption of e-learning systems has been varied and explicated in terms of the education institutions' support of the use of technology (Tarhini et al., 2017). The study by Xie et al. (2022) results that facilitation conditions did not affect behavioral intention. However, most scholars agreed on the relationship between facilitating conditions and behavioral intention (Shen et al., 2019; Teo, 2011; Venkatesh et al., 2003). According to the earlier discussions, a hypothesis is projected:

H6: Facilitating conditions have a significant impact on behavioral intention.

2.8 Behavioral Intention

In the context of online learning, Cao and Jittawiriyanukoon (2022) highlighted that behavioral intention is assumed to be "a willingness of student in using online learning or probability of a student performing a behavior of online platform usage" Min et al. (2022) referred behavioral intention to "the extent to which a person makes conscious plans to carry out or refrain from carrying out specific performance, which explains that when students potentially adopt an online system as they believe it can help them to achieve their education's goals." Consistent with research model of Al-Imarah et al. (2013), the study stated that "an individual behavior was predictable and influenced by individual intention." UTAUT affirms that behavioral intention is significantly related to use behavior (Venkatesh & Zhang, 2010). Thus, the last hypothesis is stated per the following:
H7: Behavioral intention has a significant impact on use behavior.

2.9 Use Behavior

Students' use of behavior to engage with online learning can be determined by predictors such as behavioral intention, facilitating conditions, and vice versa. The user behavior of e-learning systems is mainly theorized in TAM, UTAUT, and other technology adoption models. Subsequently, use behavior represents the final goal of successful adoption (Lin et al., 2013). According to Paul et al. (2015), facilitating conditions are considered to encourage the behavioral intention toward the use behavior of individuals. The statement explained that technical and organizational infrastructure is necessary to be ready to support the adoption of new technologies. Several studies have attempted to exclude facilitating conditions, and most have assessed only the linkage to behavioral intention. Wut et al. (2022) examined a similar model as Paul et al. (2015), but the relationship between facilitating conditions and students' intention to interact with online learning was insignificant.

3. Research Methods and Materials

3.1 Research Framework

In Figure 1, three previous studies are referred to construct a conceptual framework for this study. First, Hsiao and Tang (2014) studied students' behavioral intention toward e-textbook adoption and pointed out the relationship between attitude, behavioral intention, and use behavior. Second, Lin (2013) adopted the relationship between perceived usefulness, perceived ease of use, and behavioral intention. Last, Shen et al. (2019) examined the behavioral intention to adopt virtual learning, which contains social influence and facilitating conditions.

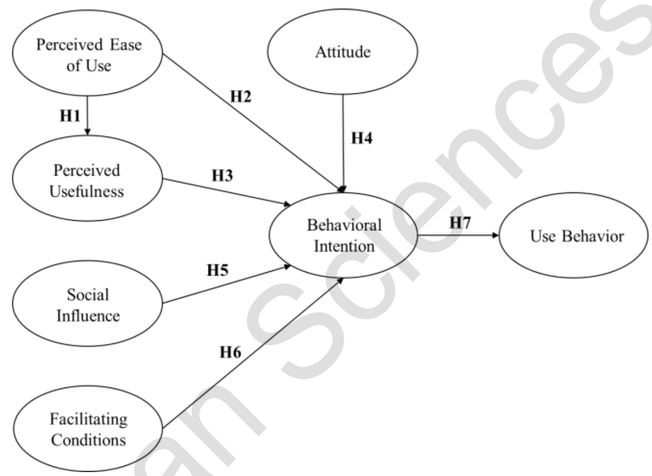

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant impact on perceived usefulness.
H2: Perceived ease of use has a significant impact on behavioral intention.
H3: Perceived usefulness has a significant impact on behavioral intention.
H4: Attitude has a significant impact on behavioral intention.
H5: Social influence has a significant impact on behavioral intention.
H6: Facilitating conditions have a significant impact on behavioral intention.
H7: Behavioral intention has a significant impact on use behavior.

3.2 Research Methodology

This study employed a quantitative method to investigate the online learning adoption of students in higher education in Chengdu, China. The sample techniques are purposive, stratified random, convenience, and snowball samplings. Before collecting the data, The Item Objective Congruence (IOC) Index and the pilot study (n=50) by Cronbach's Alpha were used to assure content validity and construct validity. The data were analyzed by Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). This questionnaire has three parts: screening questions, a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5), and demographic questions.

Index of Item–Objective Congruence (IOC) has been commonly conducted in most research as the evaluation by experts can effectively validate the content (Hambleton et al., 1978). In this research, three experts or professionals who are titled Ph.D. and Chief Executive are invited to rate one of the three scores, which are 1 as "clearly measuring," -1 as "clearly not measuring," or 0 as "unclear measuring" (Turner & Carlson, 2003). The results are that 24 items have been proved at a score of 0.6 and higher. Accordingly, this study involves 50 participants in the pilot study, which was evaluated by Cronbach's Alpha for each construct. The result revealed that the constructs have a coefficient of internal consistency under Alpha Cronbach's value above 0.6 which is considered high reliability and acceptable index (Griethuijsen et al., 2014), including perceived ease of use (0.768), perceived usefulness (0.795), attitude (0.755), social influence (0.766), facilitating conditions (0.755), behavioral intention (0.822), and use behavior (0.886).

3.3 Population and Sample Size

This study's target population is postgraduate students with at least one year of an online learning experience from the top three universities in Chengdu; Sichuan University (SCN), University of Electronic Science and Technology of China (UESTC), and Southwest Minzu University (SWUN). According to Soper (2022), the calculator recommended the minimum sample size appropriate for the complex model of SEM analysis of 425 samples. The data were properly collected from participants who were postgraduates (n=500).

3.4 Sampling Technique

This quantitative study applied probability and nonprobability sampling, including purposive, stratified random, convenience, and snowball sampling. For purposive sampling, the research selected postgraduate students who have at least one year of online learning experience from the top three universities in Chengdu; Sichuan University (SCN), University of Electronic Science and Technology of China (UESTC), and Southwest Minzu University (SWUN). This study conducted stratified random sampling based on the total number of postgraduate students of each university, as shown in Table 1. In addition, this research conducted convenience sampling by electronic survey distribution due to the current situation in China has been restricted to the "Zero Covid-19 Policy." For snowball sampling, the researcher encourages participants to invite their peers to complete the questionnaire.

Table 1: Population and Sample Size by University

Universities	Total number of Postgraduates	Sample Size of Postgraduates
Sichuan University (SCN)	20,000	222
University of Electronic Science and Technology of China (UESTC)	15,000	167
Southwest Minzu University (SWUN)	10,000	111
Total	**45,000**	**500**

4. Results and Discussion

4.1 Demographic Information

In Table 2, the demographic data shows that most respondents are males of 47 percent, followed by females 43.2, and unspecified 9.8. Most respondents are 31-40 years old (39 percent), followed by 22-30 years old (25.6 percent), For the program, Master's Degree is 78.8 percent, and Doctor's Degree is 21.2 percent, 21 years old or below (18.4 percent), and 40 years old or over (17 percent). Most students use online learning 33-48 hours/week (41.6 percent).

Table 2: Demographic Profile

Demographic and General Data (n=500)		Frequency	Percentage
Gender	Male	235	47.0
	Female	216	43.2
	Unspecified	49	9.8
Age	21 years old or below	92	18.4
	22-30 years old	128	25.6
	31-40 years old	195	39.0
	40 years old or over	85	17.0
Program	Master's Degree	394	78.8
	Doctor's Degree	106	21.2
Frequency Of Online Learning Use	1-16 hours/week	41	8.2
	17-32 hours/week	59	11.8
	33-48 hours/week	208	41.6
	Over 48 hours/ week	192	38.4

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is a validation of SEM via measurement model to measure the "Unidimensionality," "Validity," and "Reliability" of a latent variable. Confirmatory factor analysis (CFA) was analyzed by SPSS AMOS statistical software with the measurement of Cronbach's Alpha coefficient values were greater than 0.60, factor loadings were greater than 0.50, t-values were greater than 1.98, p-values were less than 0.50, composite reliability (CR) was greater than 0.70, and average variance extracted (AVE) was greater than 0.50 (Hair et al., 2010). Table 3 demonstrates that all estimates are significant and can confirm the convergent validity of this study.

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
1. Perceived Ease of Use (PEOU)	(Lin, 2013)	3	0.768	0.716-0.741	0.769	0.526
2. Perceived Usefulness (PU)	(Lin, 2013)	4	0.795	0.626-0.797	0.796	0.495
3. Attitude (ATT)	(Hsiao & Tang, 2014)	3	0.755	0.597-0.785	0.769	0.529
4. Social Influence (SI)	(Shen et al., 2019).	4	0.766	0.638-0.716	0.770	0.456
5. Facilitating Conditions (FC)	(Shen et al., 2019).	4	0.755	0.655-0.713	0.777	0.466
6. Behavioral Intention (BI)	(Hsiao & Tang, 2014)	3	0.822	0.816-0.899	0.882	0.713
7. Use Behavior (UB)	(Cao & Jittawiriyanukoon, 2022)	3	0.886	0.826-0.882	0.886	0.721

CFA can be performed prior to inter-relationship modeling in a structural model or SEM. The measurement model can also be assessed by the goodness of fit indices, reflecting how to fit the model is to the data set (Hair et al., 2010). The goodness of fit for the measurement model was measured by GFI, AGFI, NFI, CFI, TLI, and RMSEA, as shown in Table 4.

Table 4: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015)	355.463/231 = 1.539
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.944
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.928
NFI	≥ 0.80 (Wu & Wang, 2006)	0.937
CFI	≥ 0.80 (Bentler, 1990)	0.977
TLI	≥ 0.80 (Sharma et al., 2005)	0.972
RMSEA	< 0.08 (Pedroso et al., 2016)	0.033
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.

Discriminant validity or "divergent validity" refers to "the extent to which latent variable A discriminates from other latent variables" (Fornell & Larcker, 1981). The convergent validity and discriminant validity are confirmed by the square root of average variance extracted, determining all the correlations are higher than the corresponding correlation values as of Table 5.

Table 5: Discriminant Validity

	ATT	PEOU	PU	SI	FC	BI	UB
ATT	**0.727**						
PEOU	0.520	**0.725**					
PU	0.184	0.269	**0.704**				
SI	0.631	0.633	0.284	**0.676**			
FC	0.588	0.515	0.276	0.641	**0.682**		
BI	0.536	0.534	0.315	0.650	0.669	**0.845**	
UB	0.469	0.512	0.265	0.620	0.602	0.658	**0.849**

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 represents the path diagram and model, which can be assessed through the goodness of fit, standardized coefficient values, and t-value. For the application of measurement and structural model estimated in CFA and SEM, the goodness of fit indices was used to confirm that the data is in the range of acceptable values (Schermelleh-Engel et al., 2003). Subsequently, the research conducted the fit indices to examine the model, including CMIN/DF = 3.515, GFI = 0.858, AGFI = 0.827, NFI = 0.847, CFI = 0.885, TLI = 0.870, and RMSEA = 0.071.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015)	861.113/245 = 3.515
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.858
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.827
NFI	≥ 0.80 (Wu & Wang, 2006)	0.847
CFI	≥ 0.80 (Bentler, 1990)	0.885
TLI	≥ 0.80 (Sharma et al., 2005)	0.870
RMSEA	< 0.08 (Pedroso et al., 2016)	0.071
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

Awang (2012) acknowledged that SEM is "a confirmatory method providing a comprehensive means for validating the measurement model of latent constructs." The statistical tool used to test the seven hypotheses of this research is measured by the standardized path coefficient value (β) and t-value. All assumptions are significantly supported at p-value<0.05.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PEOU→PU	0.269	4.590*	Supported
H2: PEOU→BI	0.185	3.753*	Supported
H3: PU→BI	0.121	2.540*	Supported
H4: ATT→BI	0.143	3.083*	Supported
H5: SI→BI	0.406	7.897*	Supported
H6: FC→BI	0.423	8.109*	Supported
H7: BI→UB	0.825	16.608*	Supported

Note: * p<0.05

Based on the findings, all hypotheses are approved and can be explained per the followings:

H1 shows that perceived ease of use significantly impacts perceived usefulness, resulting in the standardized path coefficient value of 0.269 (t-value = 4.590). Many studies during the COVID-19 situation found a strong correlation between perceived ease of use and perceived usefulness among students' behavioral intention to use online learning (Lan et al., 2022; Min et al., 2022; Zhong et al., 2022).

In **H2**, the relationship between perceived ease of use and behavioral intention is supported by a standardized path coefficient value of 0.185 (t-value = 3.753). Bashir and Madhavaiah (2015) supported that effective online learning systems and their facilitators can enhance the behavioral intention to use such systems Zeithaml et al. (2002) extended that perceived ease of use is determined as an intrinsic motivation and behavioral intention.

For **H3**, perceived usefulness significantly impacts behavioral intention, reflecting the standardized path coefficient value of 0.121 (t-value = 2.540). The result aligns with previous studies that students believe online learning would improve their outcomes, impacting behavioral intention (Zhong et al., 2022).

H4 approves the significant impact of attitude on students' behavioral intention, representing a standardized path coefficient value of 0.143 (t-value = 3.083). Per an earlier statement, attitude is an influential driver of intentional behavior to engage in online learning among students (Lan et al., 2022; Min et al., 2022; Zhong et al., 2022).

H5 supports the relationship between social influence and students' behavioral intention with a standardized path coefficient of 0.406 (t-value = 7.897). Therefore, the social influence of students is their peers, teachers, and parents, who impact their decision to adopt an online learning system (Luo et al., 2022).

H6 confirms that facilitating conditions significantly impact behavioral intention with a standardized path coefficient of 0.423 (t-value = 8.109). Accordingly, it explains that when students engage with an online learning system, facilitating conditions are hardware, software, manual, and learning content can encourage them to use it (Rienties et al., 2016)

The results of **H7** present that behavioral intention significantly impacts the use behavior of students with a standardized path coefficient value of 0.825 (t-value = 16.608). Min et al. (2022) referred to behavioral intention as the extent to which students potentially adopt an online system, as they believe it can help them to achieve their education goals.

5. Conclusions and Recommendation

5.1 Conclusion and Discussion

This study approves that the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) can explain the online learning adoption of college students in Chengdu, China. The main variables are perceived ease of use, usefulness, attitude, social influence, facilitating conditions, behavioral intention, and use behavior. The findings show that perceived ease of use significantly impacts perceived usefulness. Behavioral intention strongly and significantly impacts use behavior. Behavioral intention is significantly impacted by perceived ease of use, usefulness, attitude, social influence, and facilitating conditions.

Based on the findings, perceived ease of use significantly impacts perceived usefulness. Patel and Patel (2018) indicated that the two main determinants of TAM are perceived ease of use and perceived usefulness. Lin (2013) reported that perceived ease of use is a predictor of perceived usefulness due to students' awareness that ease of use relates to the benefit they expect. Behavioral intention strongly and significantly impacts use behavior. The study stated that students' behavioral intention could dominate the actual use based on TAM and UTAUT (Al-Imarah et al., 2013; Venkatesh & Zhang, 2010). Subsequently, use behavior represents a successful adoption (Lin et al., 2013).

TAM and UTAUT confirm that behavioral intention is significantly impacted by perceived ease of use, perceived usefulness, attitude, social influence, and facilitating conditions. Online learning can provide convenience and improve student performance (Lin, 2013). Zhong et al. (2022) also proposed that students believe online learning would improve their outcomes, which impacts behavioral intention. Cao and Jittawiriyanukoon (2022) supported that attitude toward the use of online learning learners is the favorable or unfavorable response to such a system, which leads to successful adoption. Vululleh (2018) referred that social influence is the connection between students and other influencers, such as peers or instructors, who impact their intention. Xie et al. (2022) approves that facilitating conditions are educational institutions that provide infrastructure and equipment to facilitate online learning, which endorses students' behavioral intention.

5.2 Recommendation

The virtual classroom has continued in China due to China's "Zero-COVID" Policy after the decline of health and safety restrictions. Therefore, this study addresses the factors to improve the online learning adoption rate. Although online learning allows students to organize their time, it can lead to a false sense of time and proper dedication to serious study. Digital behavior of online learning can lead to bad attitude and time management. Therefore, attitudes towards online learning systems can greatly influence their behavioral intention and use behavior. Other challenges are discipline and motivation. Studying online seems to be anxious as qualities are relatively low. Students mostly fall to numerous distractions, such as social media and websites. Accordingly, the successful adoption of online learning can be assessed through the design of online assignments and close monitoring by educational institutions.

Online learning has dramatically increased adoption in the educational sector during the COVID-19 pandemic. After the decline of health and safety restrictions, the virtual classroom has continued in China due to China's "Zero-COVID" Policy. The importance of this study is to fill the research gap to ensure that all students can adopt digital learning successfully; educational institutions and the Chinese government needs to improve accessibility with the highest-performance online learning infrastructure for the country. Furthermore, most research has been conducted on online learning adoption during the difficult situation of the COVID-19 pandemic. This study has detoured the current situation, in which the pandemic has been controlled, and students are getting used to such a learning mode. Subsequently, whether the adoption rate of online learning could be stronger or not is questioned.

5.3 Limitation and Further Study

This study is limited to several aspects. Based on TAM and UTAUT, there are more variables to consider for further studies, such as trust and satisfaction. Next, the results were evaluated by students from only three selected universities in Chengdu. Different regions can produce different findings. Furthermore, future research can consider the qualitative study to articulate a clearer interpretation or compare the results with the quantitative data.

References

Al-Imarah, A., Zwain, A., & Al-Hakim, L. (2013). The Adoption of E-government Services in the Iraqi Higher Education Context: An application of the UTAUT Model in the University of Kufa. *Journal of Information Engineering and Applications, 3*(10), 77-84.

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). *Research methodology and data analysis.* Penerbit Universiti Teknologi MARA Press.

Bashir, I., & Madhavaiah, C. (2015). Consumer Attitude and Behavioral Intention Towards Internet Banking Adoption in India. *Journal of Indian Business Research, 7*(1), 67-102.

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

Cao, Y., & Jittawiriyanukoon, C. (2022). Factors Impacting Online Learning Usage during Covid-19 Pandemic Among Sophomores in Sichuan Private Universities. *AU-GSB E-JOURNAL, 15*(1), 152-163. https://doi.org/10.14456/augsbejr.2022.52

Chang, M. A. (2020, July 8). *Virtual Education.* CKGSB Knowledge. https://english.ckgsb.edu.cn/knowledges/virtual-education-in-china/

Chiu, Y. L., & Tsai, C. C. (2014). The roles of social factor and internet self-efficacy in nurses' web-based continuing learning. *Nurse Education Today, 34*(3), 446-450.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 19-340.

Feng, D., Xiang, C., Vongurai, R., & Pibulcharoensit, S. (2022). Investigation on Satisfaction and Performance of Online Education Among Fine Arts Major Undergraduates in Chengdu Public Universities. *AU-GSB E-JOURNAL, 15*(2), 169-177. https://doi.org/10.14456/augsbejr.2022.82

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

Griethuijsen, R. A. L. F., Eijck, M. W., Haste, H., Brok, P. J., Skinner, N. C., Mansour, N., Gencer, A. S., & BouJaoude, S. (2014). Global patterns in students' views of science and interest in science. *Research in Science Education, 45*(4), 581-603. https://doi.org/10.1007/s11165-014-9438-6

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

Hambleton, R. K., Swaminathan, H., Algina, J., & Coulson, D. B. (1978). Criterion-referenced testing and measurement: A review of technical issues and developments. *Review of Educational Research, 48*(1), 1-47. https://doi.org/10.2307/1169908

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

Lan, W., Xiang, C., & Yang, M. (2022). Impacting Factors of Postgraduates' Behavioral Intention and Satisfaction in Using Online Learning in Chengdu University. *AU-GSB E-JOURNAL*, *15*(2), 70-79. https://doi.org/10.14456/augsbejr.2022.73

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

Lin, P., Hsin-Ke, L., & Liu, S. (2013). Towards an Education Behavioral Intention Model For E-Learning Systems: An Extension Of UTAUT. *Journal of Theoretical and Applied Information Technology, 47*(3), 1120-1127.

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

Min, Y., Huang, J., Varghese, M. M., & Jaruwanakul, T. (2022). Analysis of Factors Affecting Art Major Students' Behavioral Intention of Online Education in Public Universities in Chengdu. *AU-GSB E-JOURNAL*, *15*(2), 150-158. https://doi.org/10.14456/augsbejr.2022.80

Patel, K. J., & Patel, H. J. (2018). Adoption of internet banking services in Gujarat: An extension of TAM with perceived security and social influence. *International Journal of Bank Marketing, 36*(1), 147-169. https://doi.org/10.1108/IJBM-08-2016-0104

Paul, K. J., Musa, M., & Nansubuga, A. K. (2015). Facilitating Condition for E-learning Adoption--Case of Ugandan Universities. *Journal of Communication and Computer, 12,* 244-249. https://doi.org/10.17265/1548-7709/2015.05.004

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.

Pham, L. T., & Dau, T. K. T. (2022). Online learning readiness and online learning system success in Vietnamese higher education. *International Journal of Information and Learning Technology, 39*(2), 147-165. https://doi.org/10.1108/IJILT-03-2021-0044

Rienties, B., Giesbers, B., Lygo-Baker, S., Ma, H. W. S., & Rees, R. (2016). Why some teachers easily learn to use a new virtual learning environment: a technology acceptance perspective. *Interactive Learning Environments, 24*(3), 539-552.

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the Fit of Structural Equation Models: Tests of Significance and Descriptive Goodness-of-Fit Measures. *Methods of Psychological Research Online, 8*(8), 23-74.

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

Shen, C. W., Ho, J. T., & Pham, L., & Kuo, T. C. (2019). Behavioural intentions of using virtual reality in learning: perspectives of acceptance of information technology and learning style. *Virtual Reality, 23*(3), 129-137. https://doi.org/10.1007/s10055-018-0348-1

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.

Singh, P. (2022, January 21). *How Will E-learning Transform Education in a Post-COVID 19 World?*. https://trainingmag.com/how-will-e-learning-transform-.education-in-a-post-covid-19-world/

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

Swanson, B. A., & Valdois, A. (2022). Acceptance of online education in China: A reassessment in light of changed circumstances due to the COVID-19 pandemic. *International journal of educational research open*, *3*, 100214. https://doi.org/10.1016/j.ijedro.2022.100214

Tarhini, A., Deh, R. M., 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. https://doi.org/10.1108/JIEB-09-2016-0032

Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. *Computers & Education, 57*(4), 2432-2440.

Turner, R., & Carlson, L. (2003). Indexes of Item-Objective Congruence for Multidimensional Items. *International Journal of Testing, 3*(2), 163-171. https://doi.org/10.1207/S15327574IJT0302_5

UNESCO. (2022, April 21). *How is China ensuring learning when classes are disrupted by coronavirus?*. https://www.unesco.org/en/articles/how-china-ensuring-learning-when-classes-are-disrupted-coronavirus

Venkatesh, V., & Zhang, X. (2010). Unified theory of acceptance and use of technology: U.S. vs. China. *Journal of Global Information Technology Management, 13*(1), 5-27.

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

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178.

Vululleh, P. (2018). Determinants of Students' E-Learning Acceptance in Developing Countries: An Approach Based on Structural Equation Modeling (SEM). *International Journal of Education and Development Using Information and Communication Technology, 14*(1), 141-151.

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

Wut, T. M., Lee, S. W., & Xu, J. (2022). How do Facilitating Conditions Influence Student-to-Student Interaction within an Online Learning Platform? A New Typology of the Serial Mediation Model. *Education Science, 12*(5), 337. https://doi.org/10.3390/educsci12050337

Xie, H., Kitcharoen, K., Leelakasemsant, C., & Varghese, M. M. (2022). The Effect of Behavioral Intention to Use Hybrid Education: A Case of Chinese Undergraduate Students. *AU-GSB E-JOURNAL*, *15*(2), 159-168. https://doi.org/10.14456/augsbejr.2022.81

Zeithaml, V. A., Parasuraman, A., & Malhotra, A. (2002). Service quality delivery through web sites: a critical review of extant knowledge. *Journal of the Academy of Marketing Science, 30*(4), 362-375.

Zhong, K., Feng, D., Yang, M., & Jaruwanakul, T. (2022). Determinants of Attitude, Satisfaction and Behavioral Intention of Online Learning Usage Among Students During COVID-19. *AU-GSB E-JOURNAL*, *15*(2), 49-57. https://doi.org/10.14456/augsbejr.2022.71